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PREDICTION OF THE COPPER PRODUCTION IN THE FRAMEWORK OF ELECTRICAL ENERGY CONSUMPTION USING ARTIFICIAL NEURAL NETWORK

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Abstract: The metallurgical process of the copper production is a very complex process and requires the consumption of electrical energy in large quantities. One of the challenges of today is to reduce the use of electrical energy by increasing the energy efficiency of the system. This challenge can be solved by developing energy management in mining companies. In order to approach the development of energy management, it is necessary to create models for predicting the volume of copper production by investigating electricity consumption in the main production stages. In this paper, the consumption of electricity required in the process of copper production is analyzed on the example of a local mining company. Data on electricity consumption were collected for a period longer than one year and the parameters were divided according to the main phases of the metallurgical process. Two models for predicting copper production using artificial neural network were created and the most influential parameters were identified. The significance of the models is reflected in the efficient forecasting of the copper production and therefore the demand for electrical energy. Another advantage of the models is the increased possibility for rationalization of electricity consumption on the basis of the influential parameters. The models are recognized as flexible and can find their application in related companies.

Keywords: Electricity consumption, copper production, prediction model, artificial neural network

1. INTRODUCTION

With the accelerated economic development of countries and organizations, a new challenge has emerged in the form of forecasting resources. Predicting all kind of resources either for countries or for individual companies is a vital task for planning. Forecasting resources has become complex and demanding job since the environment is constantly changing causing the modification in production processes. This problem leads to incomplete prediction models and lowers their prediction potential. Prediction models have been used for solving different energy related problems and some of them are described as follows. Kavaklioglu et al. (2009) highlights the importance of using prediction models in planning

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electrical energy resources because it allows big systems to foresee the future demand and provide secure electricity supply. Moreover, Günay (2016) reports that electricity planning is essential for achieving electricity balance, because nor lower electricity production than demand nor higher electricity production is good. Prediction models are seen as necessary in forecasting future electricity consumption in all systems because they allow faster economic development (Wang et al., 2018). Improving stability and accuracy of prediction models is a challenge faced by today's researches. Researchers are constantly developing models by adding different variables in the model structures.

Predicting electricity consumption in metallurgical industrial activities is interesting research topic since it is known that metallurgy is recognized as high energy intensive industry (Vidal, 2017). The electrical energy demand of copper production is affected by following factors: (a) mineral processing routes (hydrometallurgical or pyro metallurgical), (b) the ore grade, (c) mineral hardness, (d) mine age and type (surface or underground), (i) location of the mine and water access, (f) process design and technology selection (Moreno-Leiva et al., 2020). The artificial neural network methodology for creating prediction models has been applied in this study to investigate the future copper production. The prediction model was constructed taking into account electricity consumption in the production process, so it considers process design and technology selection factors. Accordingly, the copper production in this research was forecasted in the light of electricity consumption in the main production stages. The study is applied on organizational level.

Experts employed on developing copper production process are coping with emerging challenges of using environmental-friendly technology (Schlesinger et al., 2011). This is not an easy task since the copper production is not clean process. Continuous reduction of energy demand is among primary goals of the future technology of copper production (Schlesinger et al., 2011).

2. METHODOLOGY

Initial dataset that was used in the research was collected in a copper mining company. The period that was observed includes data from January 2018 to May 2019. More accurately, the values of the parameters have been recorded for 511 days. The study included seven parameters that concern consumption of electrical energy for the main phases of the copper production process, sulfuric acid production and the volume of the copper production. Main phases in the copper production are described as: flotation → drying concentrates → flash smelting → converting → anode refining and casting → electro refining (Schlesinger et al., 2011). All of these phases are using energy resources to ensure continuous copper production. The variable named sulfuric acid production is used because it represent an integral by-product in the production process. Some of the phases in the copper production process are requiring the use of Fe and S oxidation for heating and melting which causes production of sulfur dioxide (SO_2) (Schlesinger et al., 2011). Therefore, sulfuric acid is produced as a result of production operations that create high values of SO_2. SO_2 gases are transformed into the sulfuric acid in specialized plant that operates within the copper company. The main aim of this study was to investigate the demand for electrical energy in a copper production system. To fulfill this goal it was necessary to differentiate the phases of the copper production process with the major electrical energy demand. The demand for electrical energy and the production of the sulfuric acid were observed in relation to the results of the copper production. Furthermore, the parameters for electrical energy consumption and the volume of the sulfuric acid production were used to construct two prediction models for the copper production. First model is constructed using the parameters for the electricity consumption to predict the volume of the copper production. The second model included additional parameter named the volume of the sulfuric acid production.

Figure 1 illustrates trends of electrical energy demand in the observed period. It can be concluded from the figure that most of the electrical energy is used for in the phase of converting and refining, followed by the phase slag flotation. Phase of batch preparation records the lowest electrical energy demand.

