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Recovery Prediction of Industrial Copper Agitation leaching by Combined PCA, Neural Network and Genetic Algorithm

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Abstract

Generally to remove agglomeration of copper oxide heap leaching process in which their agglomerated particles don't have enough stability, agitation leaching is used. This method makes it easier to control the operating parameters, because it increases the amount of flexibility in downstream processes. The online controlling operational parameters need high cost of investment, calibration and maintenance.

In this paper, a new approach proposed for copper recovery prediction in agitation leaching using Principle Component Analyzes (PCA), Genetic algorithm and Neural Network (NN). To validate predicted model, the agitation leaching in industrial scale and to reduce dimensions of data, reaching principle variables, reducing neural networks nodes, simplifying structure, increasing learning speed of neural network and increasing prediction speed of mode, PCA have been used. By this method, the number of variables reduced from 12 to 5. Furthermore to determine weight factors in neural network, genetic algorithm is used. The Feed rate, pH of raffinat and PLS, solid percent, volume of produced PLS, concentration of Cu in raffinat and PLS, copper oxide and total copper in feed, ratio copper oxide on total copper grade in the feed, acid consumption per batch and total acid consumption per day were used to the simulation by PCAGANN

Keywords: Agitation Leaching, Principle Component Analyses, Neural Network, Genetic Algorithm

Introduction

Hydrometallurgical extraction of metals is a branch of industry for which the research work is ongoing to develop processes which are less costly, more environmentally friendly and acceptable economically[1]. Leaching processes of metallic copper or ores containing copper in the divalent state have been the subject of many research works [2–6].

Copper can be found in the earth's crust as pure native copper, but mostly occurs in combination with other elements. Native copper is typically found as irregular masses or veins, which fill fractures and other spaces in the earth's crust. When found in combination with other elements, copper can occur in minerals including copper sulfides (e.g., chalcopyrite and chalcocite), copper oxides (e.g., cuprite), copper carbonates (e.g., azurite and malachite), copper phosphates (turquoise), and additional mixed copper ores.

Flotation and leaching are used for beneficiation of Sulfide and oxide minerals respectively. In the hydrometallurgical extraction of copper, although other heavy minerals are dissoluble in sulfuric acid, copper is dissolved earlier from minerals such as zinc, cobalt and iron due to the higher place in the electrochemical series [7–8].

Heap leaching is the process of using percolating chemical solutions to leach out metals. Heap leaching is very commonly used for low-grade ore, which would otherwise not be economical to send through a milling process. Following mining, transporting, and crushing to a consistent gravel or golf ball-size, the crushed ore is piled into a heap on top of an impenetrable layer, on a slight slope.

Agitation leaching is a chemical process where in the soil that is to be mixed or slurred is kept in contact for a certain period of time with fluid to be extracted. The metal solubility rate is reduces quite noticeably, and the extraction gets completed on the approach of equilibrium between the metal present in the solution and the metal contained on the surface of the soil is approached

For oxide mines in which the oxide minerals are dominant with an average grade, heap leaching is used. To increase the permeability in heap leaching, usually particle agglomeration is used, however when the stability of agglomerated particles is low, agglomeration are not used. To remove agglomeration in heap leaching process for oxide copper minerals with feasible grade and low sustainability agglomerated products, agitation leaching is used. By this method, the flexibility in downstream processes will be increased due to easier control of operating parameters [9–12].

Nasim copper complex located in Khorasan Razavi province, 70 km from the city Bardaskan. Chemical composition analysis of oxide ore by X-ray Fluorescence, XRF, is shown in tables 1. The quantities X-ray powder diffraction, XRD, was done for mineralogical analysis of copper ore, and its results are shown in table 2.

Table 1; Chemical composition analysis of oxide ore by X-ray Fluorescence, XRF

		Zn	Cu	TiO2	SO3	P2O5	MnO	MgO	K2O	Fe2O3	CaO	SiO2
1	Head	0.01	0.72	0.79	0.35	0.28	0.07	1.1	3.67	5.89	9.26	56.07
2	70 mesh	0.01	0.55	0.7	0.27	0.26	0.06	0.45	3.56	4.39	7.49	56.53
3	100 mesh	0.01	0.6	0.68	0.28	0.25	0.06	0.49	3.39	4.39	7.88	56.78
4	140 mesh	0.01	0.73	0.66	0.35	0.22	0.06	1.19	3.2	4.72	8.71	56.22
5	200 mesh	0.01	0.75	0.68	0.32	0.23	0.06	1.05	3.21	4.92	13.98	58.98
6	270 mesh	0.01	0.83	0.69	0.38	0.23	0.06	0.62	3.38	5.23	8.17	54.67
7	400 mesh	0.01	0.86	0.7	0.4	0.24	0.06	0.73	3.53	5.49	7.68	55.3
8	-400 mesh	0.02	0.74	0.97	0.35	0.34	0.1	1.38	3.73	7.91	6.95	52.08

