Modeling and simulating the cyanidation process and adsorption rate of gold onto activated carbon using intelligent techniques: SVM and ANFIS

Azizi Asghar[1*], Rafiee Ramin[1], Azarfar Azita[2] and Rezakazemi Mashallah[3]
1. Faculty of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, IRAN
2. Department of Electrical and Computer Engineering, Shahrood Branch, Islamic Azad University, Shahrood, IRAN
3. Faculty of Chemical and Materials Engineering, Shahrood University of Technology, Shahrood, IRAN
*azizi.asghar22@yahoo.com, aazizi@shahroodut.ac.ir

Abstract
The cyanide leaching of gold and its adsorption process onto activated carbon is influenced by several factors; some are beyond the control and cannot be even measured quantitatively. Thus, it is essential to select an appropriate model to describe the behavior of influential factors. In the present study, intelligent systems including SVM and ANFIS were utilized and developed to model and predict the leaching recovery of gold and its adsorption rate from cyanidation solution onto activated carbon. The values of R^2 and RMSE of the model developed by ANFIS based on the testing data set were found to be 0.8602 and 0.5589 for cyanidation and 0.9621 and 1.738 for adsorption processes respectively. Its prediction results indicated an excellent agreement with the training dataset.

SVM model led to the weaker predictions compared to the ANFIS model with lower values of R^2 and higher values of RSME for test data set. The values of R^2 and RMSE were obtained as 0.6112 and 0.974 for leaching and 0.8246 and 3.6289 for adsorption respectively. Ultimately, ANFIS model was distinguished to be an alternative reliable, cost-effective, rapid and easy route with high accuracy for modeling the leaching and adsorption processes of gold.

Keywords: Gold recovery, Cyanide leaching, Adsorption, Modeling, SVM, ANFIS.

Introduction

Gold is a precious metal, which due to its resistance to oxidation and corrosion, ductility and excellent electrical conductivity, is widely used in various fields such as catalyst in different chemical processes, economic activity, jewellery, fuel cells, medicine and electronic components[1-4]. Nowadays, the demand for gold has significantly enhanced owing to relatively large stable price and hence the fields of gold exploration and metallurgy have attracted much attention[5]. The extraction of gold from ores is performed hydrometallurgically by the cyanidation process by mixing the ground ore sample (typically below 75µm) with a dilute cyanide solution[6,7]. Gold cyanidation can be described by eq. 1[8]:

$$4Au + 8CN^- + O_2 + 2H_2O \rightarrow 4[Au(CN)_2^-] + 4OH^- \quad (1)$$

After cyanidation of gold, adsorption of $Au(CN)^{2-}$ complex from cyanide liquor is subsequently performed onto activated carbon[9]. The use of activated carbon as adsorbent may be because of ecofriendly nature, large surface area, porous structure, high sorption capacity, ease of elution and a great selectivity towards gold relative to base metals[4,10-16].

The cyanide leaching and adsorption processes of gold are impressed via a number of factors such as dissolved oxygen concentration, cyanide concentration, slurry pH, particle size, surface area of gold exposed, ore mineralogy, temperature, agitation rate, quality of activated carbon, carbon particle size, pulp density, contact time and ionic strength[17-25]. Some of these parameters are beyond the control of the mineral engineer and cannot be even measured quantitatively.

On the other hand, in these studies, the classic approaches were further applied to investigate the effects of factors, which rely on the empirical models achieved from statistical correlations between independent and dependent variables and simplification is one of their limitations. Thus, it is essential to use new techniques to characterize the behavior of factors to obtain a successful cyanidation and adsorption process. Moreover, developing the ability to predict the leaching and adsorption rates of gold will allow a more accurate estimation of cyanidation and adsorption costs.

In recent years, intelligent methods such as genetic programming (GP), support vector machines (SVM), adaptive neuro-fuzzy inference systems (ANFIS) and artificial neural networks (ANN) increasingly have been applied as a very useful and powerful tool with high flexibility for modeling the complex systems and nonlinear relationships between inputs and outputs in engineering different fields[26-42].

Nowadays, ANFIS and SVM techniques are the most popular soft computing approaches to simulate and characterize the behavior of systems studied. ANFIS is a simple and rapid method to create the nonlinear relationships using training data and generally this technique is the capability to model a multivariable problem[43]. SVM has an excellent generalization capability and can achieve the best compromise between the complexity of model and learning ability when solving small samples and the nonlinear problems[44,45].

It should also be noted that this methodology has a fast construction of the classification models[46]. Hence, the present research was aimed to study the ability of ANFIS and SVM to predict the hydrometallurgical efficiencies of Au (cyanide leaching and adsorption rate) and also to compare their performances in modeling and simulation. This study investigates the application of ANIFS and SVM models in gold hydrometallurgy industry for cyanide leaching rate and also its adsorption onto activated carbon.