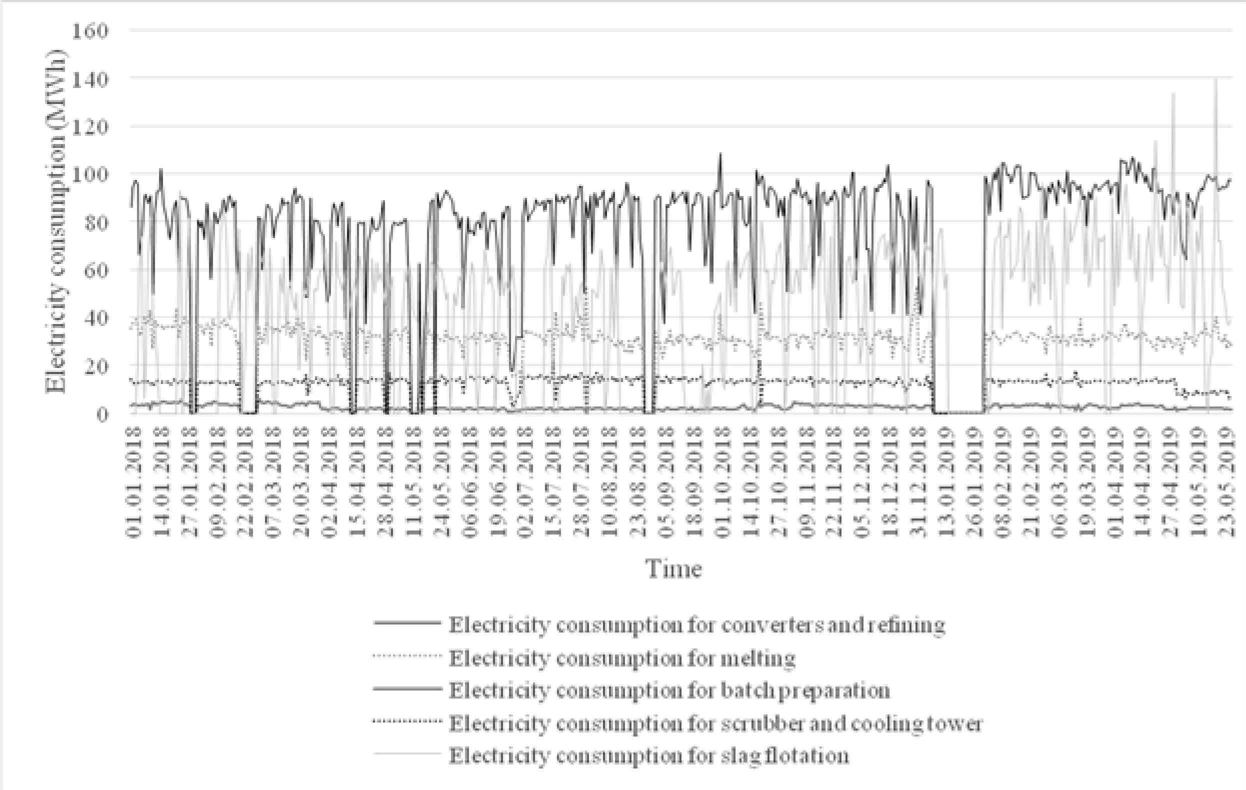


Figure 1. Trend of consumed electricity in the copper production process for the period January 2018 to May 2019

The presented data related to the electrical energy consumption were used to create prediction models for the copper production volume. Software program SPSS v.17.0 was employed to perform the analysis that included descriptive statistics and Pearson's correlation coefficients. The collected data regarding copper production volume were combined with the data about electricity consumption in different production phases and sulfuric acid production to develop prediction models for copper production. The prediction models were generated using the methodology of artificial neural network (ANN).

So far, ANN prediction models have been widely used in solving energy problems (Singhal and Swarup, 2011; Günay, 2016; Guijo-Rubio et al., 2020; Nolting et al., 2020; Piazza et al., 2020). The main reason for choosing this methodology is found in the fact that ANN has great capabilities for predicting behavior of non-linear systems and can accept variation in the data and introducing disturbance variables (Kavaklioglu et al., 2009; Shin et al., 2020). ANN models are also known as simple, easy to use, with good performances (Đozić & Urošević, 2019). The basic ANN model is multilayer perceptron (MLP) that consists of one input layer, more than one hidden layers and one output layer (Behm et al., 2020). The ANN algorithm for predicting values is based on the transmission of the information from input to output layers, passing through the hidden layers (Lopez-Garcia et al., 2020). This algorithm is simulating the function of human brain and is deciding to whom the neuron in the layer should pass the information that possess (Sharma & Garg, 2020).