Table 2: The quantities X-ray powder diffraction, XRD

1	Quartz,low	**SiO2**
2	Clino pyroxene,titanian,aluminian	**Ca(Ti,Mg,Al)(Si,Al)2O6**
3	Malachite	**CuCO3.Cu(OH)2/2CuO.CO2.H2O**
4	Anortho clase,syn	**Na0.71K0.29AlSi3O8**
5	Albite,disordered	**NaAlSi3O8**
6	Sanidine	**K0.47Na0.43Ca0.10Al1.1Si2.9O8**
7	Calcite,syn	**CaCO3**
8	Montmorillonite	**Nax(Al,Mg)2Si4O10(OH)2.z H2O**
9	Magnetite,syn	**Fe3O4**
10	Hematite	**Fe2O3**
11	Diopside	**Ca(Mg,Al)(Si,Al)2O6**

Result show that meager mineral in this samples are Malachite (Cu_2 (OH) $_2CO_3$), and small amounts of Azurite (Cu_3 (OH) $_2$ (CO3) $_2$) and Chalcocite (Cu_2S).
All minerals listed are dissoluble through acidic or alkaline forms at room temperature and at different times.
Common equations to dissolution of copper oxide minerals are as follows:

$$Cu_3(OH)_2(CO_3)_2 + 3H_2SO_4 \rightarrow 3CuSO_4 + 2CO_2 + 4H_2O \quad (1)$$

$$Cu_2(OH)_2(CO_3)_2 + 2H_2SO_4 \rightarrow 2CuSO_4 + CO_2 + 3H_2O \quad (2)$$

$$CuO + H_2SO_4 \rightarrow CuSO_4 + 4H_2O \quad (3)$$

$$CuSiO_3.2H_2O + H_2SO_4 \rightarrow CuSO_4 + SiO_2 + 3H_2O \quad (4)$$

Therefore, regardless of the chalcocite that needs more time for leaching process, other copper minerals are dissoluble in agitation leaching [9–12]. According to the results of sampling and grinding circuit in the study, about 35% of the initial load had a particle size less than 2 mm. According to the analysis the results show that sending material to the heap even by agglomeration process affects the heap permeability and reduces total circuit recovery. To avoid this issue, particles less than 2 mm are sent out of the crushing circuit and entered agitation leaching. It is noticeable that according to the laboratory tests, about 85% of the minerals are in oxide phase and the rest is in the form of chalcocite.

Principal Component Analysis (PCA)

Principal component analysis method based on illustration in two-dimensional space, greatly reduce data size and can easily illustrate complex databases in multiple dimensions to maximum variance and facilitate their interpretations. In addition, it can show well the hidden data aspects based on possible grouping among observations and correlation among variable. The problem existing in multivariable systems is that, in these systems, it is not possible to discuss in the process based on individual factors. On the other hand, presence of amounts at different scales or in other word different limitations makes comparing and following that resulting difficult and it is possible that some aspects of the process remain hidden because of the many variables in different directions. Therefore, the multivariable analysis using illustrating them and finding the main components of the most powerful methods, is for surveying such systems. Principle component analysis (PCA) is suitable for having a glimpse of the circuit operation because it can show relationships between variables and observations and do grouping observations. Likewise, it can use large number of variables and existing properties to interpret the model. The main importance of using principle component analysis method is classifying of raw data related to multivariable systems, usually in 2 to 5 directions so that with a glimpse, the relationship between observations and variables is revealed. This overview could include grouping the variables, observations and variables, and determining their directions (Figure 1) [13].

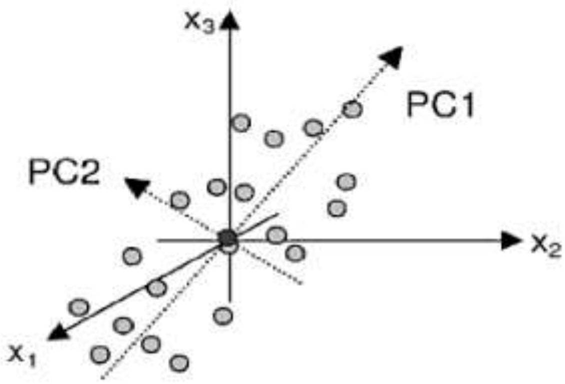


Figure 1: The main components of orientation with respect to the distribution of data [13].

