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COPPER FLASH SMELTING PROCESS. MODELLING AND CONTROL

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Abstract

The paper presents the description of the copper flash smelting process and the idea of its modelling based on Artificial Intelligence techniques: Artificial Neural Networks, Expert Systems and Data Mining. Proposed approach is illustrated by examples of obtained results. They show that models based on Artificial Intelligence tools can be useful in process analysis and in control systems.

Key words: copper flash smelting process, modelling and control of metallurgical processes, application of artificial intelligence in copper metallurgy

1. INTRODUCTION

Model of the industrial process is the basis of its numerical analysis and control. The quality of a model affects the accuracy and reliability of obtained results. In the case of complex, industrial processes, for which there is a lack of precise, mathematical deterministic models, commonly used modelling techniques are often based on the Artificial Intelligence (AI) techniques. That approach appears efficient in the case of complex processes, for which the identification is difficult or even impossible. Artificial Intelligence models are mainly based on the Artificial Neural Networks and Expert Systems.

The paper presents the overview of the main modelling ideas of the direct-to-blister (one-stage) copper flash smelting process based on the AI techniques and should be considered as an introduction to the other papers published in the current volume of the journal. These papers present the mentioned above AI techniques in application to the considered copper flash smelting process and the representive results of research conducted within the project No 3 T08B 034 30 of Ministry of Science and Higher Education in Poland.

2. COPPER FLASH SMELTING PROCESS

Technology of a copper flash smelting process was developed by Outokumpu Oy, Finland in the late forties of the XXth century. The essential reason of searching for a new technology of the copper production was the necessity of replacement of the old energy-consuming technology (realized in shaft, reverberatory or electric furnaces), by new, energy-saving one. The meaning of the process name comes directly from its nature. The process consists of the rapid melting and chemical reactions of the concentrate grains in the gas (mainly O_2). The smelting process occurs during the gravitational falling down of the concentrate grains in the reaction shaft, between the dosing nozzles and the surface of the liquid molten products in the furnace bath. Actually,

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almost 50% of the world copper matte production is based on the copper flash smelting technology. Only three plants in the world are realizing this process with direct-to-blister (one-step), flash smelting technology, which is the subject of the present work.

Copper flash smelting process is the main one in the copper production chain in "Huta Miedzi Głogów II" copper plant (figure 1).

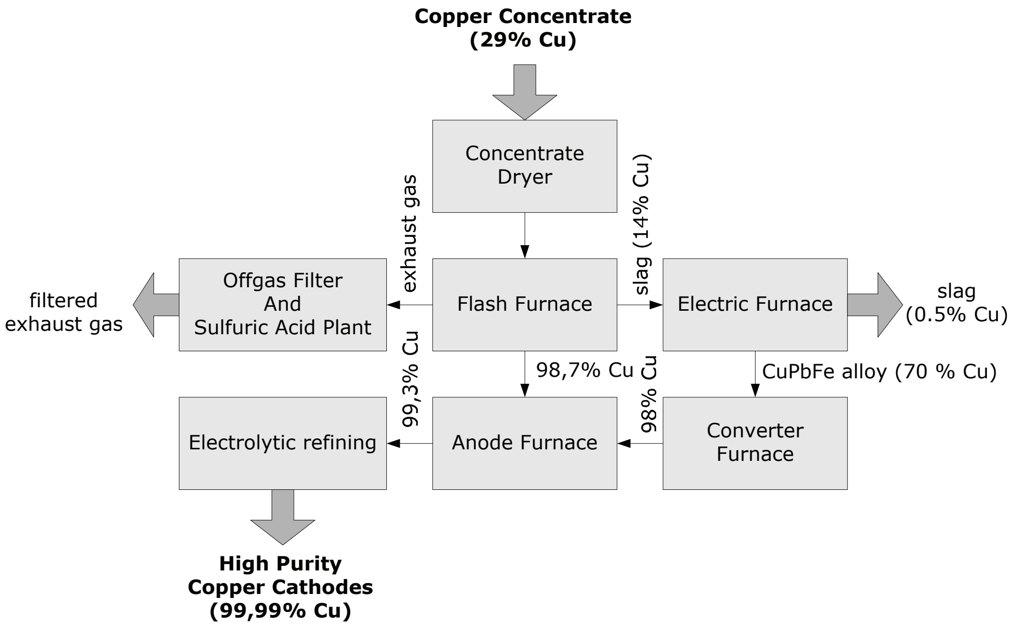

Fig. 1. *The flow chart of the copper production chain.*

The copper production chain (figure 1) is composed of the following main steps:

- pre-processing of the charge materials: grinding, grain classification and drying of the concentrates up to 0.3% H_2O;
- melting of the concentrate in the flash smelting furnace resulting in obtaining of the copper of the quality corresponding to that of the converter process;
- reduction of a flash smelting slag in the electric furnace to the copper contents below 0.6% in the waste slag;
- converter process of the obtained CuPbFe alloy results in obtaining of the converter copper containing below 0.3% Pb and 1.0 % As.

The main idea of the direct-to-blister (one-stage) copper flash smelting process is oxidation of the fine-grained, dry copper concentrate in the vertical, streamline layer formed inside the reaction shaft of the furnace. The copper flash smelting furnace is composed of three main modules (figure 2):

- reaction shaft,
- settler bath,
- gas shaft.

The detailed description of the construction of the copper flash smelting aggregate can be found in (Biswas & Davenport, 1994; Davenport & Partelpoeg, 1987; Kucharski, 2003).

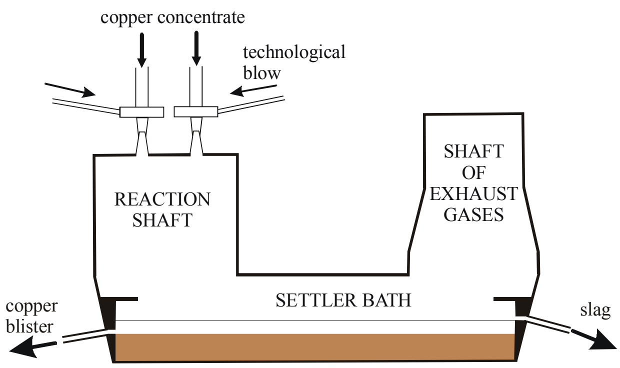

Fig. 2. *Copper flash smelting furnace.*

The charge (copper concentrates) for the furnace comes from different mines, so it should be optimised with respect to different conditions, among which the most important are:

- required average chemical composition,
- adequate grain size of the concentrate,
- low humidity of the concentrate.

The average chemical composition of the concentrate is given in table 1.

Rich in oxygen (up to 80% of O_2) blast affects the deep oxidation of the concentrate in the reaction shaft and initiates the chemical reactions (Talar et al., 2006). The necessary oxygen volume is related to the chemical composition of the concentrate. The transformation degree of individual grains of the concentrate depends on their size. The copper minerals contained in the smallest grains undergo the oxidation to the copper oxides. The medium size grains react to the metallic copper and copper oxides, while in the greatest grains, it is only the outer layer which undergoes the oxidation process. The diversified size and the density of the concentrate grains result in various times they spend in the reaction shaft and, in consequence, causes various oxidation degrees of separate particles. Further chemical reactions occur in the settler bath.

allows the elimination of the converter process for approximately of 2/3 of produced copper.

Copper flash smelting process is a complex one. Some reactions occurring in the reaction shaft as well as in the settler bath are difficult to model mathematically. The modern mathematical models based on the thermo-physics of the occurring physical and chemical reactions of the copper flash smelting process can be classified in the following three groups (Donizak et al., 2003):

- Locally Homogenous Flow models - LHF,
- Separated Flow models - SF,
- Drop-Life History models - DLH.

Table 1. *Chemical composition of the domestic concentrate charge (average values).*

Cu [%]	Fe [%]	Pb [%]	Zn [%]	As [%]	Ag [ppm]	SiO_2 [%]	CaO [%]	MgO [%]	Al_2O_3 [%]	S [%]	C_{org} [%]	K_2O+Na_2O [%]	H_2O [%]
29.27	3.16	1.55	0.39	0.103	675	17.78	6.50	3.73	5.71	11.76	7.25	2.31	0.26

Concentrate particles containing non-oxidised ingredients such as FeS, Cu_2S, and PbS, fall down to the slag layer and react with its core components, mainly with Cu_2O. Metallic copper and sulphur dioxides are the products of these reactions. Therefore, the slag containing Cu_2O becomes not only a collector of oxides, but also as a chemical filter protecting metal against its pollution by sulphur and also by metals of higher then Cu affinity to oxygen. After some chemical reactions the gravitational separation of obtained copper from the slag occurs, as a result of the their high diversity of densities (γ_{Cu} = 8.5÷8.7 g/cm^3; (γ_{slag} = 3.1÷3.4 g/cm^3).

