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SYSTEM APPROACH TO THE ANALYSIS OF COPPER CONCENTRATE PRODUCTION

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Abstract: In this paper, the production of copper flotation concentrate in the copper mineral processing plant „Veliki Krivelj“ (RTB Bor) was analysed. The correlation between the input parameters (copper content in the feed, consumption of lime, consumption of frother, collector consumption in the rough flotation stage, collector consumption in the scavenger stage and the pulp density in the rough flotation stage) and output parameters (copper content and recovery in the final concentrate) is accomplished by a systemic approach. The data for analysis were obtained in the time period November 2009 – February 2010 of the plant operation. Data were collected on a daily basis for all three shifts. For the analysis of obtained data, the techniques of linear and nonlinear statistical analysis were applied. Accordingly, the starting data were used to develop optimization model, which could be useful for the further analysis of the influence of input parameters on the final outputs – i.e. final concentrate grade and recovery.

Keywords: Systems approach, copper concentrate, flotation, linear and non-linear statistics.

1. INTRODUCTION

Modeling of the technological processes in the modern operational management, represents a significant element of its further optimization [1]. In operations management it is implied that absolute optimization of any process cannot be achieved. Therefore, each process can be re-analyzed in order to continue seeking for opportunities to improve its economic and technological parameters. The above fact is of special importance in industrial conditions, considering that contemporary technical and technological processes usually consist of a large number of phases and activities. Also in addition to optimization of technological and economic parameters, optimization from the perspective of ecology and environmental protection should be addressed. Therefore, a large number of input variables, at the same time, can have significant impact on the optimal output of the process.

In this regard, an attempt was made to define a numerical model of the processes for flotation concentration of copper. Accordingly, copper content and recovery in the final concentrate – the outputs of the process were taken as the qualitative variables. At the same time a large number of input variables were considered, according to a systemic approach of the process. Data for the analysis were obtained by process recording and acquisition of real data from the Flotation plant „Veliki Krivelj“.

Flotation plant in Veliki Krivelj represents a significant segment of the technological process of copper extraction in Mining and Smelting Complex Bor – RTB Bor. It was put into trial operation in December 1982. It was designed and built for an annual capacity of eight million tons of ore, with a three-stage crushing and two-stage grinding in three identical milling sections. After a number of reconstruction, with the introduction of modern processing equipment, today flotation plant in Veliki Krivelj works with the capacity of 10.6 million tons per year (ore from the deposit "Veliki Krivelj") [2].

Copper deposit "Veliki Krivelj" is located at a distance of about 4 km northeast of Bor and belongs to porphyry deposits of large scale. It is estimated that the balance reserves of copper ore in this deposit (with the threshold content of 0.15% Cu, categorized as B+C1 reserves) amount 474.291.085 t, having 1.533.821 tons of copper [3].

Flotation concentration is a process of separation of minerals which occurs due to differences in physical-chemical properties of mineral surfaces. It is mainly used for the concentration of metallic ores, for cleaning of solid fuel or enrichment of non-metallic minerals, but can also be applied to extract solid particles from liquids or the separation of non-mineral particles one from another [4].

Given the complexity of considered technological process, the most important input parameters were selected: copper content in the feed, consumption of lime, consumption of frother, collector consumption in the rough flotation stage, collector consumption in the scavenger stage and the pulp density in the rough flotation stage. Those input parameters were analyzed simultaneously with their influence on the output parameters: copper content and recovery in the final concentrate, using statistical techniques and tools. Given that a large number of parameters are simultaneously monitored, the correlation between inputs and outputs is followed by a systematic approach. The considered technological process is a complex transformational system with specific subprocesses and inputs, therefore modeling and optimization of this system is very complex. The biggest problem is made by certain input parameters that are optimal for one sub-process, while at the same time not optimal for the other sub-process. The technological process, as a complex production transformational system, will be briefly described in the second part of the paper [5].

The aim of this research is to perform modeling of the flotation process, in order to simulate and test the resulting model so that the range of the input parameters, consisting mostly of reagents, could be optimized. Namely, the selection of reagent dosages as input parameters is justified from economic point of view, because the increase in overal copper recovery for 1-2% –caused by reagent optimization– is considered as exceptional economic result. Therefore, in commercial plants, control of reagents is the most important part of the flotation strategy [6,7].

The modeling procedure was performed using linear and nonlinear statistical analysis.

The first attempt of modeling was carried out on the basis of Multiple Linear Regression Analysis (MLRA). This statistical tool did not provide satisfactory results, therefore further modeling of the process was based on the use of non-linear statistics - Artificial Neural Networks (ANN). Since this technique was also proven as insufficient, modeling was carried on by using different presentation of input data through fuzzy numbers and application of Adaptive Network-based Fuzzy Inference System (ANFIS). However, none of the above modeling methodologies did not provide adequately useful model, hence further modeling was based on the application of structural equations (SEM). For these purposes, LISREL was used as a tool for SEM modeling. Utilization of the SEM methodology provided the corresponding useful results.

2. DESCRIPTION OF TECHNOLOGICAL PROCESS - SUBJECT OF MODELING

In order to understand the modeling of flotation process, the flotation process itself must be understood. The following text contains a short overview of the basic stages of this technological process, including the phases of grinding and classification, preceding it. It should be noted that the description of the technological process refers to the period of the plant operation in which the data were collected, ie. the period November 2009 – February 2010. Today plant is reconstructed and involves the operating of the new flotation cells, hydrocyclones, pumps and other auxiliary equipment and installations. However, the basic parameters of the process such as the number of flotation stages, grinding fineness, type and consumption of reagents, etc., practically remained the same.