Material and Methods

Two datasets including 50 cyanide leaching tests and 30 adsorption tests onto activated carbon were utilized to model and simulate the cyanidation and adsorption processes of gold, which were obtained as per Azizi et al[47] and Khosravi et al[4]. According to Azizi et al[47], the cyanidation experiments were performed on the sample derived from the Aghdareh gold mine (crushing circuit input) in west Azerbaijan province, Iran (contained 1.17 ppm Au). Experiments were performed on a 300 g representative sample at ambient temperature using a tumble bottle. For each test, the pulp was first prepared in the tumble bottle and then the slurry pH was modified using lime at the desired value.

After that, the sodium cyanide (made by Merck) was added into the pulp at the value targeted and then the pulp was mixed. Ultimately, the reactor content was filtered and the liquid phase was analyzed using atomic absorption spectroscopy to determine the gold concentration[47]. The leaching rate (R) of gold was calculated via eq. 2. The operating conditions and the values of gold leaching rate calculated for each experiment are presented in table 1.

$$R = \frac{M_1}{M_2} \times 100 \qquad (2)$$

where M_1 represents the weight of gold in the leach liquor and M_2 depicts weight of gold in the ore sample.

According to Khosravi et al[4], adsorption experiments were conducted using activated carbon on cyanidation solution (contained 1.8-2 ppm Au) obtained from treatment of Sarigoni (Qorveh) gold ore in Kordestan province, Iran. After each cyanidation experiment, the leach liquor was transferred to a tumble bottle and all adsorption tests were performed by means of the traditional bottle-on-rolls method at the targeted pH and agitation speed by placing a weighed amount of the activated carbon with 1000 ml of the gold cyanide solution.

After each test, the reactor content was filtered and the solution was analyzed for gold content by atomic absorption spectroscopy. The adsorption efficiency (CR) was measured by the gold concentrations before (C_0) and after (C_t) adsorption process as given in eq. 3. Table 2 displays the design matrix of adsorption experiments and the calculated values of efficiencies.

$$CR = \frac{C_0 - C_t}{C_0} \times 100 \qquad (3)$$

Theoretical background

Adaptive Neuro-Fuzzy Inference System (ANFIS): ANFIS is a hybrid system incorporating the learning abilities of artificial neural network and excellent knowledge representation and inference capabilities of fuzzy logic[48] that can modify their membership function to achieve the desired performance. Thus, this technique is a blend of fuzzy inference system and ANN and these two methods complement each other.

ANFIS can be applied to solve problems related to parameter identification using a hybrid learning algorithm combining the least-squares approach and back-propagation gradient descent. Fig. 1 shows a graphical representation from the structure of the ANFIS network based on Sugeno fuzzy system with two input and two rules.

Rule 1: If x is A_1 and y is B_1, then $f_1 = \alpha_1 x+\beta_1 y+c_1$
Rule 2: If x is A_2 and y is B_2, then $f_2 = \alpha_2 x+\beta_2 y+c_2$

where α_i, β_i and c_i are the design parameters decided through the training process; A_1 and B_1 are fuzzy sets; x and y inputted and f_i is the output within the fuzzy region described by the fuzzy rule[43].

Support vector machine (SVM): SVM is a novel machine learning route based on statistical learning theory[44] proposed by Vapnik and Chervonenkis[49] in 1964 as a generalization of the Generalized Portrait algorithm. SVMs are a very specific class of algorithms characterized by the usage of kernels, absence of local minima, the sparseness of the solution and capacity control obtained by acting on the margin, or number of support vectors etc. SVMs have a better generalization capability with minimization of the structural risk besides the empirical risk and can be utilized not only to classification problems but also to the case of regression.

Fig. 2 shows an example of a support vector machine (SVM) classifier. In a support vector machine model, a regression hyperplane with a ε-insensitivity loss function is a convex dual optimization problem. The solution can be obtained from the optimization algorithm[50]. The deterministic function of the SVM can be determined by the equation 4:

$$f(x) = w.\phi(x) + b \qquad (4)$$

where b and w_i are bias and weight vector respectively and x is mapped to a high-dimensional feature space by nonlinear transfer function ϕ.

Table 1
Design matrix of experiments and measured values of gold leaching rate[47].