Modeling using neural and genetic systems

Since many different methods for predicting the results of the leaching process have been used. Some of these methods include statistical methods, methods based on modeling, neural networks and genetic algorithm [14–16]. Neural networks are more appropriate than other methods because of the process of weighting the variables and the ability to train and test data. Also in the linear systems, an acceptable standard deviation for solving complex problems will be given. However in non-linear functions, they will be caught at local optimums. The process of optimizing are usually affected from the initial points If the initial points are close to local optimum rather to the global optimum, in order to achieving overall optimization, several layers should be used. In this case, the genetic algorithm can solve this problem easily. Genetic Algorithm is not limited to the search environment and can obtain the overall optimization method for issues with large number of dimensions containing high deficits. The incorporation of neural networks with genetic algorithms increases the accuracy and speed of modeling. In this paper, the genetic algorithms is used for optimizing weights relevant to existing variables in system in several layers of neural networks to increase the speed of predicting. Several variables can affect the extent of copper recovery in agitation leaching. These variables have non-linear relationship with the copper recycling. Thus reducing the variables to achieve the main variables must be considered. So the Principal Components Method is used for reducing the size of variables. The difference between this paper and the previous papers is using Principal Component Analysis (PCA) to reduce the size and increase the speed of learning process.

Combination of Principal Component, Neural Networks and Genetic Algorithms

A combination of Principal Component Analysis (PCA), Neural Networks and Genetic Algorithms to predict copper recovery is used in the agitation leaching. The principal component analysis is used to reduce the size of data and obtain the main variables. The Principal Component Analysis is used for reasons as follows:

1. Reduction of the number of nodes in the input layer of neural network.

2) Simplification of the neural network structure

3) Improvement of the speed of neural networks learning and the model prediction using genetic algorithms optimization for neural network parameters.

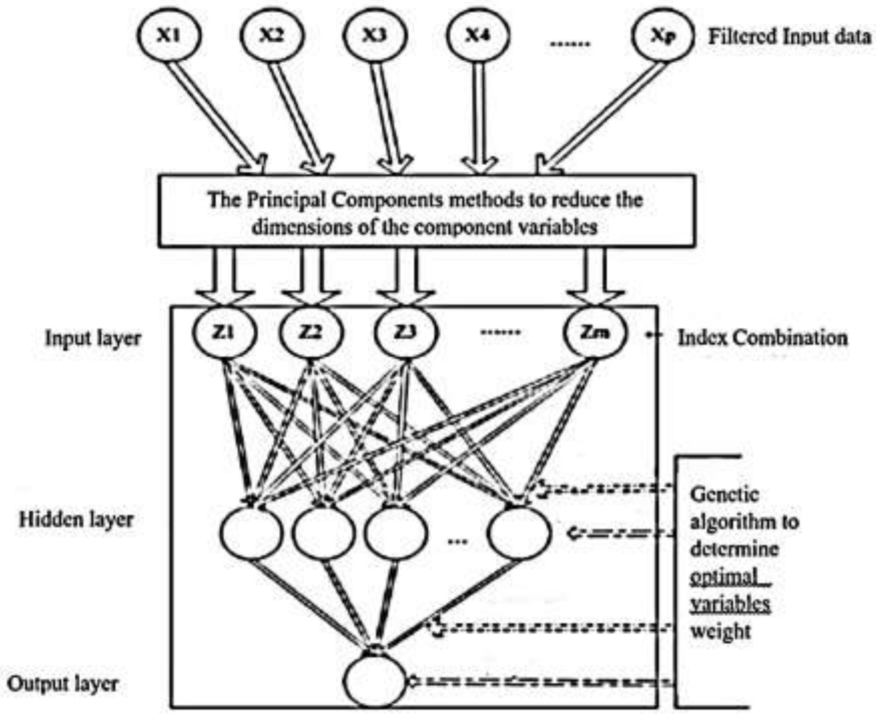


Figure 2: flow sheet of the incorporation of the principal components statistical method, genetic algorithm and neural networks.

In this article, a combination of principal component analysis method, neural networks and genetic algorithms is used to predict the copper recovery in agitation leaching process. .therefore, this method, not only can ensure the accuracy of recycling but we can also increase the speed anticipation.