2.1. GRINDING AND CLASSIFICATION

Grinding of crushed ore and its further classification occurs in three identical milling sections, so the following text will describe the operation of one of the sections.

Belt feeder transpotrs crushed ore (with upper grain size limit of 20 mm) from the fine ore bunker onto the corresponding conveyor belt and, subsequently, rod mill. With the aim of ore capacity control, beltweighter is instaled on this belt conveyor system.

Besides the ore, rod mill feed includes limewater (which is dosed by means of manual and automatic valves) for pH regulation and water for slurry preparation. Solid contents in the rod mill is about 75%. The rod mill discharge flows by gravity to the cyclone pump tank, together with ball mill dicharge and process water. Cyclone feed pump transports the slurry to the hydrocyclone battery to be classified. Battery consists of 7 hydrocyclones, each 700 mm in diameter. Hydrocyclones are arranged around the central distributor of the pulp. The hydrocyclone underflow (diluted by water) as a ciculative load is fed to the ball mill for secondary grinding. The hydrocyclone overflow, as a final product of grinding is transported to flotation gravitationally, by canals. Solids content in the hydrocyclone overflow is approximately 26%, in the hydrocyclone underflow 78% and 71% in ball mill. Mill loading by grinding media is about 40% for both of mills.

2.2. ROUGH FLOTATION OF COPPER MINERALS

Hydrocyclone overflow, containing about 58% of the class –0.074 mm, gravitationally through canals goes to rough flotation stage. The overall hydrocyclon overflow of the first section goes into the agitator and from there to flotation banks. For rough flotation of copper minerals, two flotation banks are in use, and each of them contains 16 flotation cells. Hydrocyclone overflows of the second and third section are merged and gravitationally transported into three flotation banks, each of them containing 21 flotation cells.

Tailing from rough flotation represents the final tailing which, by gravity, via concrete canal is transported to the tailing dump. Rough flotation, according to the designed parameters, is operating with the pulp density of 1190-1230 kg/m^3, pH = 9.5-10.5, with a PEX dosage in an amount of 30-40 g/t, frother 5-7 g/t, while the flotation time is about 21 min. The lime is used as a pH regulator, in the form of 6% solution. It is added in rod mills using an automatic valve, which regulates the dosage based on impulses from the pH-meter, located in the canal for the hydrocyclone overflow of each section. Addition of lime water into rod mills is performed from two connected conditioners, while the third conditioner serves for lime water addition into cleaning. Surplus of lime water returns to the conditioners through the recirculative part of pipeline.

2.3. CLEANING AND SCAVENGER FLOTATION OF COPPER MINERALS

Rough collective concentrate contains 3-5% copper. Rough copper concentrate and flotation concentrate obtained during scavenger are mixed and sent to the cyclone pump tank, where it merges with the regrinding mill discharge. Cyclone pump transports the slurry to the battery of 6 hydrocyclones for classification. Both cyclone pumps have their own separate pressure lines and a separate battery of hydrocyclones. The hydrocyclone underflow (diluted by water) returns to the mill for regrinding, as a circulative load. Overflow of the hydrocyclones with the fineness of 85-90% –0074 mm is transported by gravity to separator and the first cleaning stage. The first cleaning of the copper concentrate is performed in two flotation banks with 9 flotation cells each, at pH=11.0-11.5 and flotation time of 10 min. Tailings of the first cleaner is sent by pumps to scavenger flotation stage, while the concentrate of the first cleaner is transpored by pump to the next cleaning stage.

Scavenger flotation is performed in flotation banks with 8 cells. Scavenger concentrate is sent to regrinding, and its tailing to the tailing dump. Second cleaning of copper concentrate is performed in two flotation banks with 8 cells, during the time of about 20 min.

Concentrate of the second cleaner is transported by pumps to the third cleaning stage, while its tailing returns to the first cleaning stage. The third cleaning is carried out in the two flotation banks with 18 cells during the flotation time of about 19 min. Concentrate of the third cleaner goes, by gravity, to the thickener, while the tailing returns to the second cleaner. Technological scheme of the grinding and flotation processes is shown in Figure 1 [8].