Summarizing, the following process products are the result of melting of the concentrate in the copper flash smelting aggregate:

- Blister copper of less then 0.3 % of lead and up to 0.5 % of oxygen;
- Flash smelting slag of high copper content of 11% to 15 %;
- Dusts containing sulphates and oxides of calcium, magnesium, copper, iron and others;
- Exhausts gases of high SO_2 concentration (12 to 18 % vol.).

The quality of the produced blister copper is determined mainly through the content of lead, which should not exceed 0.3%. Only such product fulfils the requirements of the fire refining process in the anode furnace. Blister copper of the high quality

The first two groups are oriented on the flow description in the macroscopic scale, while the last one focus on the analysis of phenomena occurring on the interface surface of a single particle. All models have the common feature of the separate mathematical description of the flow of both phases. These models are expressed by the mass and substances balances of gas and condensed phases, equations of the momentum and energy balance, as well as equations of kinetics of chemical reactions and the particles transport. Since the smelting process is a dynamic one, there are many simplifications in these models, which cause that they are not reliable in the case of the variations of the process input parameters. Moreover, they require a lot of computation time, which makes them useless from the point of view of the on-line control system.

All these facts inspired the partners in the project No 3 T08B 034 30 to searching for other computing efficient models.

3. MODELLING OF THE COPPER FLASH SMELTING PROCESS USING THE ARTIFICIAL INTELLIGENCE METHODS

Because of the problems of mathematical modelling of the considered copper flash smelting process, the partners of the realized project decided to undertake an attempt of application the Artificial Intelligence methods, especially Artificial Neural Networks (ANN), Expert Systems (ES) and Data Mining techniques (DM), to model that process. The brief description of the used techniques and the illustrative examples of obtained results are presented below.

3.1. Neural Networks

Artificial neural networks (ANN) (Arbib, 1995; Osowski, 1996; Tadeusiewicz, 1993) have become a powerful tool in simulation and control of various processes (Omidvar & Elliott, 1997). The commonly used architecture of neural networks is a Multi-Layer Perceptron (MLP) (Gomm et al., 1993). That network consists of an input layer, hidden layers (typically one or two hidden layers are used) and an output layer. The MLP network is trained using the supervised learning methods (Arbib, 1995). It means that during training of a network, both the input and corresponding output data are used. The most common is the backpropagation algorithm (Gupta et al., 2003). An input pattern is applied to the network and an output is generated. This output is compared to the corresponding target output and an error is produced. The error is then propagated backwards through the network, from the output to the input, and the network weights are adjusted in such a way, that the error is minimized. The important feature of the MLP is that this network can accurately represent any continuous non-linear function relating the inputs and outputs. It causes that MLP network is often used in modelling and control of real non-linear processes (Page et al., 1993).

As the example of the ANN modelling of the copper flash smelting process, the results of the MLP predictions of the lead concentration in blister copper are presented in figures 4 (Talar et al., 2006).

More results of the application of the Neural Networks in modelling of the concentration of exhaust gases can are presented in the work (Stanisławczyk & Kusiak, 2009a).

3.2. Expert Systems

Expert Systems (ES) (Hopgood, 2000; Mulawka, 1996) belong to the methods of Artificial Intelligence. These systems are an intelligent computer programs, which use knowledge and inference procedures to solve problems. The typical expert system consists of:

− knowledge database,
− inference engine,
− explanation subsystem.