The computational equation for the simple three-layer ANN model is the following (Li et al., 2015):

$$Y = f\left(b_0 + \sum_{j=1}^{k} h\left(\Psi_j + \sum_{i=1}^{m} p_i w_{ij}\right) b_j\right) \qquad (1)$$

where the following labels can be described as:

Y – predicted values,
$f(.)$ – nonlinear transfer function,
b_0 – output bias,
$h(.)$ – activation function of the hidden layer,
ψ_j – hidden layer bias,
p_i – input values,
w_{ij} – weights from input layer to the hidden layer and
b_j – weights from hidden layer to the output layer.

By learning the patterns obtained from the past data, ANN models modify and calculate the future data values. When comparing ANN and multiple linear regression (MLP) analysis that is also used for creating prediction models, ANN is recognized as more sophisticated methodology that can solve different non-linear problems, which differentiates it from MLP methodology (Nolting et al., 2020).

General structural model that was used to construct prediction models using artificial neural network is presented in the Figure 2. It consists of input variable that is consumed electrical energy (X_1-X_5), one disturbance size sulfuric acid production (Z), transformation process that is copper production and output variable that is the amount of the produced copper (Y). The parameters for electrical energy consumption in the copper production process were recorded separately, for each copper production phase and are reported in the Figure 2 as variables that range from X_1 to X_5.

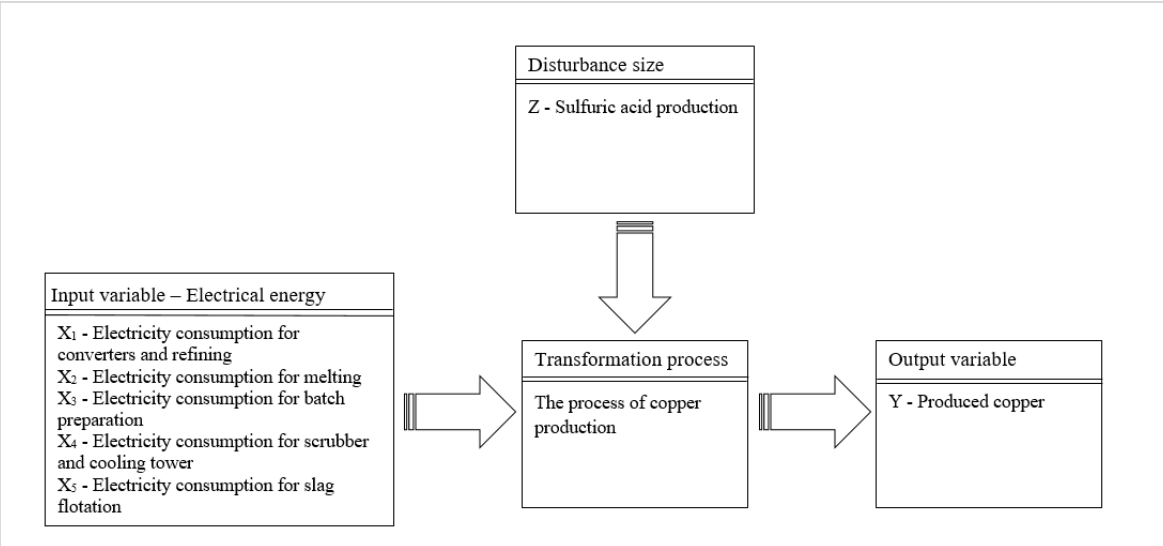


Figure 2. General structural model – systematic approach

The integral variables of the structural model presented in the Figure 2 were used to constitute two different prediction models. Their structures are illustrated in the following Figure 3.