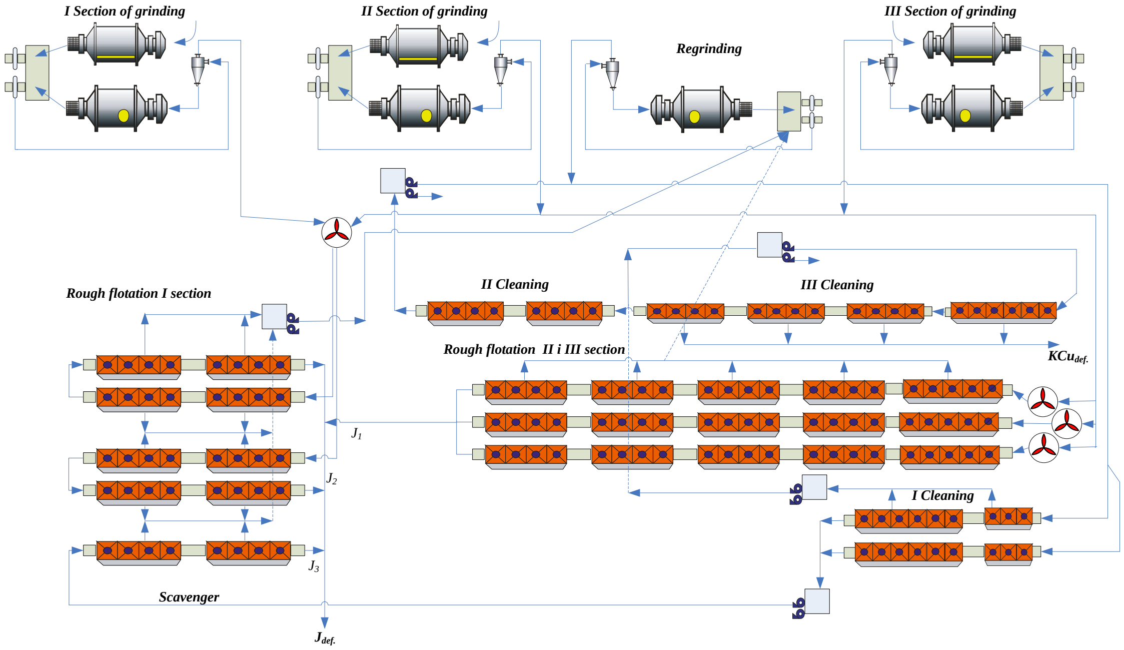

Figure 1. Technological scheme of milling and flotation process in Veliki Krivelj plant [8]

3. RESULTS AND DISCUSSION

Consideration of flotation concentration process, which was used for analysis and modeling presented in this paper covers the period of the plant operation from November 2009 to February 2010. Data were collected on a daily basis in shifts. Considering the fact that relatively narrower time period is analyzed, including only four months, obtained results presented in this paper can be regarded only as testing the possibilities of modeling the observed processes. The final model of the process, which could provide high degree of prediction of the outputs, based on various combinations of input values, would involve much larger time range of acquisition of the process variables.

The results, supporting tables and graphs have resulted as outputs of software packages SPSS, MATLAB and LISREL, which are applied in order to define the conceptual model of considered process.

Before statistical analysis, the standardization[58] of all data obtained by measuring the observed process was carried in relation to the date of the beginning of the observation. So, the first date is taken as the zero point. Subsequently, thus obtained standardized parameters, were introduced in the SPSS software package for further analysis. Table 1 shows the representation of the variables of considered system.

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[58] In order to standardize variation data changes

Table 1. Defining variables

Description	**Variables**
Cu content in the feed (%)	X_1
Consumption of lime (kg/t)	X_2
Consumption of frother (g/t)	X_3
Collector consumption in the rough flotation stage (KEXo + NaIPX, g/t)	X_4
Collector consumption in the scavenger stage (KEXp, g/t)	X_5
The average value of the pulp density in rough flotation stage (kg/m^3)	X_6
Copper content (% Cu)	Y_1
Recovery in the final concentrate (%)	Y_2

The measured values of the input parameters of the technological process (X_1-X_6) and indicators of the quality of copper concentrate and efficiency of the technological process (Y_1-Y_2) are presented in the form of descriptive statistics given in Table. [9]

Table 2. Descriptive statistics of input and output data

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
X_1	294	.230	.150	.380	.262	.039	.001
X_2	294	4.255	2.319	6.574	4.128	.871	.759
X_3	294	13.317	1.000	14.317	6.438	2.694	7.258
X_4	294	36.700	5.225	41.925	24.892	8.815	77.696
X_5	294	6.550	1.350	7.900	5.016	1.372	1.882
X_6	294	1047.500	201.667	1249.167	1109.630	215.043	46243.603
Y_1	294	16.450	8.400	24.850	17.100	2.986	8.918
Y_2	294	32.616	66.111	98.727	85.737	5.112	26.131
Valid N (listwise)	294						

It should be noted that X_1 has a low variance (0.001), however, this parameter represents the copper content of the crushed ore which is the main raw material of the production process. So this parameter can not be omitted in further analysis. Small changes in the copper content in the raw material will lead to significant changes in the output parameters and the quality and efficiency of copper concentration process. [9]

Before defining the dependence of output parameters (Y_1-Y_2) as a function of input parameters (X_1-X_6) it is necessary to perform correlation analysis of all variables. Pearson's correlations (PC), with appropriate coefficients of statistical significance, are obtained as result of this analysis, which are shown in Table 3.

Table 3. Correlation matrix for the input (X_1–X_6) and the output (Y_1-Y_2) variables

		X_1	X_2	X_3	X_4	X_5	X_6	Y_1	Y_2
X_1	Pearson Correlation	1	.075	.277**	.228**	-.015	.122*	.353**	.135*
	Sig. (2-tailed)		.203	.000	.000	.799	.036	.000	.021
	N	294	294	294	294	294	294	294	294
X_2	Pearson Correlation	.075	1	-.346**	-.333**	.273**	-.130*	.334**	.090
	Sig. (2-tailed)	.203		.000	.000	.000	.026	.000	.123
	N	294	294	294	294	294	294	294	294
X_3	Pearson Correlation	.277**	-.346**	1	.683**	-.233**	.375**	.154**	-.106
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.008	.068
	N	294	294	294	294	294	294	294	294
X_4	Pearson Correlation	.228**	-.333**	.683**	1	.033	.437**	.069	-.020
	Sig. (2-tailed)	.000	.000	.000		.578	.000	.236	.739
	N	294	294	294	294	294	294	294	294
X_5	Pearson Correlation	-.015	.273**	-.233**	.033	1	.346**	.017	.169**
	Sig. (2-tailed)	.799	,000	.000	.578		.000	.775	.004
	N	294	294	294	294	294	294	294	294
X_6	Pearson Correlation	.122*	-.130*	.375**	.437**	.346**	1	.043	.069
	Sig. (2-tailed)	.036	.026	.000	.000	.000		.459	.239
	N	294	294	294	294	294	294	294	294
Y_1	Pearson Correlation	.353**	.334**	.154**	.069	.017	.043	1	.086
	Sig. (2-tailed)	.000	.000	.008	.236	.775	.459		.141
	N	294	294	294	294	294	294	294	294
Y_2	Pearson Correlation	.135*	.090	-.106	-.020	.169**	.069	.086	1
	Sig. (2-tailed)	.021	.123	.068	.739	.004	.239	.141	
	N	294	294	294	294	294	294	294	294