Run	pH	Solid content (%)	NaCN concentration (ppm)	Leaching time (h)	Particle size (μm)	Au leaching rate (%)
1	10.0	35	600	12	75	86.50
2	11.0	35	800	24	37	90.68
3	10.5	40	700	18	56	89.72
4	11.0	45	600	24	37	88.38
5	10.0	45	800	12	75	87.96
6	9.5	40	700	18	56	89.98
7	11.0	45	800	24	37	89.15
8	11.0	35	600	24	75	87.61
9	11.0	45	800	12	75	86.64
10	10.0	45	800	24	37	90.16
11	10.5	40	700	18	56	89.84
12	11.0	45	600	12	37	87.70
13	10.5	40	700	18	56	89.40
14	10.0	45	600	12	37	88.48
15	10.5	30	700	18	56	90.40
16	10.0	35	800	12	75	88.19
17	10.0	45	600	24	37	89.28
18	11.0	35	600	12	37	86.92
19	10.0	35	600	24	37	89.66
20	10.0	35	600	24	75	88.51
21	10.0	45	800	24	75	89.95
22	11.5	40	700	18	56	89.40
23	10.0	35	800	24	37	91.43
24	10.0	35	600	12	37	88.50
25	10.0	35	800	24	75	89.89
26	10.0	45	600	12	75	87.88
27	10.5	40	700	6	56	86.12
28	10.5	40	700	30	56	90.16
29	11.0	35	600	24	37	89.95
30	10.5	40	700	18	100	87.52
31	10.5	40	900	18	56	86.75
32	10.0	45	600	24	75	88.27
33	10.5	40	500	18	56	85.50
34	11.0	35	600	12	75	86.05
35	11.0	35	800	24	75	88.80
36	10.5	40	700	18	20	90.78
37	11.0	35	800	12	37	89.12
38	10.5	50	700	18	56	89.40
39	10.0	35	800	12	37	89.72
40	11.0	45	600	24	75	88.68
41	11.0	45	800	24	75	87.90
42	11.0	35	800	12	75	86.74
43	11.0	45	800	12	37	87.17
44	11.0	45	600	12	75	86.65
45	10.0	45	800	12	37	88.00

Table 2
The conducted experiments conditions and measured values of gold adsorption rate [47].

Runs	pH	Agitation rate (rpm)	Activated carbon concentration (g/L)	Adsorption time (h)	Au adsorption rate (%)
1	11.0	40	1.25	3.0	92.37
2	10.5	45	1.00	2.5	68.42
3	11.0	50	1.25	3.0	93.11
4	11.5	45	1.00	2.5	67.89
5	10.0	40	1.25	2.0	78.12
6	10.0	50	0.75	3.0	72.51
7	9.5	45	1.00	2.5	62.13
8	10.5	45	1.00	2.5	65.18
9	10.0	40	0.75	3.0	68.16
10	11.0	50	1.25	2.0	78.52
11	11.0	40	0.75	3.0	73.42
12	11.0	40	0.75	2.0	65.86
13	10.5	45	1.00	2.5	62.58
14	10.5	45	1.50	2.5	93.92
15	10.0	40	1.25	3.0	80.72
16	10.0	40	0.75	2.0	61.62
17	10.5	55	1.00	2.5	69.71
18	11.0	50	0.75	2.0	64.81
19	10.5	45	0.50	2.5	57.53
20	10.0	50	1.25	3.0	89.22
21	10.0	50	1.25	2.0	70.64
22	10.5	45	1.00	1.5	55.73
23	10.5	45	1.00	2.5	68.67
24	11.0	40	1.25	2.0	77.13
25	10.5	35	1.00	2.5	69.81
26	10.5	45	1.00	3.5	70.67
27	10.5	45	1.00	2.5	65.19
28	10.0	50	0.75	2.0	58.32
29	11.0	50	0.75	3.0	66.73
30	10.5	45	1.00	2.5	62.15

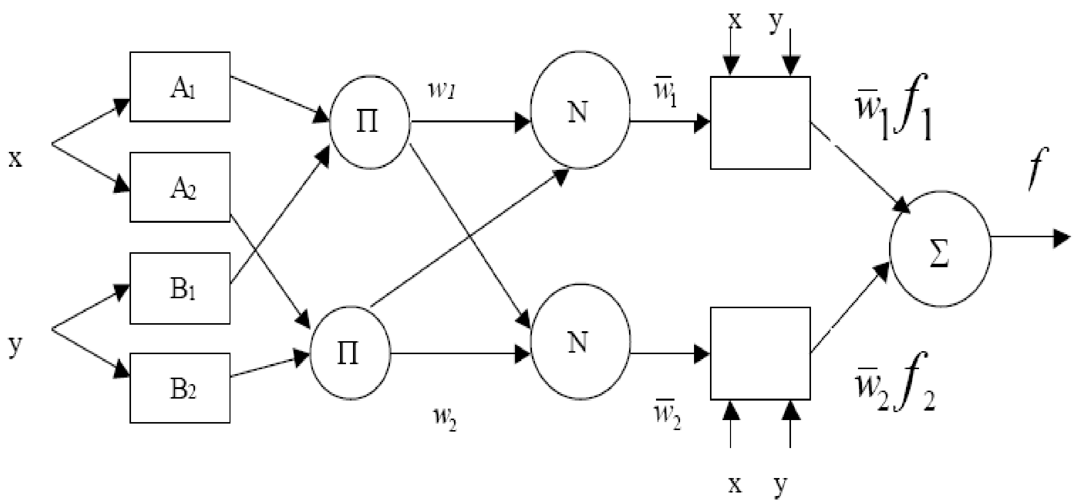


Figure 1: Structure of the ANFIS network.[41]

