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Original Research Article

An attempt of optimization of zinc production line

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ABSTRACT

The goal of the research is an attempt of optimization of the hydrometallurgy-based zinc production line, consisting of three stages: mixing of raw materials, oxidative roasting and leaching. The output product of one stage is an input to the next stage. Goal of mixing is preparation of zinc concentrates mix on the basis of zinc concentrates originated from different mines. The output semi-product of the next stage, the oxidative roasting process, is calcine, which is the input of the leaching. The result of the leaching is zinc sulfate solution and the goal of leaching is to carry out the maximum amount of zinc to solution. The preliminary step of any optimization is modeling of the analyzed processes. Modeling of considered three stages of zinc production line, based on the real industrial data of one of zinc production plants, was performed using different techniques. The elaborated models were the basis of the optimization for given objective functions of each of the production stages. The optimization methodology of multi-stage processes developed by the authors was applied. Obtained results of modeling and optimization are presented.

1. Introduction

The well-known hydrometallurgy-based zinc production plant was selected. Zinc production plant is generally multiline, consisting of many stages giving various products or semi-products, such as zinc, sulfur acid, etc. [1]. The flow chart of a typical production line for hydrometallurgical zinc production is shown in Fig. 1.

The goal of the research is modeling and optimization of three consecutive stages of the hydrometallurgical zinc production line: mixing, oxidative roasting and leaching (see red box in Fig. 1). In the mixing stage the zinc concentrates are mixed, in order to obtain a specific chemical composition. The obtained concentrate is the input material of fluidized-bed furnace, where the oxidative roasting process occurs. In the last considered stage the roasted zinc undergoes leaching, which results in obtaining the solution of zinc sulfate.

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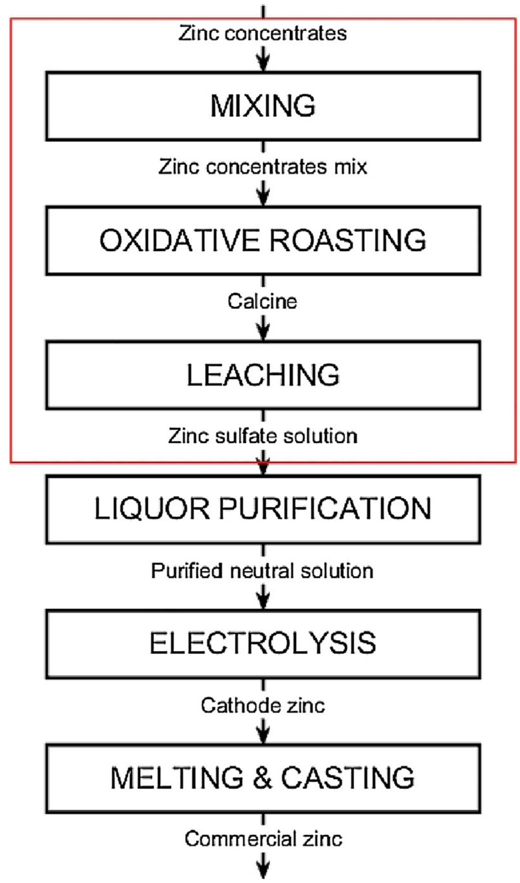

Fig. 1 – Flow chart of considered zinc production line with considered stages marked by the red line.

In terms of control the most demanding process occurs in oxidative roasting stage. It tends to eliminate sulfur from input concentrate through oxidation of sulfides into oxides or sulfate to achieve the minimal concentration of sulfide sulfur in the roasted products. The humid sulfide concentrate reacts with the air blow giving the zinc oxides and the gases containing SO_2.