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

To define the dependence of the output parameter as the function of the input parameters, using the multiple linear regression analysis (MLRA) with acceptable level of fitting (strong correlation), it is necessary that the value of PC is near 0.5 with statistical significance. [10]

An analysis of the data presented in the Table 3 reveals that this constraint is attained in following cases: Y_1-X_1: PC=0.353 (p=0.000), Y_1-X_2: PC=0.334 (p=0.000). This was also the case for the following interdependence between the predictors of the process: X_3-X_4: PC=0.683 (p=0.000), X_6-X_4: PC=0.437 (p=0.000), X_6-X_3: PC=0.375 (p=0.000). Considering that only the dependent variable Y_1 has a significant correlation with the independent variable X_1 and X_2 , only this dependent variable was modeled using the methods of linear statistics. Attempt of modeling the dependent variable Y_2 was not made due to a low PC coefficient.

What follows is an attempt of modeling based on the principle linear statistics. The method used was MLRA-enter method that introduces all variables in a linear model at the same time. As a dependent variable, and the variable whose variance we want to explain the quality of the final copper concentrate was taken (Y_1).[11] Obtained MLRA result are shown in Table 4.

Tabela 4. Results of MLRA analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.508[a]	.258	.243	2.59882

a. Predictors: (Constant), X6, X1, X2, X5, X4, X3

The result shows that MLRA linear model has a correlation coefficient R = 0.508, which is a medium correlation. What is more important is that the value of the coefficient of determination is low $R^2 = 0.258$, which indicates that only 25.8% of the variation of the dependent variable Y_1 is explained by the independent variables. This means that this model could predict the value of the quality of the final copper concentrate, with 25.8% accuracy, knowing the values of selected input variables of the technological process. However it is a very low value of fitting, and this means that the resulting model does not have predictive validity. For this reason further modeling methodology was attempted by using artificial neural networks (ANN).[9]

Artificial neural networks represent a class of tools that can facilitate the exploration of large systems in ways not previously possible. These methods have observed explosive growth in the last decade and are still being developed at a breathtaking pace. In many ways, neural networks can be viewed as nonlinear approaches to multivariate statistical methods, not bound by assumptions of normality or linearity. Although neural networks have originated outside the field of statistics and have even been viewed as an alternative to statistical methods in some circles, some signs indicate that this viewpoint is making way for an appreciation of the ways in which neural networks complement classic statistics.

In general neural networks comprise an input layer, one or more hidden layers and an output layer. Each layer contains of one or more neurons. Neurons are connected to each other by means of weighting factors. Neuron in a given layer, receives the information from all the neurons that are found in the previous layer. It adds information corresponding to the priorities of network connections and then transmits this sum to all neurons of the next layer using a mathematical function. [9]

ANN used to develop the model is shown in Figure 2. As it can be seen, this network consists of three layers of nodes. The layers described as the input, hidden and output may in general contain *i*, *j*, *k* for the processing nodes respectively. Each node in the input (hidden) layer is connected to all nodes in the hidden (output) layer using weighted connections.

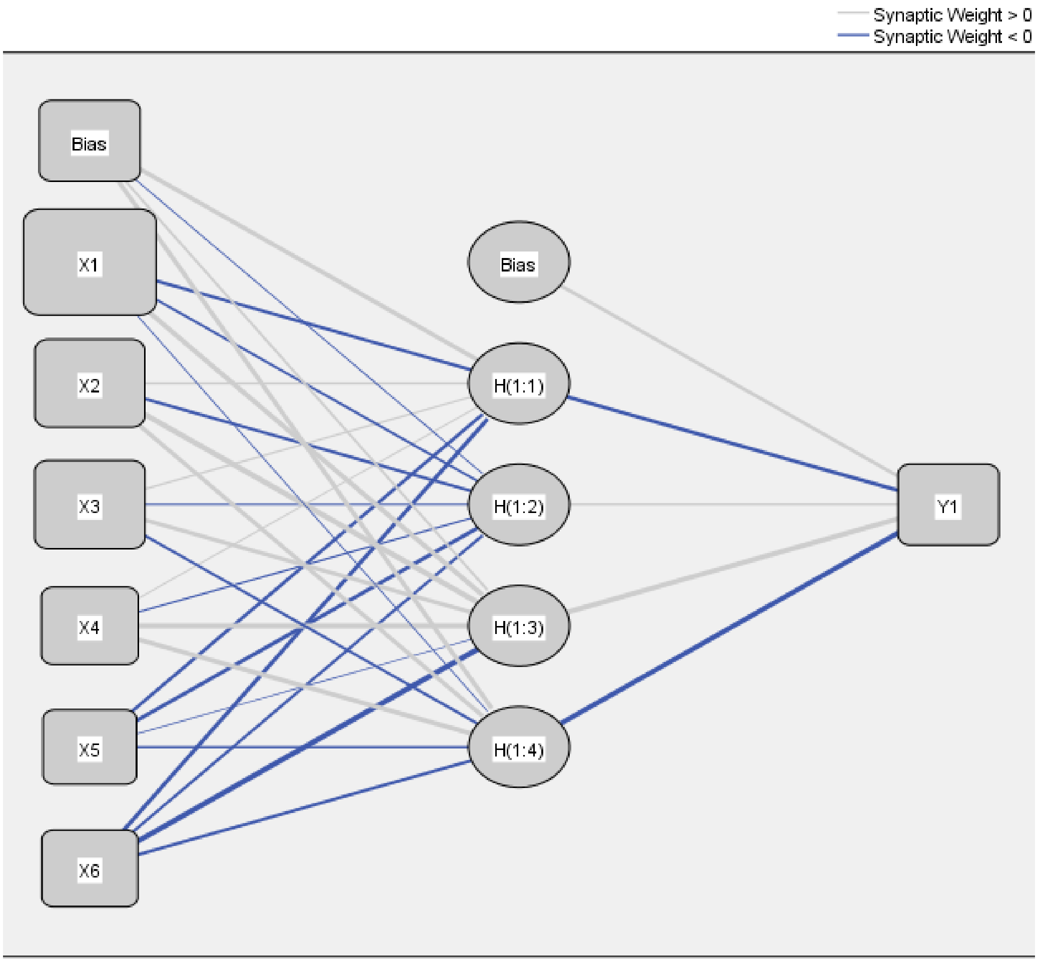
In addition to the *i* and *j* number of input and hidden nodes, the ANN architecture also houses a bias node (with fixed output +1) in its input and hidden layers, and they provide additional adjustable parameters (weights) for the model fitting. The number of the nodes *i* in the ANN network input layer is equal to the number of inputs in the process whereas the number of output nodes *k* equals the number of the process outputs. However, the number of hidden nodes *j* is an adjustable parameter magnitude, which is determined by issues such as the desired approximation and generalization capabilities of the network model.