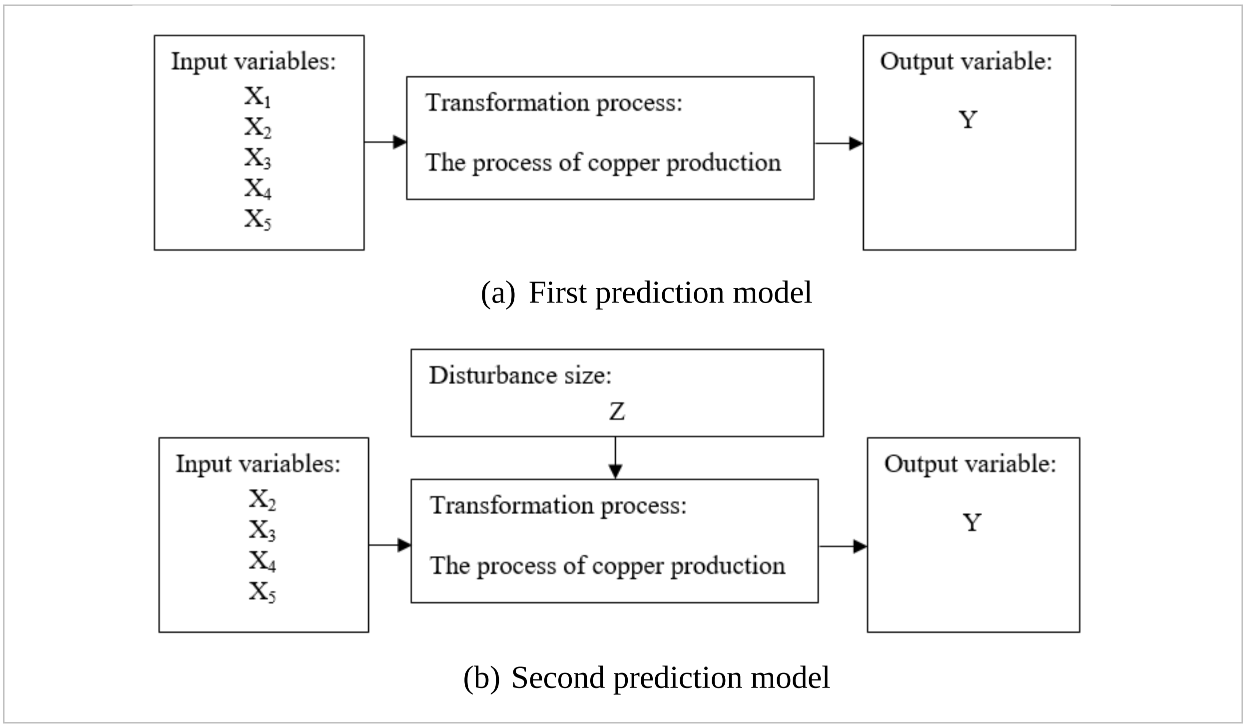


Figure 3. Structure of the (a) first and (b) second prediction model

3. RESULTS AND DISCUSSION

The process of constructing prediction models for the volume of copper production took several stages and various analysis. First among them was the descriptive statistics analysis and Pearson’s correlation. Interpretation of the results of descriptive statistics and correlation are reported in the following part of the study.

Table 1 contains data about several statistical parameters for the considered variables that include range, minimum and maximum values, mean, standard deviation and variance. In addition, Table 2 reports the results of the Pearson’s correlation coefficients that reveal the relationships between the variables. The outcome of the correlation analysis showed strong positive correlations among majority of the independent variables that are statistically significant ($p<0.05$). The highest positive correlation is recorded between the independent variables X_1- electricity consumption for converters and refining and X_2- electricity consumption for melting where $r=0.902$ and $p=0.000$. Detected correlation suggest that these two phases in the copper production process are highly correlated and increase in electricity consumption in the phase of melting will induce the escalation of electricity consumption for converters and refining. Furthermore, independent variable X_4- electricity consumption for scrubber and cooling tower achieved high positive relationship with variables X_1 and X_2, where correlation coefficient equals to 0.830 for variable X_1 and 0.824 for variable X_2 and both are statistically significant ($p=0.000$). These results are expected since all individual phases in the copper production process are interdependent. Lower correlation coefficients are perceived in relation between variable X_5- electricity consumption for slag flotation and other independent variables (X_1-X_4). When referring to the relationship between dependent variable Y- copper production and other observed independent variables (X_1-X_5), variable X_1 is achieving slightly higher positive correlation with the output variable than other input variables. This relationship is characterized by the Pearson's correlation coefficient that equals to 0.499 and the level of statistical significance of 0.000. Further analysis identifies strong positive Pearson's correlation that is statistically significant between disturbance variable sulfuric acid production (Z) and copper production that equals to 0.721. Identified positive Pearson's correlation among all variables showed that copper production process is dependent on electricity consumption and higher production volume follows higher electricity demand. The same relationship can be identified between sulfuric acid production and copper production.

Table 1. Descriptive statistics

	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
X_1	108.62	.00	108.62	75.644	1.284	29.034	842.991
X_2	53.40	.00	53.40	28.723	.461	10.426	108.721
X_3	5.75	.00	5.75	2.464	.055	1.244	1.548
X_4	22.29	.00	22.29	11.792	.194	4.388	19.255
X_5	139.81	.00	139.81	41.893	1.313	29.685	881.221
Z	1393.00	.00	1393.00	860.754	13.502	305.216	93156.596
Y	450.00	.00	450.00	230.064	4.232	95.684	9155.461

Table 2. Correlations

		Y	X_1	X_2	X_3	X_4	X_5	Z
Pearson Correlation	Y	1.000						
	X_1	.499	1.000					
	X_2	.350	.902	1.000				
	X_3	.205	.678	.714	1.000			
	X_4	.300	.830	.824	.629	1.000		
	X_5	.332	.268	.197	.204	.150	1.000	
	Z	.721	.642	.455	.332	.366	.304	1.000