One of the main problems which appear in this process is too high concentration of sulfide sulfur in the calcine, mainly in the form of ZnS, FeS, FeS_2 and PbS. According to the literature and the technologists' experience the content of sulfide sulfur in the calcine should not exceed 0.5 wt.%. However, the analysis of industrial data shows that in many cases this concentration reaches even 1 wt.%. The main reason of such high level sulfide sulfur is the improper temperature of the roasting process. As it is described in Section 2.2, the temperature inside the furnace cannot be controlled in direct way, i.e. the process operator can change the temperature by changing some related parameters, like concentrate fed or air blow under the furnace hearth. However, the influence of control parameters on the temperature and thus on concentration of sulfide sulfur depends on the input concentrate composition causing difficulties in process controlling. An example of the system dedicated to control the oxidizing roasting process can be found in [2].

The paper presents the results of an attempt of the optimization of the mentioned above three stages of zinc production, where the output product of one stage is an input to the next stage. The main objective of the optimization was obtaining the maximal value of zinc concentration in zinc sulfate solution. Quality, and in consequence the price of the final product, depend on the quality of semi-products of subsequent production stages.

The quality assessment in the first considered stage (mixing) takes into consideration two objective functions: chemical parameters of the concentrates mix and its final price. The main goal of oxidative roasting stage is minimization of concentration of sulfide sulfur in calcine because of its negative influence on the zinc extraction to zinc sulfate solution. It is the main quality determinant of this stage. In the last stage (leaching) quality is measured by zinc extraction to zinc sulfate and the leaching time. In the process of search for optimal solution a methodology of optimization of multi-stage processes developed by Jarosz et al. [3] was applied (described in detail in Section 3.1) and the results are presented.

2. Modeling of zinc production line

Optimization (as well as the automatic control) of any industrial process requires its mathematical model. Therefore, the preliminary step of any optimization is elaboration of mathematical model of analyzed process. three considered stages of zinc production (mixing, oxidative roasting and leaching) should be modeled prior to optimization. Due to their nature, each stage was modeled using different technique.

2.1. *Modeling of mixing stage*

The first step in the hydrometallurgy-based technology of a zinc production line is a mixing stage. Its goal is a preparation of zinc concentrate mix on the basis of zinc concentrates originated from different mines, characterized by different chemical compositions, qualities and prices. These concentrates are being mixed in assumed proportions and a zinc sulfide concentrate of specific chemical composition is obtained. The raw materials are characterized by the percentage content of four main elements: zinc, lead, iron and sulfur. The following linear models of chemical composition of zinc sulfide concentrate, as the result of mixing of raw materials originating from n different providers, were considered:

$$\%p^{OUT} = \sum_{i=1}^{n} x_i \cdot \%p_i^{IN} \tag{1}$$

where x_i is the mass of ith concentrate; $\%p_i^{IN}$ are percentage contents of considered elements (Zn, Pb, Fe and S) in ith input raw material coming from ith provider and n is the number of providers; $\%p^{OUT}$ are percentage contents of considered elements (Zn, Pb, Fe and S) in the sulfur zinc concentrate. It was assumed that ingredients are uniformly mixed and chemical composition is the same in whole volume of mixed concentrate. Zinc sulfide concentrate is mixed with water, and concentrate becomes the input material of fluidized-bed furnace, where the oxidative roasting process occurs.

2.2. Modeling of oxidative roasting stage

In considered hydrometallurgy-based technology of zinc production, the humid zinc concentrate undergoes the roasting process in the fluidized-bed furnace.

The analysis of literature of roasting in the fluid bed does not provide information on the modeling, nor optimization of this process. Sztangret et al. [4] attempted to model the process based on data from the industrial process. This method has partly been used in this work.

Due to multidimensionality of the space of input parameters, process high non-linearity and by a high dynamics of occurring chemical reactions to model the oxidizing roasting process that allows prediction of a concentration of sulfide sulfur in calcine, artificial neural network (ANN) approach was applied. The ANN based modeling technique is well known for at least two decades and there a number of textbooks providing detailed description of this approach, e.g. [5]. The selection of ANN technique among many others was made based on previous Authors' research published in [6]. There are a lot of ANN types which differ in their topology and thus their purposes. In case of approximation problem, the feed-forward MLP (multi-layer perceptron) type of network is usually used. The main advantage of ANN is its ability of learning any input-output relation based on the training dataset.