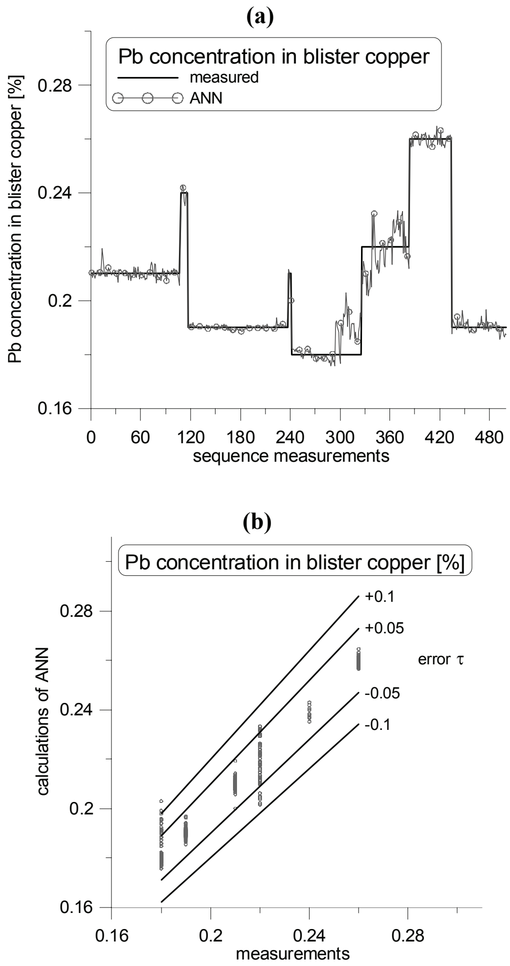

Fig. 4. Comparison of measured and calculated by ANN values of Pb concentration in a blister copper (a), and the error of ANN predictions of Pb concentration in a blister copper (94% and 100% results of ANN are within the ranges of ±0.05 and ±0.1, respectively) (b) (Talar et al., 2006).

The knowledge database stores the encoded knowledge about the analysed problem. There are many types of the knowledge representation, but the most popular is the form of rules: "if *premise* then *conclusion*". An inference engine uses the reasoning mechanism to draw the conclusions from premises and generates the solution of the problem. An inference engine decides which, and in what order, the rules should be selected for firing.

Knowledge Engineers acquire the knowledge from human experts or other sources and encode it to the expert system. The problem of transferring human knowledge into the expert system is very difficult and time-consuming. Therefore, the machine learning algorithms are used for elaboration of the knowledge base. In that case, the industrial data sets can be used to the exploration of knowledge using machine learning algorithms. For example, the C4.5 algorithm developed by Quinlan can by applied to generation of the decision trees. The knowledge in the form of decision trees can be transformed into the decision rules and than implemented in the knowledge base of the expert system. The C4.5 algorithm builds decision tree by recursively selection of attributes. The criterion used for selecting an attribute is information gain. For more details about C4.5 algorithm see (Quinlan, 1993).

Results of application of expert systems to modelling of the copper flash smelting process are presented in (Talar et al., 2006), where the C4.5 algorithm was applied to generate the rule-based expert system prediction of the *boiling level* of the copper bath. The obtained results were comparable to those of the Neural Network predictions.

More results of the Expert System models of the copper flash smelting process are presented in the work (Talar et al., 2009).

3.3. Data Mining analysis

Interesting, and close to the Artificial Intelligence, is the data mining analysis. The Data Mining algorithms allow searching for the existing relationships between the process parameters, within the huge data bases. Usually, it is very difficult or even impossible to discover these relationships using the conventional statistical analysis. It is possible to use the Data Mining algorithms to the analysis of the copper flash smelting process and to look for the existing, but hidden association rules (cause and effect relationships) between chosen process parameters. The results of the association analysis are presented in table 1, in which found association rules between the copper contents in slag and the process input parameters are collected.

Found association rules enhance the comprehension of the complex copper flash smelting process and can be implemented in the process control system. More details about the analysis of associations and obtained results can be found in the work (Jarosz et al., 2009).

4. OPTIMIZATION AND CONTROL OF THE COPPER FLASH SMELTING PROCESS

The Artificial Intelligence method can be implemented to the optimization and control of the copper flash smelting process. The general idea of such control system is presented in figure 5. The control system allows achieving the required quality of the output products of the copper flash smelting process (Talar et al., 2006; Talar et al., 2005).