The back propagation algorithm modifies network weights to minimize the mean squared error between the desired and the actual outputs of the network. Back propagation uses supervised learning in which the input, as well as desired outputs, are controlled and selected.

The use of ANN usually comprises three phases. First is the training phase, which is facilitated on 70% to 80% of the randomly selected data from the starting data set. During this phase, the correction of the weighted parameters of the connections is achieved through the necessary number of iterations, until the mean squared error between the calculated and measured outputs of the network is minimal. During the second phase, the remaining 20% to 30% of the data is used for testing of the ‘‘trained’’ network. In this phase, the network is using the weighted parameters determined during the first phase. This 20% to 30% of the data, excluded during the learning of the network, is now incorporated in it as a new input values X_i which is then transformed to the new outputs Y_i. The third phase is the validation of the network on completely new data set. Usually, this data set consists of the data from new experimental measurements of the same process. The validation phase presents the final level of successful or unsuccessful prediction using the network developed in the previous two stages, on a future database.

ANN methodology was applied to the modeling of flotation concentration of copper in industrial conditions; using available data with descriptive statistics which is shown in Table 2. Starting set of 294 input and output lines of data were divided into two groups. The first group consisted of 210 (71.4%) randomly selected lines of data were used for training the network, while the second group consisted of 84 (28.6%) of the remaining lines of data from the initial databases that were used to test the network.

For the development of relational ANN configurations, previously defining input parameters X_1-X_6 and Y_1 output parameter (the quality of concentrate) were used as the elements of the network architecture (Figure 2).



Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

Figure 2. The ANN architecture for determination of the copper concentration in the final concentrate on the basis of the input process parameters.

Coefficient of determination, obtained by a network represented in Figure 2, in the training phase was R^2=0.428. During the testing phase of the ANN the coefficient of determination (R^2) is slightly decreased relative to the stage of training and now amounts to 0.338. Figure 3 provides a comparative overview of measured and calculated values using ANN approaches on analyzed processes, during the testing stage.

The results indicate that the ANN modeling of the industrial data collected in this study can not be used to accurately predict the quality of copper concentrate, based on available data set.

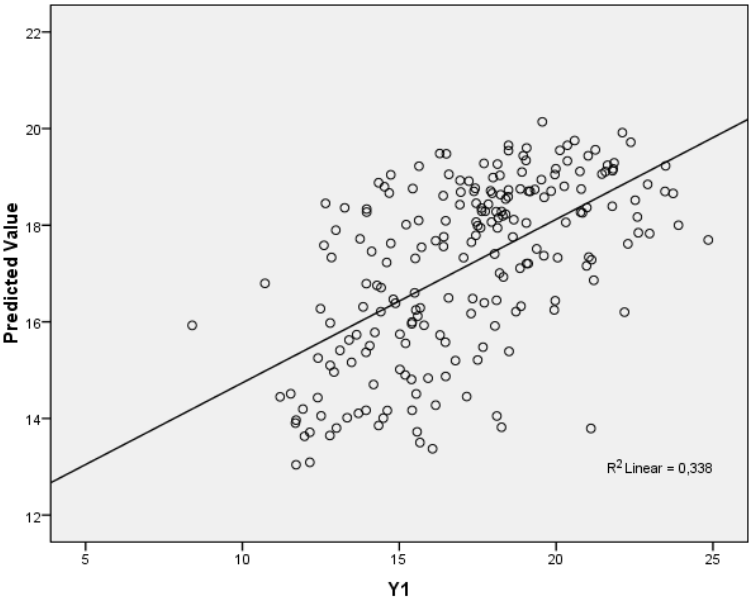


Figure 4. Comparison of measured and calculated values using ANN to predict the quality of copper concentrate (Y_1)

Low coefficient of determination among observed variables does not automatically mean that the interdependence of their behavior does not exist. It just indicates that modeling using linear statistics can not performed and further modeling should be based on the dynamic behavior of the variables. Since modeling through non linear approach using ANN did not offer satisfactory results an attempt of application of methodology through case when the input variables do have a wide range during the entire period of observation, or otherwise known as Adaptive-network-based fuzzy inference system (ANFIS), was used. [12]

As a basis for the construction of a set of fuzzy if–then rules, the ANFIS system based on selected membership functions can be used. The ANFIS structure is obtained by embedding the fuzzy interference system into the framework of adaptive networks. An adaptive network is a network structure consisting of a number of nodes connected through directional links. The outputs of these adaptive nodes depend on modifiable parameters pertaining to these nodes. The pattern in which these parameters should be iteratively varied, aimed at minimizing the final error, is specified by the learning rule. [12] Moreover, according to Takagi and Sugeno, the fuzzy inference system (FIS) is a framework based on fuzzy set theory and fuzzy if–then rules. [13] The three main components of a FIS structure

are: a rule base, a database and a reasoning mechanism. The appropriate number of if – then rules for levels of ranges of the input variables is located in the rule base. An example of a rule used in the investigations presented in this paper might be “quality of copper concentrate will be higher if the Cu content in the ore is higher”, where items such as low and high represent linguistic variables.