The collected dataset used for ANN's training contains measurements of more than fifty parameters of the process, chemical composition of concentrate as well as the concentration of the sulfide sulfur in calcine [4]. All these data were divided as follows:

- parameters of the process – this set covers twenty one days of one continuous work of furnace with one second sampling time. 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 decrease sampling time to 60 s, maintaining satisfactory reliability of the process description,
- chemical composition – the main parameters of the concentrate i.e. concentration of Zn, Pb, Fe and S were measured and registered every six hours. However, the concentration of sulfide sulfur in calcine was collected only once a day. In both cases, low frequency of the data sampling was caused by the necessity of laboratory tests, which usually are time and cost consuming. To obtain the same frequency of measurements the linear interpolation was used.

From the set of all measured parameters, main 20 parameters were selected as the most significant for the ANN model. The selection was based on technological knowledge about the process and preliminary correlation analysis. Afterwards, this set of parameters was divided into three groups:

- independent parameters – in most cases these parameters are related to the input zinc sulfide concentrate (chemical composition, humidity, etc.). These independent parameters are: concentration of Zn, Pb, Fe and S in the concentrate,
- 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, mass of concentrate, air pressure, etc.), and influence the capacity of sulfide sulfur in a final product. The dependent parameters are: temperatures in all layers of the furnace, temperature behind the boiler, concentration of SO_2 behind converter, pressure in the top of the furnace, air pressure under the furnace heart,
- control parameters – the set of signals (e.g. air pressure or mass of concentrate), which can be used to control the process. These parameters are independent from the others. The control parameters are: concentrate mass, 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.

The goal of the model is to predict the value of the concentration of sulfide sulfur in calcine. The process was modeled by two sub-models: auxiliary and main ANNs (see Fig. 2). The objective of the auxiliary model was prediction of the dependent parameters on the basis of independent and control parameters. The main ANN predicts the concentration of sulfide sulfur in calcine, taking in the consideration all input parameters (independent, dependent and control).

The gathered dataset consisting of over 30,000 records was divided to ANN's training (90%) and testing (10%) data. Due to the fact that ANN's accuracy depends on its topology each network was trained 10 times and different topologies were examined. The number of hidden layer was equal to 1 or 2 and the number of neurons was randomly selected from range [10–30] and [5–15] for first and second hidden layer, respectively. The each network error was computed using the formula:

$$\epsilon = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i^{ANN}-y_i^{TEST}}{y_i^{TEST}}\right)^2} \tag{2}$$

where y^{ANN} is the value returned by network, y^{TEST} is the value from testing dataset, n is the number of testing points.

The final topologies of each network, as well as modeling errors are presented in Table 1.

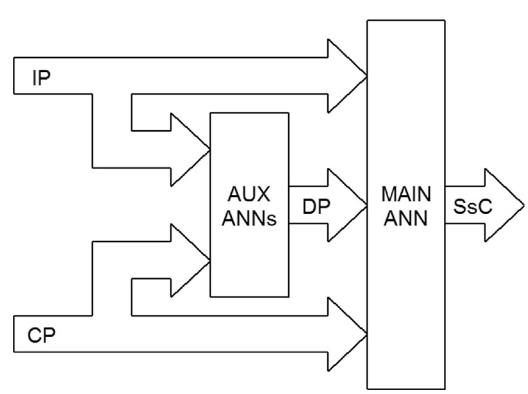

Fig. 2 – The scheme of ANN model of the oxidative roasting stage. IP – independent parameters, CP – control parameters, DP – dependent parameters, SsC – sulfur sulfide Concentration in calcine.

Table 1 – The topologies and modeling errors of ANN's.