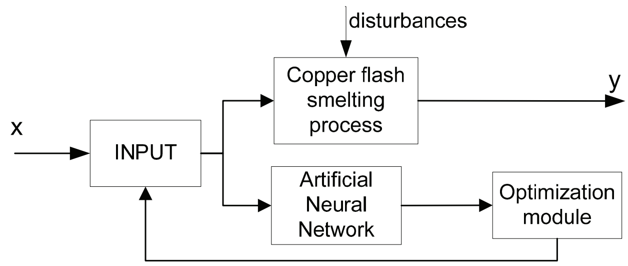

Fig. 5. *The general idea of the control system of the copper flash smelting furnace.*

In the case of the static model of the process, the control system is equivalent to the optimization procedure. The goal of this procedure is to find values of the input vector, which ensures required values of output vector of considered copper flash smelting process (Stanisławczyk et al., 2007). The model of the process is based on Artificial Neural Network approach described above. The control system of the composition of polluted exhaust gases is presented below as an example of the system based on the ANN model. The composition of these gases can be characterized by the following three main parameters – concentrations of: sulphur dioxide (SO_2), car-

Table 2. *Association rules between the copper contents in slag and the process input parameters*

No.	Cause	Effect	Support	Confidence
1	High copper contents in slag	WE23_SiO2_konc > 20,175	43,51	78,32
2	Mean copper contents in slag	WE_6-10_IOS_P1-5 > 5,835 & WE21_S_konc < 11,390	65,31	80,33
3		WE_6-10_IOS_P1-5 > 5,835 & WE20_Cu_konc < 30,240	64,25	79,67
4		WE_6-10_IOS_P1-5 > 5,835	37,57	60,87
5	Low copper contents in slag	WE27_nad_sita > 3,050	64,60	84,62
6		WE27_nad_sita > 3,050 & WE5_Pyly > 8,515	59,24	78,79

bon dioxide (CO_2) and nitrogen oxides (NO_x). Objective function is given by the formula:

$$\varepsilon = \sqrt{\frac{1}{3}\sum_{i=1}^{3}\left(\frac{y_i - y_i^*}{y_i^*}\right)^2}\ 100\ [\%]$$

where: y_i is a current value of i-th output (concentration of sulphur dioxide, carbon dioxide and nitrogen oxides respectively), y_i^* is the required value of i-th output. The required values of considered parameters of exhaust gases respectively are: 16.5 % of SO_2, 45 % of CO_2 and 900 ppm of NO_x. As the result of the optimization procedure, the observed error was up to 0.242%. Such low value of the error means that the found values are optimal and give the required level of the output parameters, despite the existing disturbances. Detailed description of the process control system is presented in work (Sztangret et al., 2009).

5. SUMMARY

Artificial Intelligence becomes an useful tool in solving complex problems related to modelling and control of complex industrial processes, for which there is a lack of the precise mathematical models. Present work is an overview on the ideas of application Artificial Neural Networks, Expert Systems and Data Mining algorithms to the modelling of the copper flash smelting process. Some results of chosen examples of the application of the AI models to the control system are presented. More details of the described models can be found in works (Stanisławczyk & Kusiak, 2009b; Stanisławczyk et al., 2009; Talar et al., 2009; Jarosz et al., 2009; Sztangret et al., 2009). The performed analysis and obtained results of the application of the artificial intelligence techniques in the modelling of the copper flash smelting process presented in these publications, prove also the usefulness of the proposed approach to the analysis of complex, industrial parameters of numerous parameters, for which the conventional numerical modelling is difficult and time-consuming. Moreover, it shows, how important is a thorough pre-processing of the overload of the datasets, as well as how these data are the source of interesting and revealing knowledge.

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ZAWIESINOWY PROCES WYTOPU MIEDZI. MODELOWANIE I STEROWANIE

Streszczenie

W pracy przedstawiono proces zawiesinowego wytopu oraz ideę jego modelowania z wykorzystaniem narzędzi sztucznej inteligencji. Omówiono idee modeli opartych o sztuczne sieci neuronowe oraz systemy ekspertowe. Ponadto, przedstawiono możliwości wykorzystania algorytmów eksploracji danych do analizy danych procesu. Przedstawione przykładowe wyniki potwierdzają przydatność modeli na bazie sztucznej inteligencji w analizie procesu, jak również w systemach sterowania.

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