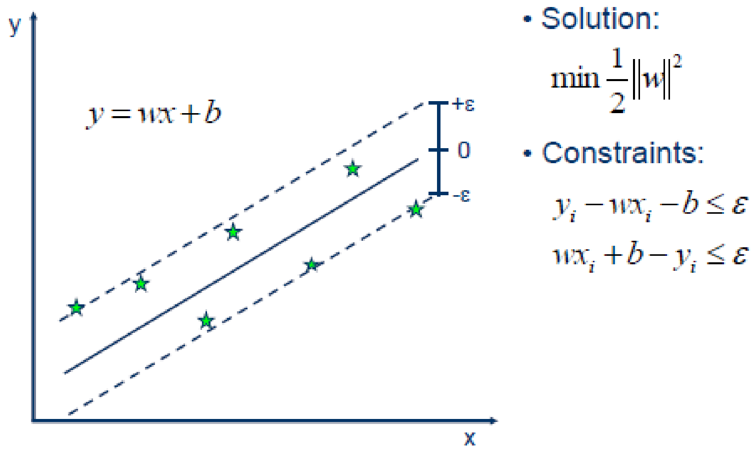


Figure 2: Support vector machine (SVM) classifier (one-dimensional linear regression function with – epsilon intensive–band)[42]

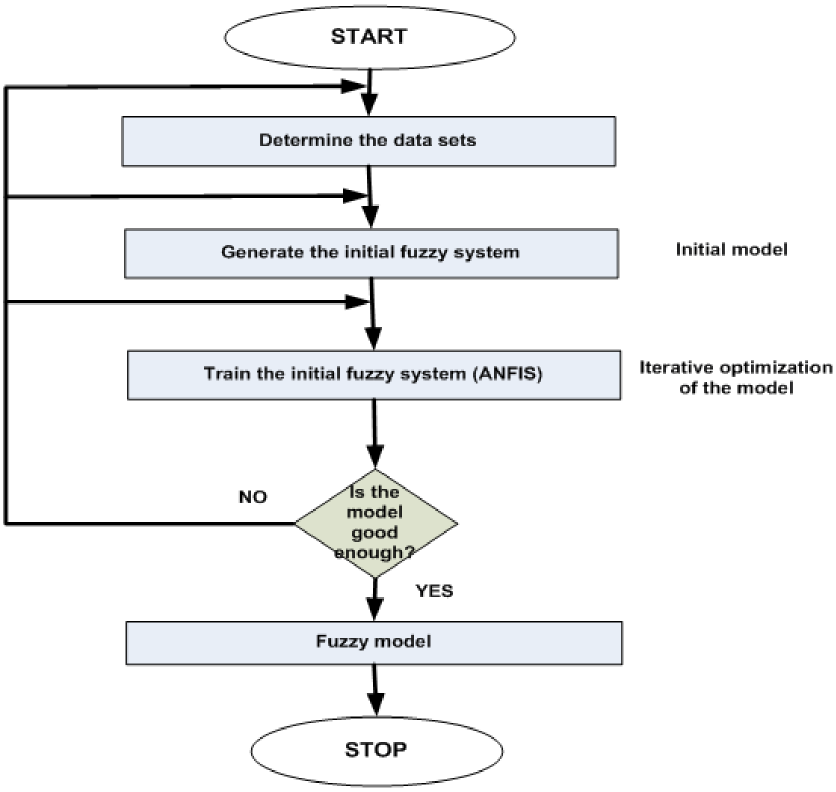


Figure 3: Steps of ANFIS method for estimation of cyanidation and adsorption rate of Au.

Results and Discussion

Prediction of Au leaching and adsorption rate by ANFIS: To investigate the behavior of cyanidation and adsorption processes of gold, it is first necessary to select a proper model and network. Thus, for this purpose, two ANFIS and SVM techniques were utilized to construct a model based on experimental data in tables 1 and 2. At first, the ANFIS method is used to build a prediction model for estimation of Au leaching and adsorption rate using MATLAB software. The steps of the ANFIS method in the software are presented in fig. 3. The structure of the ANFIS model for cyanide leaching and adsorption processes is also shown in fig. 4. As can be seen in figure, the particle size, leaching time, NaCN concentration, solid content and pH are the input of model and the rate of Au leaching is the output of the model.

Also, it shows an adsorption rate of Au from leach liquor onto activated carbon as a function of the pH, adsorption time, activated carbon concentration and stirring speed. The datasets for prediction of Au leaching rate in this study include 45 data point. Among these data, 35 data points (about 80%) are considered as training data and 10 data point (about 20%) are considered as test data. Randomly, about 80% of the datasets were also chosen as train data for adsorption process and 20% data to test objectives to validate the Au predictive model.

It is noteworthy that to construct the ANFIS model and before the training data, first, the membership functions for each of the corresponding input factors and the shape of the membership functions should be determined. In this study, a Gaussian shaped membership function with three membership function is considered for input factors. For instance, the pH membership function is shown in fig. 5.

The ANFIS model is trained using the hybrid training algorithm with 5 epochs (running time). After 5 epochs of training, the accuracy of training reaches the requirements and the outputs of the ANFIS were precisely consistent with the desired outputs. The output of ANIS model for training data is shown in figs. 6 and 7.