ANN	Predicted parameter	Topology	Error [%]
MAIN ANN	Concentration of sulfide sulfur in calcine	20-29-8-1	2.2836
AUX ANN 1	Temperature inside the furnace	11-21-8-1	0.7409
AUX ANN 2	Temperature of the fluid bed No. 1	11-26-11-1	0.7124
AUX ANN 3	Temperature of the fluid bed No. 2	11-25-1	0.8459
AUX ANN 4	Temperature of the fluid bed No. 3	11-13-15-1	0.7623
AUX ANN 5	Temperature at the top of fluid bed furnace	11-24-6-1	0.2335
AUX ANN 6	Temperature at the back of the boiler	11-25-1	0.549
AUX ANN 7	Air pressure under the furnace hearth	11-28-7-1	0.4868
AUX ANN 8	Concentration of a SO_2 before contact device	11-27-11-1	3.3872

2.3. *Modeling of leaching stage*

Neutral leaching [7] is carried out in a continuous process. Returning electrolyte and calcine are fed into cascade tanks. In subsequent tanks the pH value increases. Basic process can be described by the following relationship:

$$ZnO + H_2SO_4 = ZnSO_4 + H_2O \quad (3)$$

The result of the leaching is zinc sulfate solution (pH~5). The goal of leaching is to carry out the maximum amount of zinc to solution. The degree of transition of zinc to solution depends on many factors. The most important are:

- content of sulfide sulfur in calcine, which is almost entirely associated with zinc in insoluble zinc sulfide,
- lead content,
- iron content.

Leaching laboratory tests for calcine characterized by various values of these parameters led to obtaining an empirical relationship describing the maximum of zinc extraction η_{Zn}^{MAX} in the output solution as a function of these parameters, which is as follows:

$$\eta_{Zn}^{MAX} = 100 - 2Ss - 0.6Fe - 0.055e^{1.2Pb} - a \quad (4)$$

where Ss is content of sulfide sulfur in calcine [%], Fe is iron content in calcine [%], Pb is lead content in calcine [%], a describes zinc losses (2%).

Given relation refers to the calcine with similar physical properties and its chemical composition differs slightly in contents of sulfur (0.3–0.7%), lead (1.8–3.0%) and iron (5.6–7.2%). The model of the process was obtained by describing kinetics relations of leaching for several different final zinc extractions (see Fig. 3). This model was used in the optimization of leaching process. Design parameter was leaching time and the objective was searching of the maximum zinc extraction to zinc sulfate solution.

The relationship presented in Fig. 3 was approximated using the following formula:

$$\eta_{Zn}(t) = \eta_{Zn}^{MAX}\left(1 - \frac{a}{a-b}e^{-t/a} + \frac{b}{a-b}e^{-t/b}\right) \quad (5)$$

where a and b are approximation parameters, responsible for the rate of zinc extraction growth and its values are depended on the value of η_{Zn}^{MAX} (see Fig. 3). The most important part of leaching stage model is evaluation of the relationship between approximation parameters (a and b) and the maximum extraction of zinc η_{Zn}^{MAX}. This relation was modeled using the first order spline functions based on five curves (two exemplary curves are shown in Fig. 3). The obtained spline functions are shown in Fig. 4.

The error of elaborated model of the leaching stage was expressed by the formula:

$$\epsilon = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{1}{m-1}\sum_{m}^{j=2}\left(\frac{\eta_{Zn\,i,j} - \eta_{Zn\,i,j}^{TEST}}{\eta_{Zn\,i,j}^{TEST}}\right)^2} \cdot 100\,[\%] \quad (6)$$

where n is the number of test curves, m is the number of points in the curve, η_{Zn} and η_{Zn}^{TEST} are values of percentage zinc extraction returned by model and value from testing dataset, respectively. The index j begins from 2 because the value of

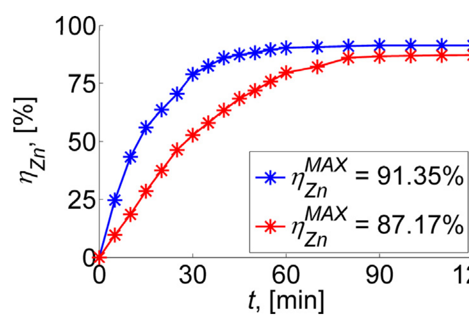

Fig. 3 – Relationship of zinc extraction vs. time.