1-4 Method

1-4-1. Sampling Method

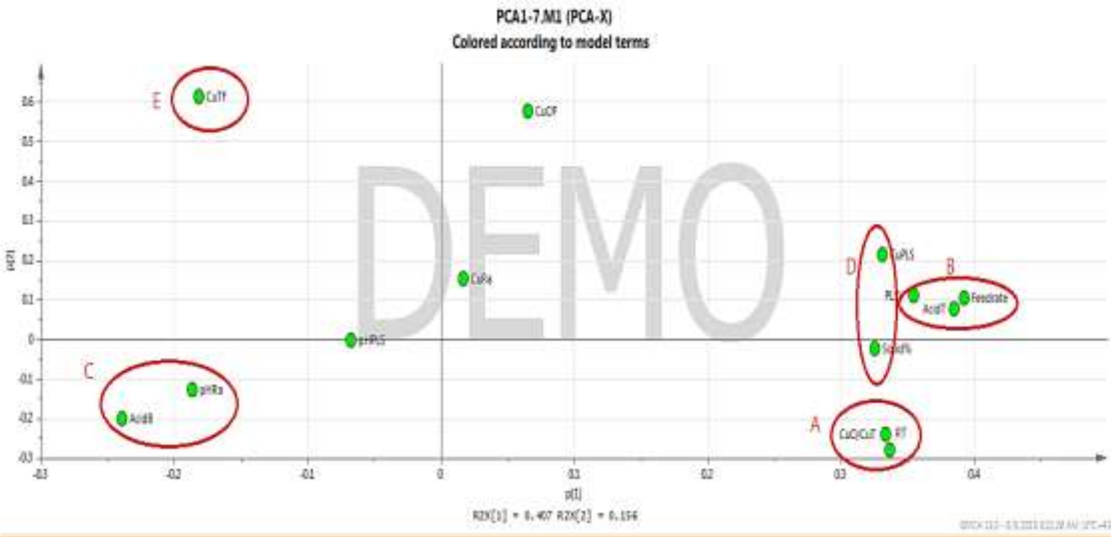
After defining the agitation leaching circuit efficiency, 65 series of sampling are done, based on the recovery of copper oxide. Boarding prepared samples from input soil, returned solution to the tank is used as rafinate and is transferred to the laboratory .In order to reduce the lab error rate, the samples are divided into two parts and they are analyzed separately. Also using equipped weighting system in mixing tanks, the amount of consumed acid, soil, water and processing time is recorded in per batch. Sampling points in agitation tanks is shown in Figure 3.

Figure 3: View of the entrance and existence of the agitation leaching tanks

1-4-2- The results of principal component analysis method

The principal components method was used in Demo of Software SIMCA 13. Based on the samples related to weight, it is observed that due to the scores obtained by the measured variables; more or less all variables impact the model greatly. (Figure4).

However, effect of copper oxide to feed total copper grade, amount of total input copper in feed, pH of raffinatt, amount of acid in each batch, and amount of daily input feed per day are greater.