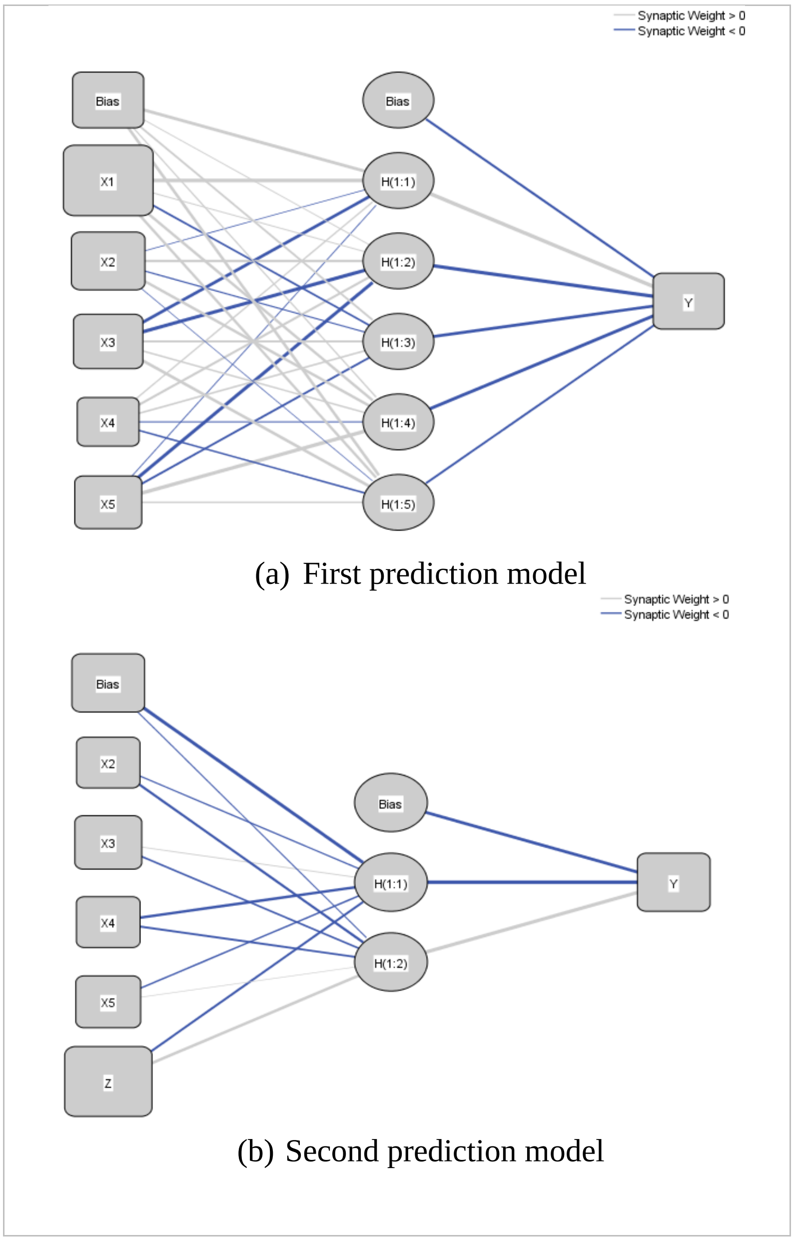
Correlation is significant at the 0.05 level (2-tailed)

Moreover, a multi-collinearity test was performed in order to test the relationship between the variable data. The obtained collinearity statistics reports variance inflation factor (VIF) is less than 10 for all observed variables. The outcome of the test is acceptable and allows further analysis using ANN methodology. The significance of the prediction models is evaluated by calculating coefficient of determination. Results of the multiple linear regression analysis showed acceptable outcome since Pearson's correlation for the first model equals to r=0.603 and coefficient of determination is R^2=0.364. Provided results are statistically significant (p=0.000). In addition, Person's correlation for the second model equals to r=0.737, coefficient of determination is R^2=0.543 and the model is statistically significant (p=0.000).

The next step was to generate ANN prediction models for the copper production in relation to the electricity consumption. The structure of the ANN prediction models was previously presented in the Figure 3.

The first model sample was divided into two groups, first group was training sample that included 66.9% of the total sample and second group was testing sample with 33.1% of the total sample. Figure 4(a) provides graphical representation of the artificial neural network result for the relationship among independent and dependent variables. The first constructed ANN prediction model consists of five input layers, five hidden layers and one output layer.

The second model sample was divided into training sample that included 66.9% of the total sample and testing sample that included 31.1% of the total sample. The structure of the second ANN prediction model is illustrated in the Figure 4(b) and consists of five input layers, two hidden layers and one output layer.