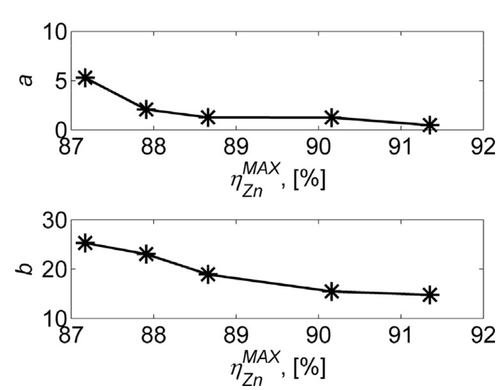

Fig. 4 – The relationship between approximation parameters and maximal percentage of zinc extraction.

percentage zinc extraction at time $t = 0$ is equal to $\eta_{Zn}(0) = 0$ (see Fig. 3). The obtained error of the model was $\varepsilon = 4.47\%$.

3. Optimization of zinc production line

3.1. Optimization strategies

There are two main strategies which can be applied in optimization of the process chain composed of several stages of linear structure: simultaneous (SIM) and sequential (SEQ) [3]. In sequential approach, the optimization of each stage is performed separately. We look for the values of control parameters for each stage that gives the optimal value of the quality criterion given for the analyzed stage. Next, the output (semi-product of that stage) corresponding to found values of control parameters is transferred to the subsequent stage as the input signal and the optimization procedure is run for that consecutive stage. That way optimization procedure should reach the last aggregate successfully generating the final product of required quality. This approach, which definitely should lead to some solutions, has one disadvantage. There is no control of the final product quality during the optimizations of intermediate stages. On the other hand its advantage is that dividing the optimization into small steps makes the whole process much faster by decreasing the number of control variables.

In contrast, the simultaneous optimization strategy (SIM) searches the optimal solution for all stages at once. Precisely speaking, in SIM approach we check the vector of aggregating control vectors at all stages. Because aggregated vector of long production chains is a composition of numerous control vectors, multidimensionality problems may arise. Additionally, optimization constraints are compositions of constraints of single stages. If set of admissible parameters of any stage is very narrow, then finding a set of admissible values of initial aggregated vector may be almost impossible, especially when we use probabilistic methods when defining initial vector.

In mixing stage the linear objective function was defined. A non-linear and multimodal objective function was used in second stage. The third stage was optimized using the non-linear but unimodal objective function. Therefore, each stage of the zinc production process was optimized separately (SEQ strategy) using different optimization methods, adequate for the analyzed problem. In the case SIM we could not apply these specific methods, since after composition, objective function of the whole process is nonlinear. This would significantly reduce the optimization efficiency which does not guarantee a reliable solution. In the studied problem SIM approach was totally unsuccessful.

3.2. Optimization of mixing stage

During optimization of mixing stage two objective functions were employed. First one involved the cost of the zinc concentrate ($f_C \rightarrow min$), the second took into account its quality ($f_Q \rightarrow max$). Both functions are linear and they are defined as follows:

$$f_C = \sum_{i=1}^{n} 0.85 \cdot LME \cdot \%Zn_i \cdot x_i \tag{7}$$

$$f_Q = \sum_{i=1}^{n} q_i \cdot x_i \tag{8}$$

where *LME* is the price of one ton of zinc concentrate at the London Metal Exchange (*LME* = 2600 \$/tonne), $\%Zn_i$ is the percentage fraction of zinc in ith concentrate, q_i is a quality of ith concentrate, x_i is the percentage share of ith concentrate in zinc concentrate mix, n is the number of available zinc concentrates.

During optimization six zinc concentrates were considered. The chemical composition of all concentrates, as well as their associated quality functions are presented in Table 2 (values of qualities are based on subjective technological experience).

The technological aspects of the process resulted in following constraints:

- the percentage fraction of lead in zinc concentrate mix must not be higher than 3%,
- the percentage fraction of iron in zinc concentrate mix must not be higher than 6%,
- the percentage share of zinc concentrate I in zinc concentrate mix must be higher than 50%.