The database defines the membership functions applied in the fuzzy rules and the reasoning mechanism performs the inference procedure.

In this way, for example, if there are two input variables (X_1 and X_2), and assuming that their ranges can be divided into two levels, there would be the rule base with two rules for modeling the value of the output variable Y:

Rule 1. If X_1 is in the range A_1 and X_2 is in the range B_1, then:

$$f_1=p_1x_1 + q_1x_2 + r_1;$$

Rule 2. If X_1 is in the range A_2 and X_2 is in the range B_2, then:

$$f_2=p_2x_1 + q_2x_2 + r_1;$$

In the case when f (x_1,x_2) is a first-order polynomial, the model is called a first-order Sugeno fuzzy model.

Applying this methodology to the considered system of the process of production of the copper concentrate by flotation, with the parameters defined in Table 1, the following results of prediction are obtained. Prediction of the model output values (Y_1 and Y_2) during the phase of training, are given in Figure 5, while the ANFIS model forecasting for the testing phase are given in Figure 6.

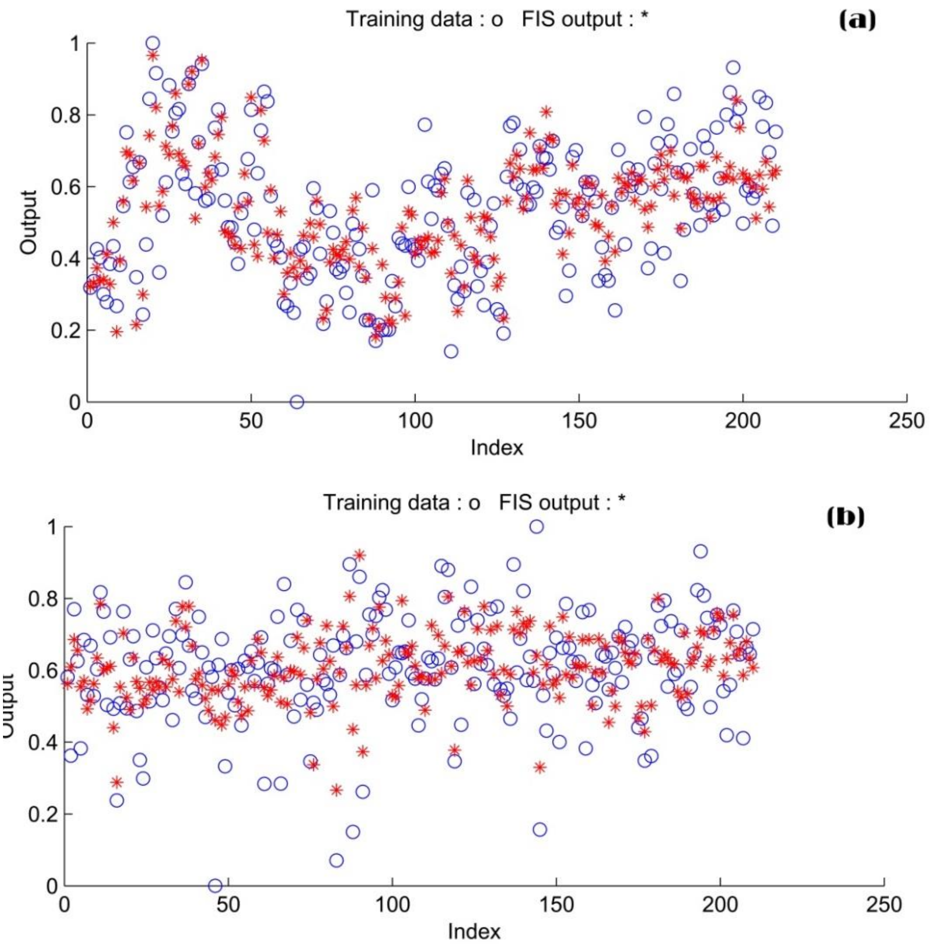


Figure 5. Results of applying of the ANFIS models, in the training stage of the network (a) Y_1 and (b) Y_2