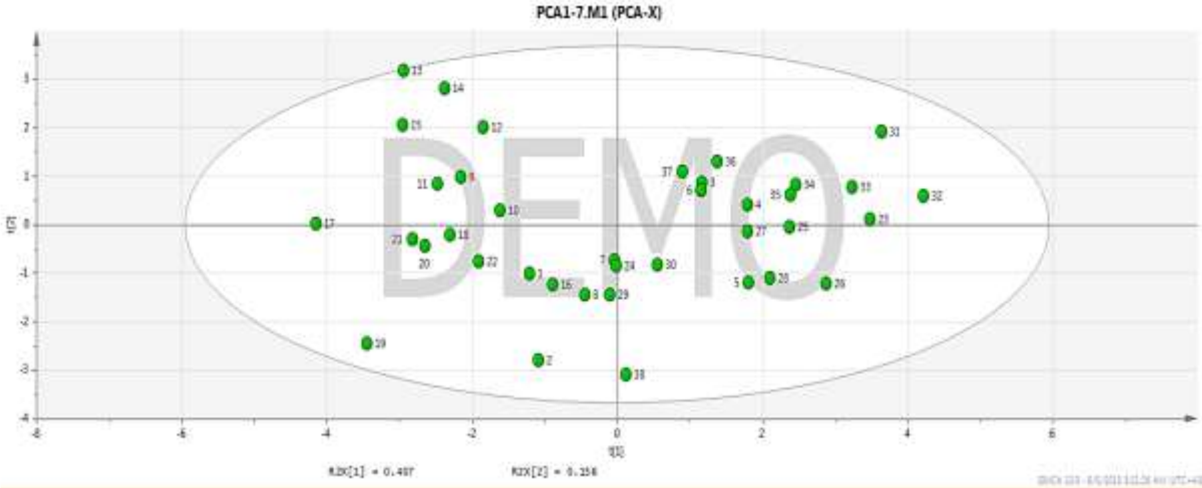


Figure 4: weight graph and points gained by variables. CuTF: Total copper content in feed, CuO: feed Copper oxide content, COuPLE: Copper concentration in the PLS, PLSV: produced PLS volume, Solid%: agitation leaching Solid percent, Acid T: daily Amount of acid consumption, Feed Rate: Solid tonnage entering the circuit, Acid: The acid consumption per batch, CuTE / CuT: Copper oxide ratio to total copper of the feed, RT.

Based on the above, these results and relations can be concluded:

1- According to the obtained weight and score charts by variables, all variables can be categorized into 6 groups A, B, C, D, E and F group variables with low impact on the model.

2- According to weight and score charts, the copper concentration in the raffinatt and the pH related to PLS do not have a significant impact on the recovery of copper.

3- The reason why related pH to PLS is not effective, can be follow the range of pH in the operation.

4- The variables of group B exhibit strong correlation. By increasing the input tonnage, the volume of produced PLS and the total amount of consumed acid increases per day. Therefore, instead of using three mentioned variables, only entrance feed was used.

5- By increasing the solid percent in agitation leaching, copper concentration in the PLS has increased

6- The correlation variables of group C shows that by increasing raffinat pH, the amount of consumed acid in each batch increases.

7- Due to the strong correlation between the different group's variables, instead of defining 12 variables for input of the Neural Network and Genetic Algorithm combination, we used a 5 group with a single output.

8- By increasing pH of raffinate, the amount of consumed acid in each batch increased. This leads to reduction the overall recycling circuit compared to low raffinat pH.

1-4-3- The result of method integrating Principal Component Analysis, Neural Networks and Genetic Algorithms

One of the main factors affecting network modeling construction, is weighing variables in different layers. In this project, MATLAB 2012 software was used. Likewise, the Genetic Algorithm was used to determine the optimal weight related to layers of Neural Networks.

In this process, the mutation and intersection operation in Genetic Algorithm with 0.9 and 0.01 probabilities were considered respectively. 20% of the total samples were used for training and 80% of them were used for testing. Best selection with respect to minimum of RMS and maximum adaptation based on test data was carried out. The number of hidden layers, the input and output in integrated Network Algorithm, were considered respectively 1, (2 and 3), 5 and 1.According to obtained Results, the most appropriate number of hidden layer was 2. The best model was obtained in the form of 1-5-6-7. The best presented model in the integrative model to predict copper recovery in the process of testing and training was about 93%.The results of the relationship between observed and predicted values are shown in Figure 5.

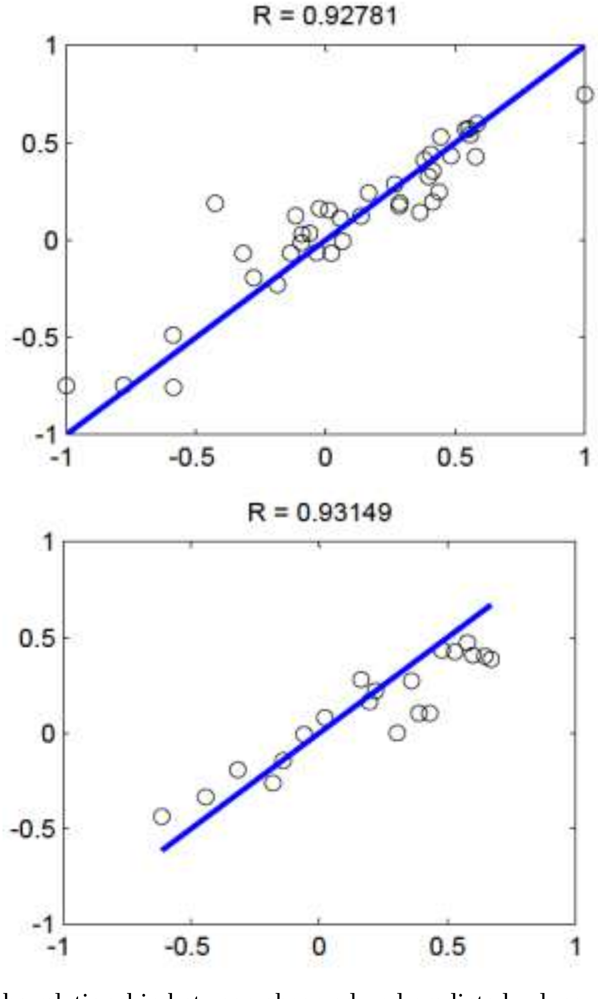


Figure 5: The results of the relationship between observed and predicted values

The results for RMS error and correlation coefficient for testing step and training to predict copper recycling are given in Table 3.