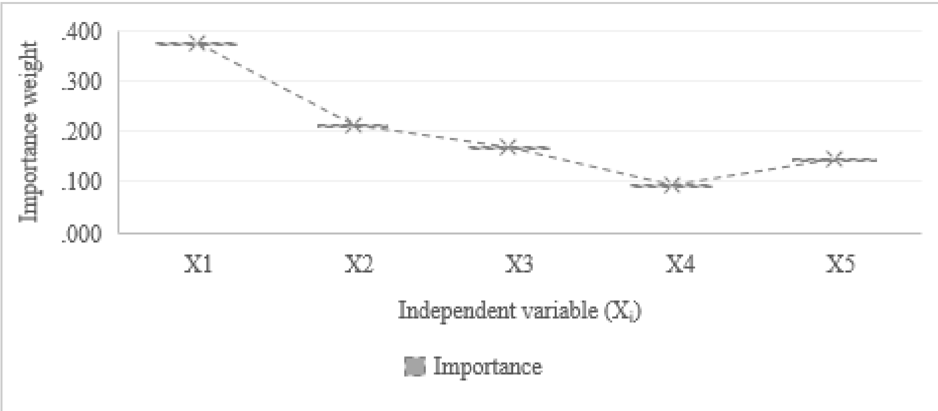


(a) First prediction model

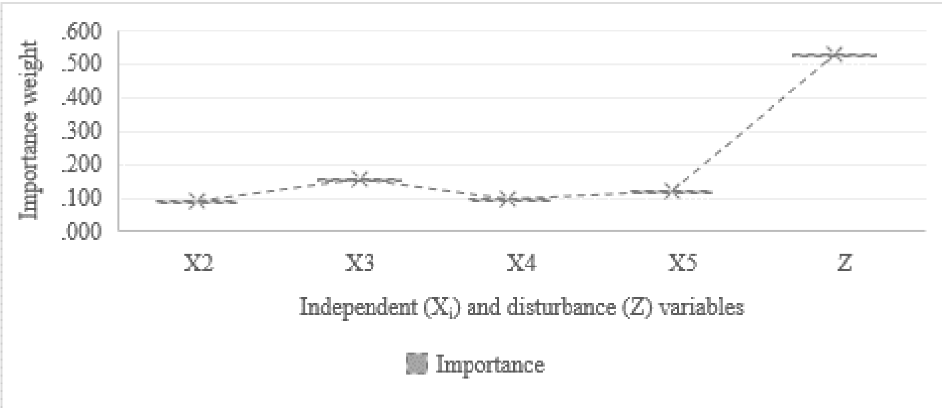
(b) Second prediction model

Figure 4. Artificial neural network for (a) first and (b) second prediction model

As an integral part of the ANN analysis, the importance of each input variable was calculated and the outcome of the calculation is presented in the Figure 5. Independent variable electricity consumption for converters and refining (X_1) is evaluated as the most important variable in the first ANN prediction model with its importance weight of 0.374, followed by electricity consumption for melting (X_2) with importance weight of 0.213. Third ranked variable is X_3-electricity consumption for batch preparation (0.170), fourth ranked is X_5- electricity consumption for slag flotation (0.147) and fifth ranked is X_4- electricity consumption for scrubber and cooling tower (0.095). The outcome for the second prediction model illustrated in the Figure 5(b) showed the high importance of the disturbance size Z-sulfuric acid production with importance weight of 0.530 while the rest of the independent variables importance weights range from 0.094 to 0.158.



(a) First prediction model



(b) Second prediction model

Figure 5. Importance of independent variables in (a) first and (b) second prediction model using ANN

Furthermore, constructed ANN prediction models provided prediction values for the copper production and those values have been compared with the realized values of the copper production. The comparison results are illustrated in the Figure 6. The peak of the copper production is recorded in May 2019. However, detected discontinuities in production were explained as maintenance of production technology. Predicted values in the graph show slight deviations from the realized values. Both realized and predicted values show the trend of growth for copper production. Comprehensive analysis of predicted values for both (a) first and (b) second prediction model suggest that better results were achieved by the second prediction model.