The optimization problem is defined by two linear objective functions and linear constraints, therefore the Danzig simplex method was used. The two criterion problem was transformed into one criterion using the weighted sum method [8]:

$$f = w \cdot f_C + (1-w) \cdot f_Q \tag{9}$$

where considered values of weights were $w = 0, 0.01, \ldots, 1$.

Table 2 – Chemical composition, costs and qualities of zinc concentrates.

Element	Zinc concentrate					
	I	II	III	IV	V	VI
%Zn	56.03	50.35	53.6	53.92	50.03	51.23
%Pb	2.62	2.35	4.7	2.12	1.95	1.65
%Fe	5.16	9.5	4.2	5.63	11.2	10.07
%S	33.8	27.7	31.5	30.5	31.6	32.12
Cost [$/tonne]	1238.3	1112.7	1184.6	1191.6	1105.7	1132.2
Quality	1	0.9	0.8	0.93	0.88	0.9

Moreover, to ensure the equal impact of functions f_C and f_Q for function f, the values of f_C and f_Q were scaled into the range [0, 1].

The optimization was performed 101 times, that is one time for each value of weight w. The optimal solution was always one of the four points in Fig. 5 which define Pareto front for considered problem.

The percentage fraction of zinc concentrates in zinc concentrates mix is presented in Table 3.

The chemical composition of zinc concentrates mixes is presented in Table 4.

3.3. *Optimization of oxidative roasting stage*

From technological point of view, the concentration of sulfide sulfur in calcine should be as low as possible. As the result of the analysis of the available dataset of calcine (see Fig. 6), the required value was set to 0.65%. Therefore, the aim of optimization was to find the values of control parameters which ensure the concentration of sulfide sulfur in calcine equal to 0.65%. Optimization of oxidative roasting stage was performed for four obtained zinc concentrate mixes.

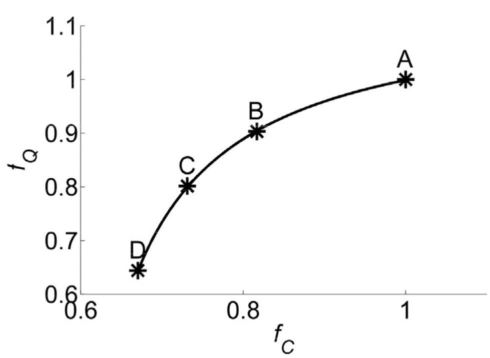

Fig. 5 – Pareto-front obtained in optimization of the mixing stage.

Table 3 – The percentage fraction of zinc concentrates in zinc concentrates mixes.

Zinc concentrate mix	Zinc concentrate					
	I	II	III	IV	V	VI
A	1	0	0	0	0	0
B	0.81	0.19	0	0	0	0
C	0.5	0.16	0	0.34	0	0
D	0.5	0.24	0.22	0.04	0	0

Table 4 – Chemical composition of considered four zinc concentrate mixes.

Element	Zinc concentrates mix			
	A	B	C	D
%Zn	56.03	54.93	54.42	54.05
%Pb	2.62	2.57	2.4	3
%Fe	5.16	6	6	6
%S	33.8	32.62	31.71	31.7
Cost [$/tonne]	1238.3	1214	1202.6	1194.5

Due to the non-linearity and multimodality of the objective function the particle swarm optimization (PSO) method was used. Due to the stochastic nature of the PSO method, the optimization was performed 100 times. The boxplots of the concentration of sulfide sulfur in calcine for all four zinc concentrates mixes are presented in Fig. 7.

It can be noticed that for all zinc concentrates mixes it is possible to obtain the required value of the concentration of sulfide sulfur in calcine.

3.4. *Optimization of leaching stage*

The optimization of leaching stage was performed in order to find the minimal time which ensures the percentage zinc extraction not less than 99% of maximal percentage zinc extraction. Due to the nature of optimization problem Monte-Carlo method was used. The computation was made for four concentrates (A, B, C, D) for which the objective function value in second stage was the best.

The values of maximal percentage zinc extraction for each concentrate are shown in Table 5.

The optimization results are presented in Fig. 8.