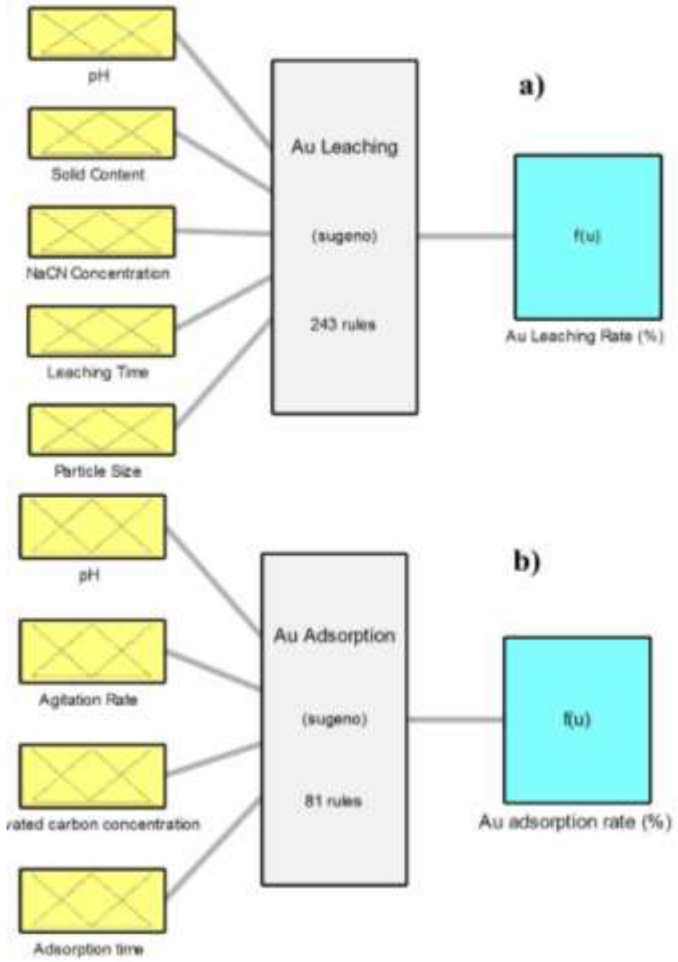


Figure 4: The structure of ANFIS model in MATLAB (a): cyanidation, (b) adsorption.