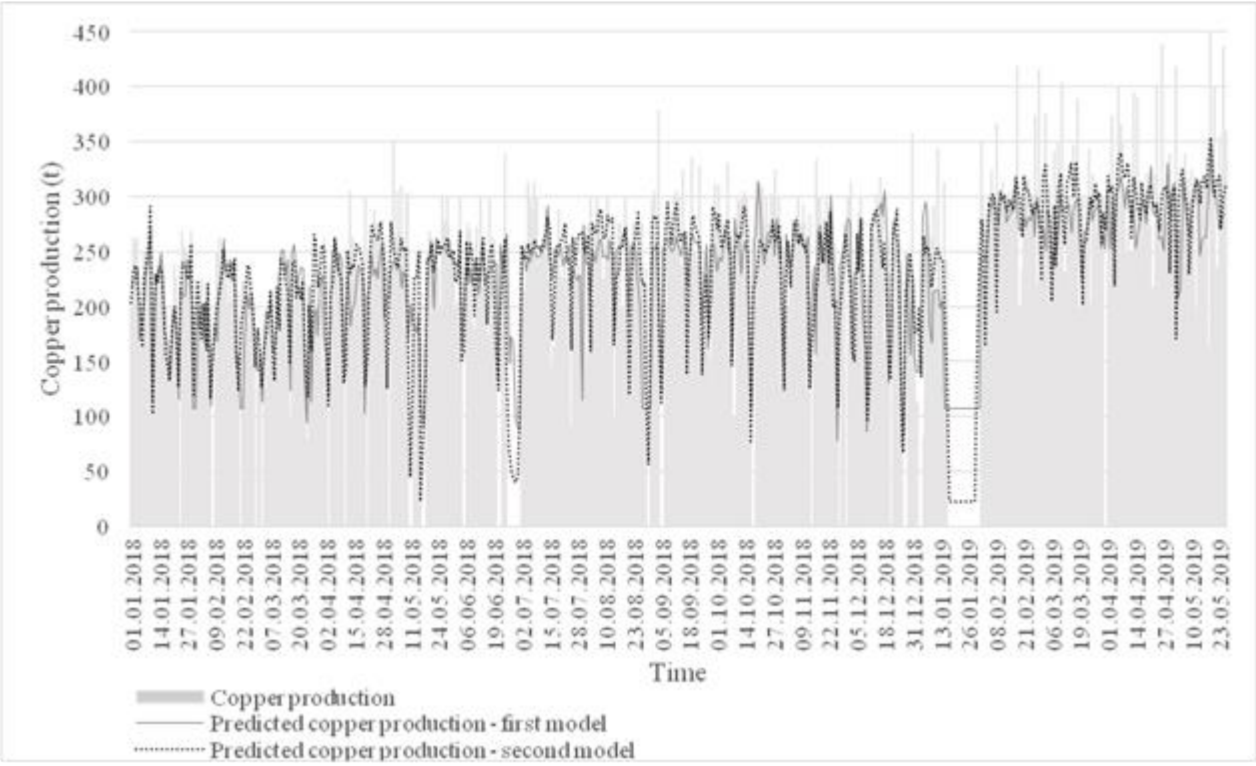
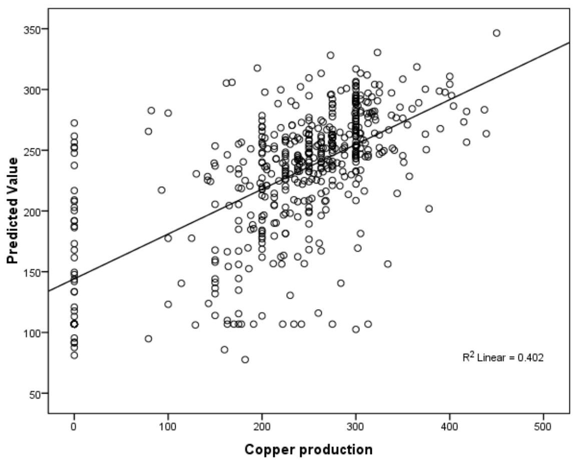
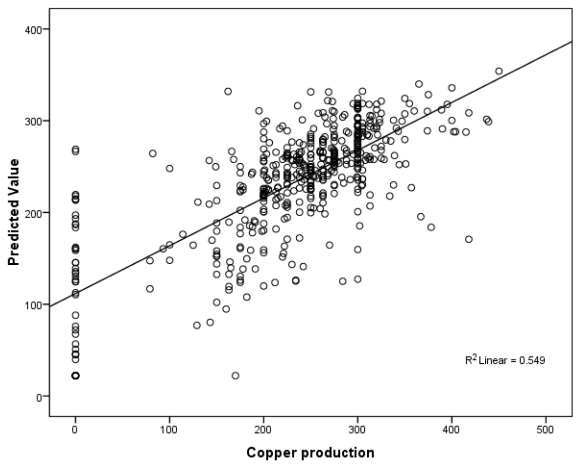


Figure 6. Predicted amount of copper production using ANN

Next Figure 7 (a) and (b) illustrates the relationship between realized and predicted values of the copper production. The linear trend confirms the growth tendency of the produced copper but also highlights the major deviations from the average values. Figure 7(b) reports less deviation values than Figure 7(b).



(a) First prediction model



(b) Second prediction model

Figure 7. Realized and predicted amount of copper production in (a) first and (b) second prediction model using ANN

As it can be concluded from the outcome of this study, the process of copper production is considered for a large electrical energy consumer. Phases that are fundamental parts of the production process are highly energy dependent. Among them is highlighted the phase of converters and refining as the leader in electricity consumption. In addition, the phase of scrubber and cooling tower achieves the lowest electrical energy consumption. The results of the Pearson’s correlation imply on positive, statistically significant, relationship between electricity consumption in all individual phases of copper production with the volume of the production. The identified correlation is confirming the dependence among electricity consumption and copper production where any increase in copper production is leading to the increase in electricity consumption. The disturbance size that measures the volume of the sulfuric acid production reports high Pearson’s correlation with the volume of copper production. Moreover, the empirical evidence from the descriptive statistics showed the increasing trend in the volume of copper production. This increasing tendency is connected with the total electrical energy demand. It leads to the conclusion that higher volume of copper production is demanding higher electrical energy consumption and reverse. This conclusion is logic and expected and it is interesting for further analysis of the observed variables.