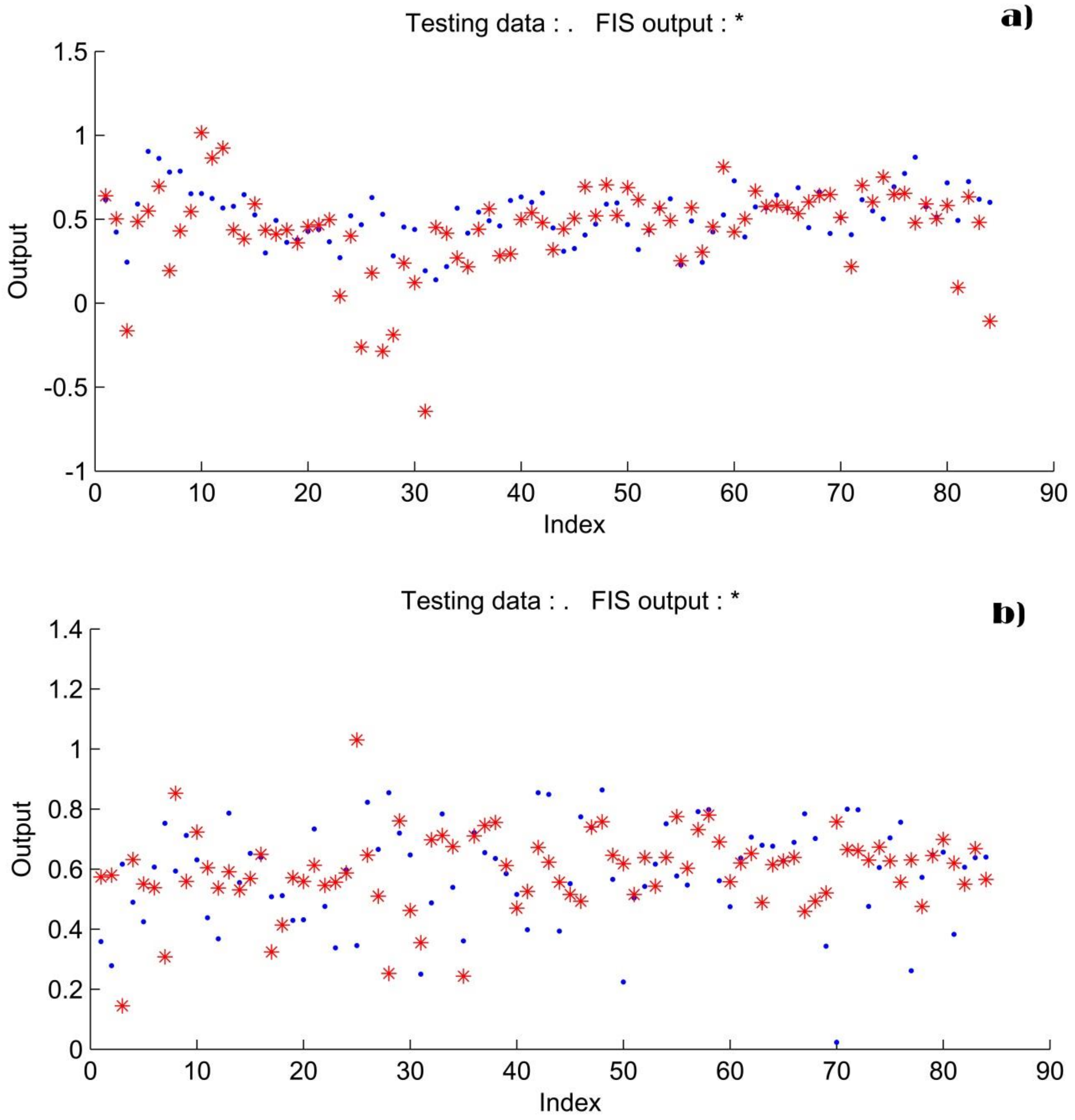


Figure 6. Results of applying of the ANFIS models, in the testing stage of the network (a) Y_1 and (b) Y_2

The data sets used for the ANFIS modeling methodology are of the same ranges in the training and testing phase, as in the case ANN procedure. At first glance, the results in Figures 5 and 6, could be considered as relatively well-fitting of the model. However, when taking into account the error of the model prediction, shown in Figure 7 (b), where in some areas the value exceeds 50%, it can be concluded that neither ANFIS methodology does not provide sufficiently reliable results of modeling.

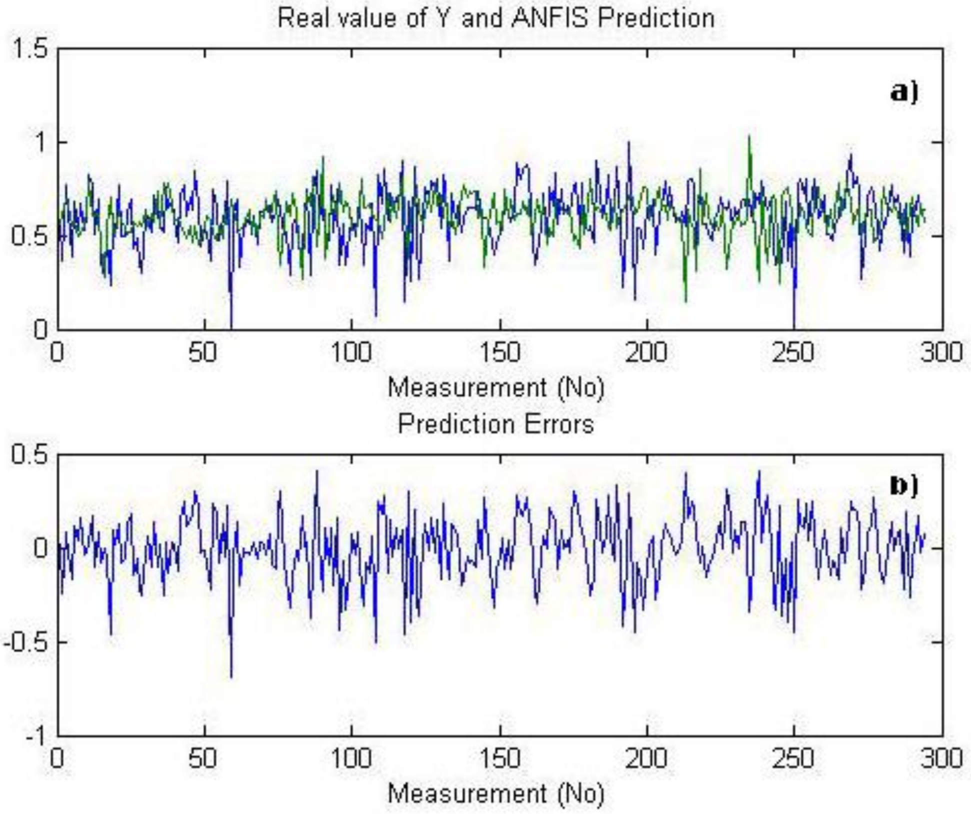


Figure 7. Results of modeling using the ANFIS model, in case of the output variable Y_2 (a), with obtained error of modeling (b)