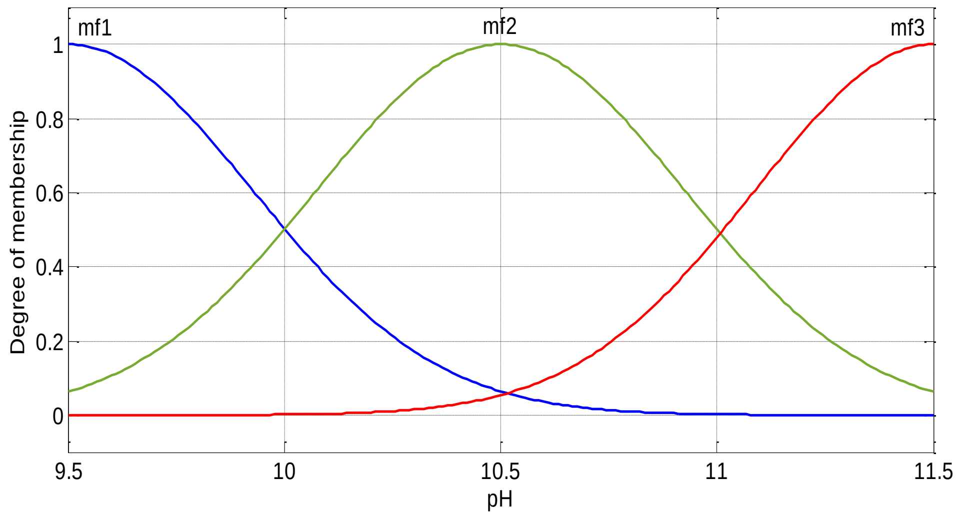


Figure 5: The Gaussian membership function of pH for Au leaching

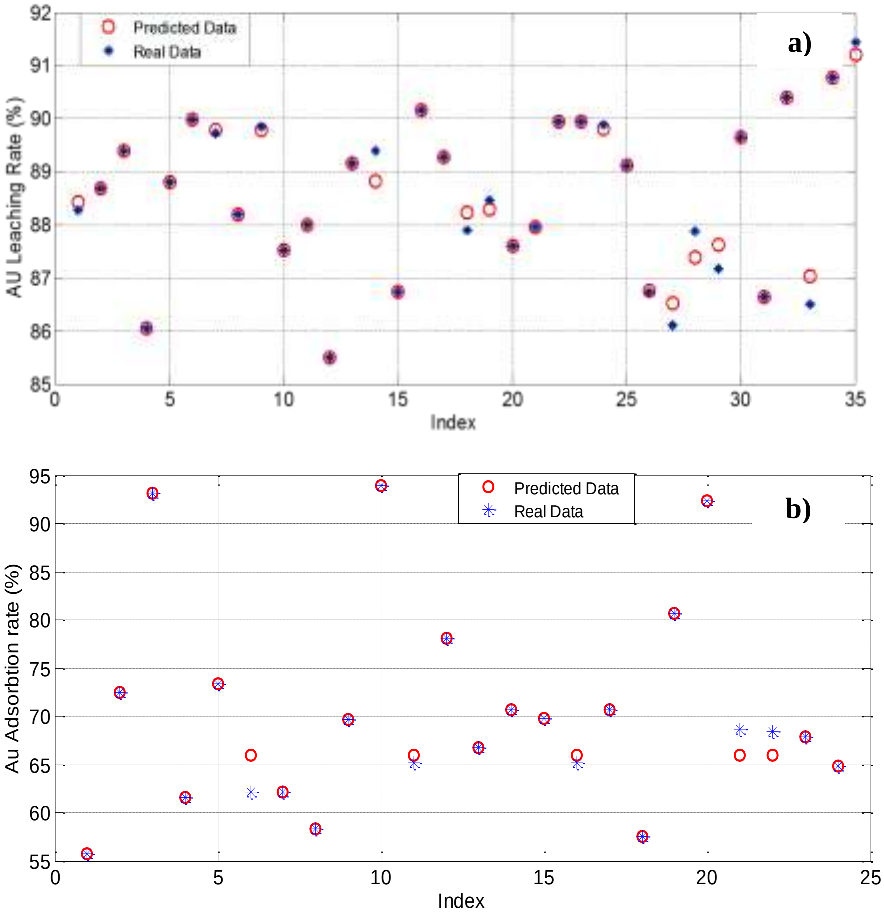
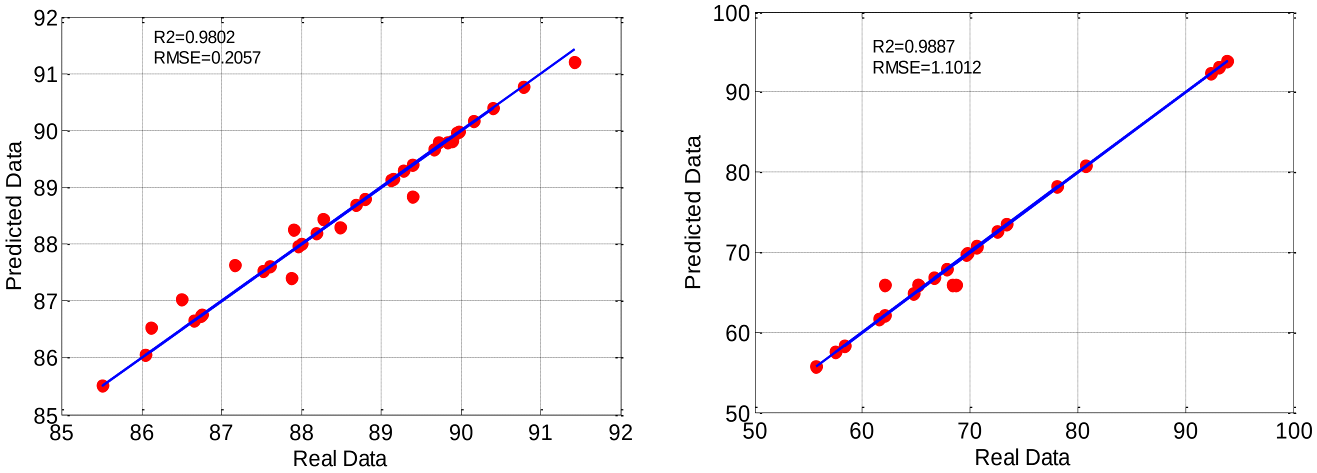


Figure 6: The results of ANFIS model for training data (a): leaching, (b): adsorption



(a) **(b)**

Figure 7: The correlation between real and predicted data based on ANFIS model for training data (a): leaching, (b): adsorption

The results obtained by models are compared and checked with experimental data by the root mean square error (RMSE) and the coefficient of determination (R^2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

where y_i and $\hat{y}_i$ are the measured and the predicted outputs respectively, N represents the number of training or testing samples and $\bar{y}$ denotes the mean value of the corresponding training or testing measured outputs.

RMSE is a frequently used measure of the differences between values predicted by model or estimator and the actual values determined from experiments and for building a good model, it must be minimum[51]. The correlation between the real data and predicted data is shown in fig. 7. As it can be observed from figs. 6 and 7, the ANFIS model has good results and the real and predicted data fit together. As shown in these figures, the model was constructed with a high value of R^2 of 0.9802 and 0.9887 and the low amounts of RMSE of 0.2057 and 1.1012 for leaching and adsorption, respectively.

To validate the suggested model, the constructed ANFIS model is implemented for test data. The results of the model are shown in figs. 8 and 9. It can be observed from figs. 8 and 9 that there is a good correlation on test data and the values of Au leaching and adsorption rates are predicted with good accuracy. As considered, the values of R^2 and RMSE were obtained 0.8802 and 0.5589 for cyanide leaching and 0.9621 and 1.738 for adsorption of gold onto activated carbon. The ANFIS model predictions are distinguished to be in very well agreement with the experimental data and thus this method can be successfully used to model, simulate and predict the cyanide leaching of gold and subsequently its adsorption from leach liquors onto activated carbon.