Further analysis is considering construction of prediction models for the volume of copper production in the function of electricity consumption. The first constructed prediction model is illustrating the share of electricity consumption of each production phase. The prediction model is underlying the importance of converting and refining operation on the volume of copper production. More specifically, almost 37% of the total share of electricity consumption is referred to the phase of converting and refining and is mostly shaping the results of the prediction model. This outcome is consistent with the previous results of the descriptive statistics that characterize the same production phase as the largest electricity consumer. The second important phase is the phase melting that participates with approximately 21% in the total share of electricity consumption. The third phase by its importance is the phase of batch preparation (17%), followed by the phase slag flotation (≈15%). The least effect is achieving the phase scrubber and cooling tower (≈10%). The model provided interesting results referring to the importance of the lowest electricity consumption phase that is the phase of batch preparing, reporting that even though is the lowest electricity consumer it is more important than higher electricity consumption phases like slag flotation and scrubber and cooling tower. Ranking by importance weights follows different path in the second prediction model. In the second prediction model, the most important independent variable is sulfuric acid production with ≈53% share of the importance in comparison to the importance of the rest independent variables. The empirical evidence suggest that the volume of the copper production is more efficiently predicted using more production parameters.

The predicted values of the copper production using artificial neural network are following the realized values and manifest some deviations in certain production periods. Predicted values are following the rising trend of the volume of copper production. This means further growth of electrical energy demand and emerged need to efficiently plan the production volume. With the help of the prediction models, it is possible to plan all sorts of resources, including electrical energy demand. The use of prediction models is recognized as essential for smart energy management. Constant monitoring of the production results and electrical energy resources could bring to the use of more efficient technological solutions in those production phases that are considered as high electrical energy consumers. Energy efficient solutions would have as a result low electrical energy demand.

4. CONCLUSION

The main contributions of this paper are following:

- Electrical energy demand for the process of copper production has been observed for the period longer than one year. The most important phases in the copper production have been identified and electrical energy consumption for those phases has been recorded on a daily basis. The observed parameters have been divided into input, disturbance and output groups of variables.

- The gathered data have been used to conduct further analysis of the electricity consumption using SPSS software package. Empirical evidence obtained from the SPSS showed the descriptive statistics of the dependent and independent variables and Pearson's correlation matrix. The highest positive correlation has been recorded among variables X_1- electricity consumption for converters and refining and X_2- electricity consumption for melting where r=0.902 and has achieved acceptable level of statistical significance ($p<0.05$). The outcome of the multiple linear regression analysis for the first prediction model showed statistically significant value of Pearson's correlation that equals to r=0.603 and coefficient of determination is $R^2=0.364$. Obtained values provided acceptable results and approved the construction of this prediction model. Results for the second prediction model that are statistically significant, indicate on high value of the Pearson's correlation coefficient that equals to 0.737 and coefficient of determination is $R^2=0.543$. The obtained performances of the second prediction model showed better outcomes than first prediction model.

- Five input variables and one output variable have been employed to construct the first artificial neural network prediction model. Input variables included parameters concerning electricity consumption in five phases of copper production and output variable included the volume of copper production. ANN results revealed five hidden layers in the prediction model. The most important independent variable in the prediction model was X_1- electricity consumption for converting and refining with the importance weight of 0.374. This highlights the variable X_1 as the most influencing variable in the prediction model. The second prediction model included five input variables; among them is one disturbance size, two hidden and one output layer. The most important independent variable is Z- sulfuric acid production with its weight of 0.530. The high importance of this variable allows it to shape the results of the output values in major share.

- The outcome of the prediction models was used to calculate prediction values for the volume of the copper production and was compared to the realized volume of the copper production in the observed period. The comparison results showed occasional variation in the prediction values. The results indicate that second model provides higher-quality predictions values than first prediction model.

- The major advantage of the constructed prediction model is identified in the possibility to adapt it to different situations and add other variables. The same concept can be used in other industries that are marked as high electrical energy consumers. The results of the study can be useful in further investigation of the electrical energy consumption in copper production process and influence of copper production volume on electrical energy demand.

- Further analysis of the relationship between electrical energy demand and the volume of the copper production can be done using more variables that are recorded in the production process. It is evident from the study that adding different input and disturbance sizes can cause changes in the predicted output values. Supplementary variables could explain the relation between copper production process and production parameters in more details. This is also considered as the main limitation of the study.

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XVI INTERNATIONAL MAY CONFERENCE ON STRATEGIC MANAGEMENT – IMCSM20

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