For the reasons stated above, further work was attempted to form a structural equation model (SEM) to be used to predict of the output values as a function of changes in the input variables of the process. *Structural Equation Modeling* (models based on structural equation - SEM) is a multivariate statistical analysis technique used to analyze the structural relationship between measured and latent variables. Its largest advantage is that it assesses multiple dependencies through one analyze.

In this analysis, there are two types of variables: *endogenous* - variables specific for the system or variables that emerge from the model, which are the equivalent of the dependent variables and *exogenous* - variables that are outside the model, that is, their value is accepted as a given; the equivalent of the independent variables. Also, in SEM there are two types of models:

1. Models for measuring: represent the manner that determines how the measured variables are displaying the theory
2. Structural models: represent the manner that shows how the associated components are connected in the model

SEM tests and evaluates connections using a combination of statistical data and qualitative causal assumptions. It can be used simultaneously to confirmation and development theory or in confirmative or research purposes. One of the great strengths of this model is the ability to build latent variables, variables that can not be measured directly, but are estimated in the model based on other, measured variables. These variables are actually factor groupings of individual measured variables. To facilitate this level of development of a model structure it is necessary to perform grouping of the starting variables using, for example the factor analysis. Thus grouped measured variables provide larger accuracy of the final structural equation model. By applying the SEM modeling to the case discussed in this paper, structural model presented in Figure 8, was defined.

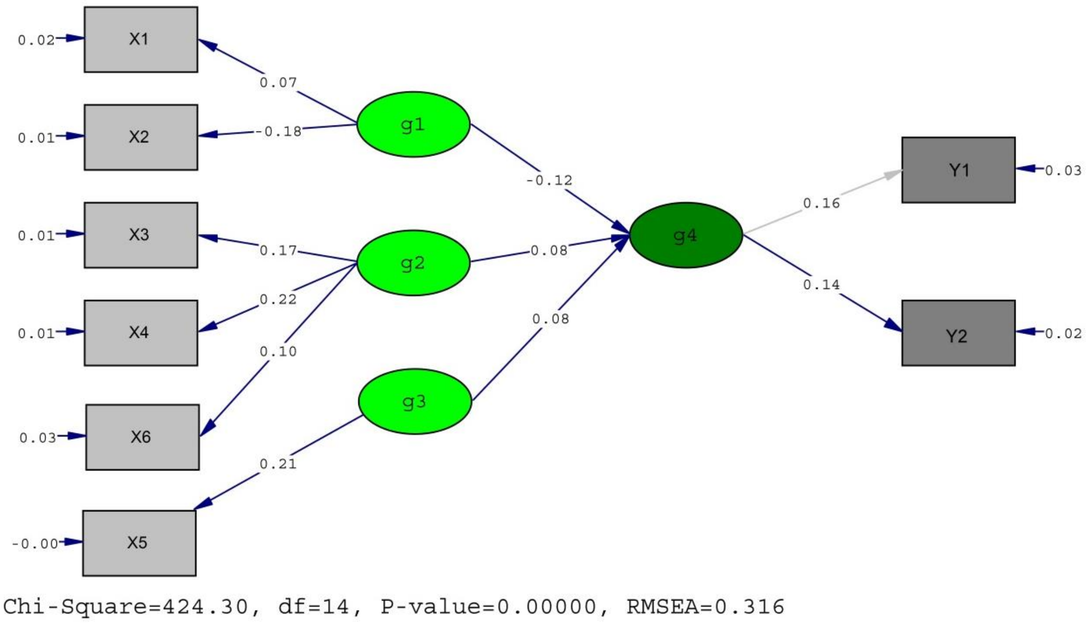


Figure 8. SEM structure prediction model of the output values Y_1 and Y_2

For the model presented in figure 8, factor analysis of input variables was previously done, and input variables have been grouped in g1, g2 and g3. The model presented in Figure 8, have parameters of accuracy at limited acceptability level, so it can be used for preliminary analysis and forecasting of outputs parameters of the process based on a combination of inputs. However, in order to claim that the model have predictive validity, the analysis with a significantly larger number of data lines (input values), obtained in the longer time range of measurement in industrial conditions, would have to be repeat.

4. CONCLUSION

In this paper, the attempt to develop an optimal model of the technological process of copper concentrate flotation is carried out. The results obtained by measuring the current production process, were used as the initial data. As influential input parameters of the process the following parameters were used: the content of copper in the input raw material; consumption of lime; consumption of frother; consumption of collectors on the basic flotation; consumption of collectors on extended flotation and pulp density in basic flotation, while as output of the process content and the utilization of copper in the final concentrate were selected. In the process of modeling, methods of linear (ANN) and nonlinear (ANN and ANFIS) statistical analysis were used, as well as modeling based on the principle of structural equations (SEM). Of these methods, only the SEM analysis has given results that can be considered as limiting acceptable values for forecasting of the output values of the process, as a function of changes in the set of input values. However, in order to use this model for predictive purposes, it would be necessary to repeat the analysis on a much larger set of data obtained by measuring at this technological line.

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