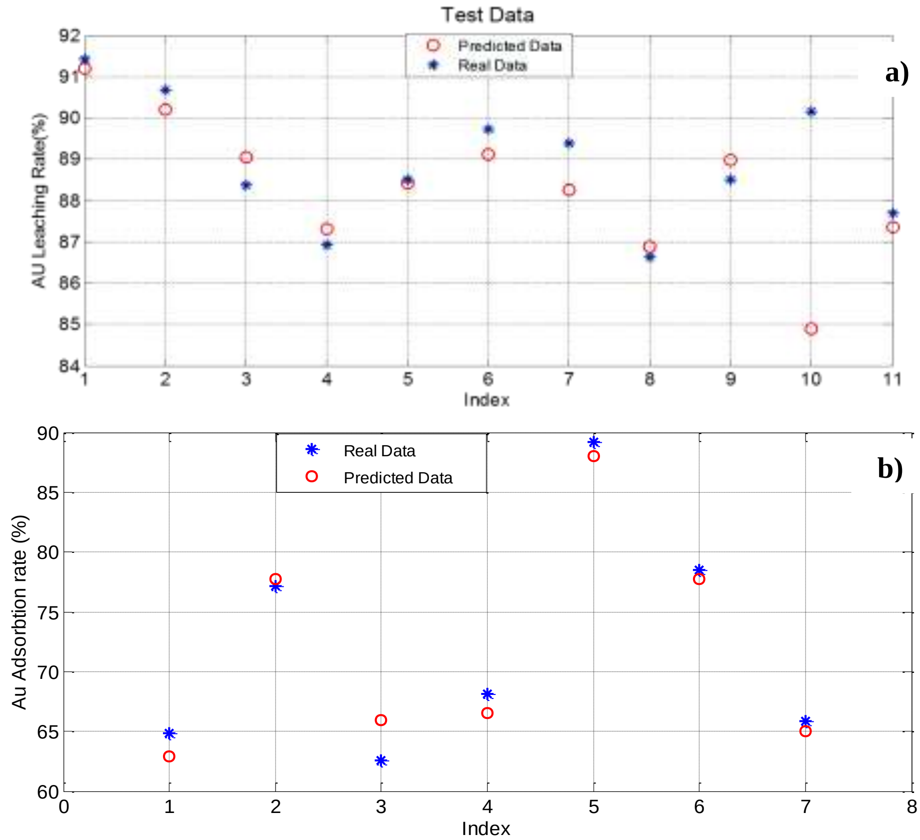
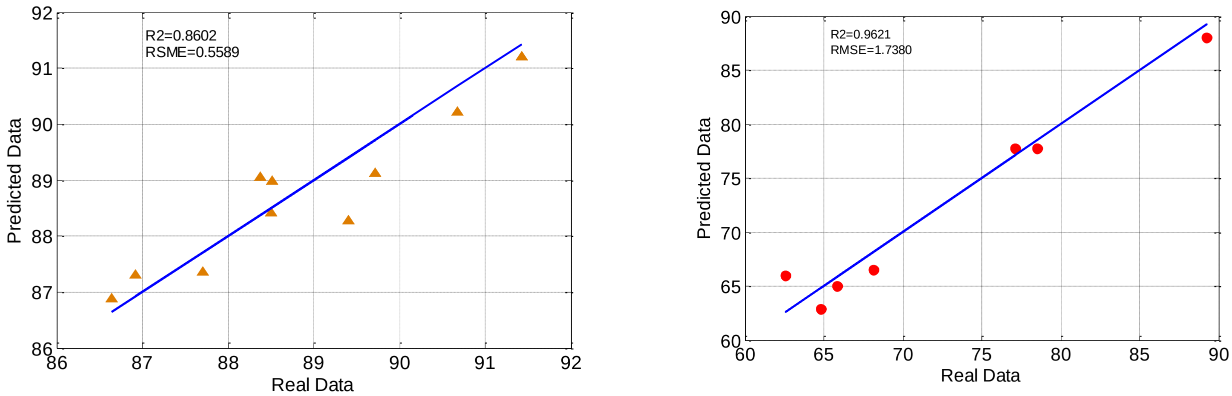


Figure 8: The results of ANFIS model for test data (a): leaching, (b): adsorption.