Based on Fig. 8 it is possible to conclude that using the better zinc concentrate mix (A) guarantees the better zinc sulfate solution (with higher content of zinc). Moreover, the time of leaching stage is shorter, which reduces the costs of this stage and increases the plant production capacity.

4. Summary

The goal of the research was an attempt of optimization of three stages (mixing of raw materials, oxidative roasting and

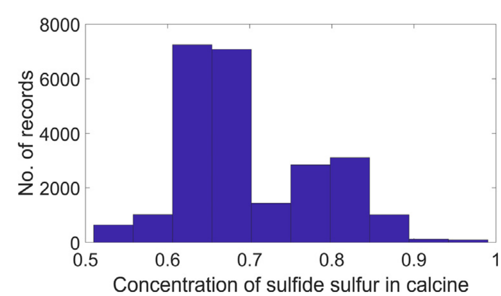

Fig. 6 – The histogram the concentration of sulfide sulfur in calcine of analyzed dataset.

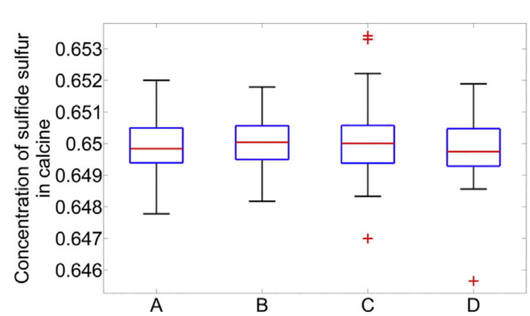

Table 5 – Maximal percentage zinc extraction for four optimal concentrates.

Concentrate name	Maximal percentage zinc extraction
A	91.45%
B	91.01%
C	91.34%
D	89.70%

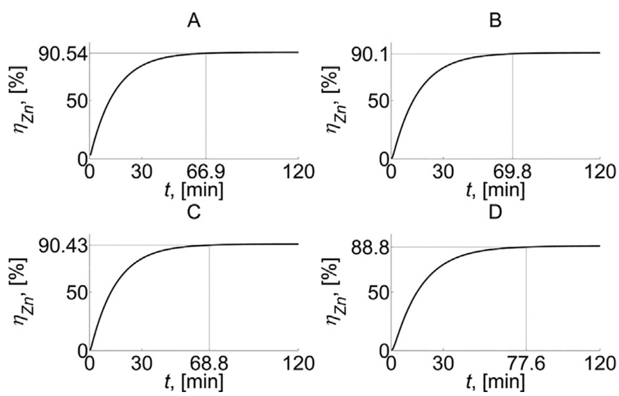

Fig. 8 – The optimization results of leaching stage.

leaching) of the hydrometallurgy-based zinc production line. Each separate stage generates semi-products, whose quality may or may not lead to optimal quality of the final product. Therefore, the qualities of these semi-products were assessed, and when sufficiently high, they were transferred to further processing in subsequent stage. At the preliminary step, these processes were modeled using the regression analysis and artificial neural networks approach. Because of the nature of the zinc production line, where success of one stage depends highly on quality achieved in previous stages, only elaborated sequential optimization strategy can be applied. Different optimization techniques were used in analysis of considered stages. The general conclusions regarding the optimization results can be summarized as follows:

- Optimal compositions of concentrate mixes differ in content of ingredients, especially of zinc and sulfur. This results indifferent prices of each of these mixes.
- Regardless of the composition of the concentrate mix as the input to the fluidized bed furnace, it is possible to obtain the optimum level of the concentration of the sulfide sulfur in calcine. This can be achieved by setting appropriate, optimal process control parameters. However, a better concentrate mix gives a better zinc extraction at the exit of the leaching stage.
- The effect of quality of the concentrate mix is noticeable only after leaching. The most expensive A concentrate mix produces the best zinc extraction. At the same level, however, is the zinc extraction from the C mix. Since its cost is lower than the A mix, it is economically more advantageous for the process.
- For the cheapest D mix, the low zinc extraction translates into a lower value than the A and C mixes.

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