Table 3: Results from RSM and correlation coefficient in the training and testing steps.

RSM	MSE	
0.029	0.17	Training Phase
0.025	0.158	Trial Phase

The presented model conformance degree to the observed and predicted values is shown in Figure 6.

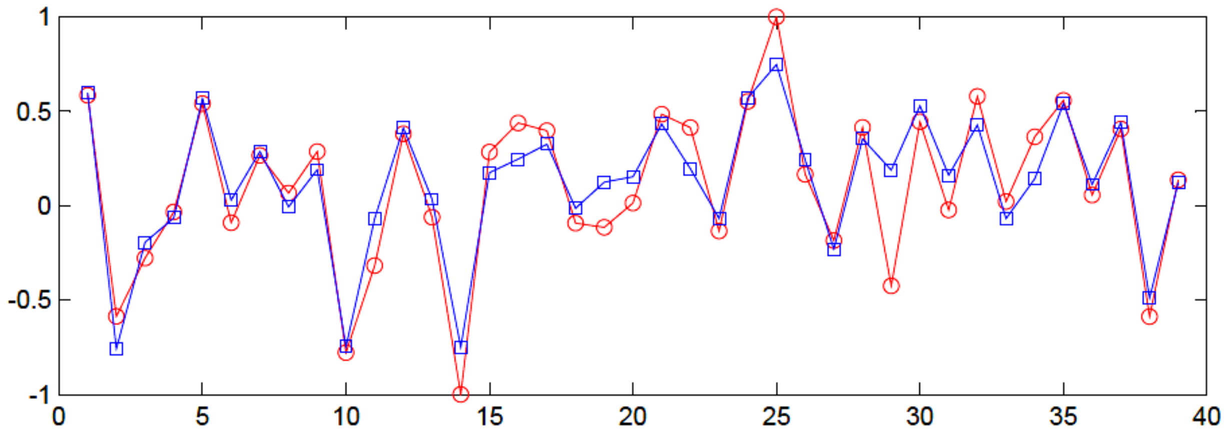


Figure 6: The results of presented model conformance degree to the observed and predicted values

According to the obtained results of the rating charts, the total amount of copper in feed, daily input tonnage to the circuit, the amount of copper concentration in PLS, the ratio of copper oxide to the total copper in the feed and pH of raffinat were chosen as circuit input variables and total copper recycling as the output of the circuit.

1-5-Conclusion

In order to remove the agglomeration in heap leaching process for copper oxide mines in which the stability of agglomerated product is low, agitation leaching was used. By using this method, flexibility of downstream processes will be increased, due to easier control of operating parameters. Continuous measurements of the recycling rate need high investment, calibration and maintenance costs.

In this study, integrated model based on Principal Component Analysis, Genetic Algorithms and Neural Networks was presented on an industrial scale to predict the copper recovery in agitation leaching. The input variables included total copper content in the feed, the content of copper oxide feed, the copper concentration in the PLS, the PLS volume production, solid percent in agitation leaching, the amount of consumed acid in the day, solid tonnage entered the circuit, the amount of consumed acid in each batch, the amount of oxide copper to total copper in feed, related pH to PLS and raffinat, that after applying PCA method to them, their number were reduced to 5. Genetic Algorithms was also used to increase the speed and accuracy of prediction models. Throughout the process, 20% of the input data was used for testing and 80% of them was used for training. In Neural Network, 1-5-7-6 structure was used to predict the copper recycling in the circuit. The presented integrative model of Principal Component Analysis, Genetic Algorithms and Neural Networks for predicting copper recycling in agitation leaching showed required efficiency with high accuracy. The correlation coefficient for predicting the copper recycling in the learning and testing steps equaled 93%. The obtained results indicated that the mentioned method has the potential to be used in an industrial scale. The applied method and its results can be used in agitation leaching circuit to optimize the variables and relationship between them and achieving good copper recovery without performing laboratory tests.

1-6- Acknowledgments
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