(a) **(b)**

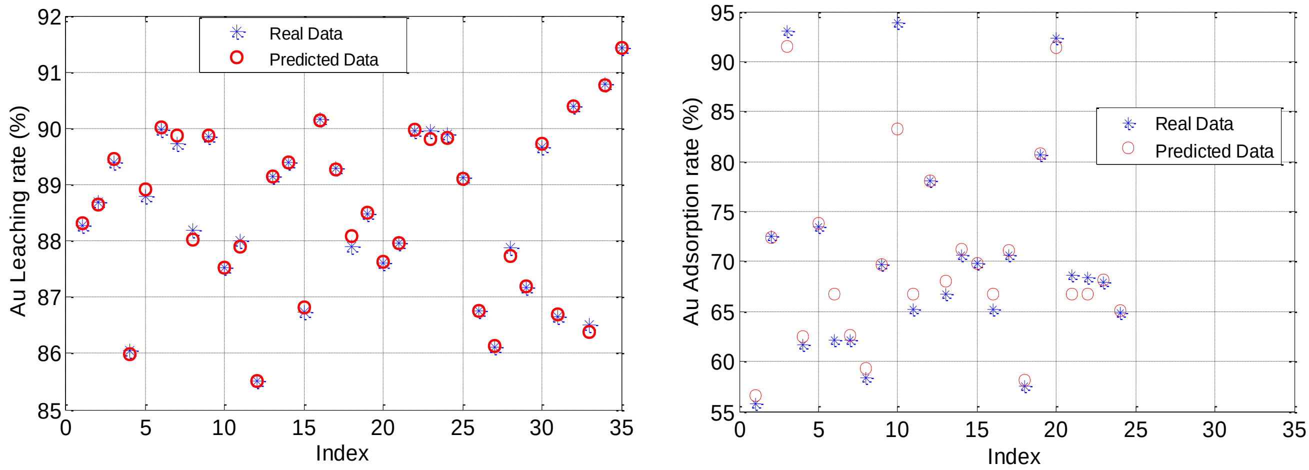
Figure 9: The correlation between real and predicted data based on ANFIS model for test data (a): leaching, (b): adsorption

Prediction of Au leaching and adsorption rates by SVM: In addition to the ANFIS model, support vector machine (SVM) model was employed to simulate and estimate the rate of Au cyanide leaching and its adsorption onto activated carbon. Similar to ANFIS model, SVM models were trained using 80% of the total data randomly and the remaining 20% data were utilized for testing purposes. Based on the dataset, the support vector regression (SVR) models were implemented by the SVM toolboxes and the predictions were carried out in MATLAB software. The output of the SVR model for training data is displayed in fig. 10. Also, the correlation between the real and predicted data is illustrated in fig. 11.

Figs. 10 and 11 indicate the SVM performance for the training data. It is also observed that the value of R^2 to the linear fit (y=ax) on leaching data is 0.9975 with an amount of RMSE = 0.739. This indicates an almost perfect fit for the training of the network (Fig. 11). Also, the values of R^2 and RMSE for the model constructed on adsorption data are found to be 0.9398 and 2.5457. Therefore, the very good fitting values demonstrate that the training was performed very well.

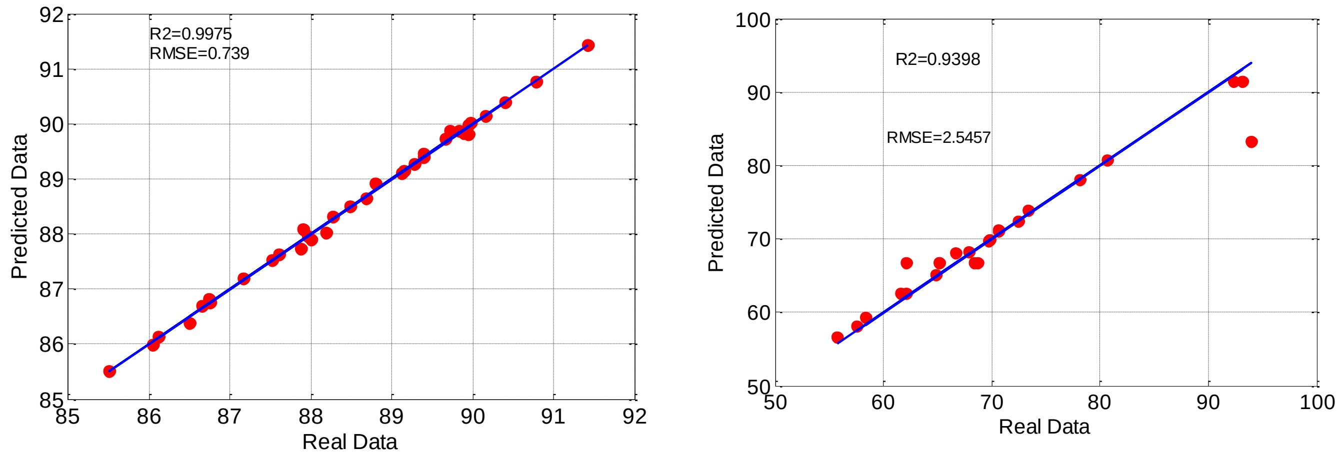
To validate the proposed model, the constructed SVR or SVM model was implemented for test dataset which results for comparison of the measured values of the testing stage with the predictions of the network as shown in figs. 12 and 13.

The coefficient of determination and RMSE values are achieved respectively: 0.6112 (R= 0.7818) and 0.974 for cyanide leaching and 0.8246 (R= 0.9081) and 3.6289 for adsorption of gold. This demonstrates that the SVM model at testing stage does not give very good predictions compared to training data set; however, the values of R^2 and RMSE still are in an acceptable range for engineering fields.



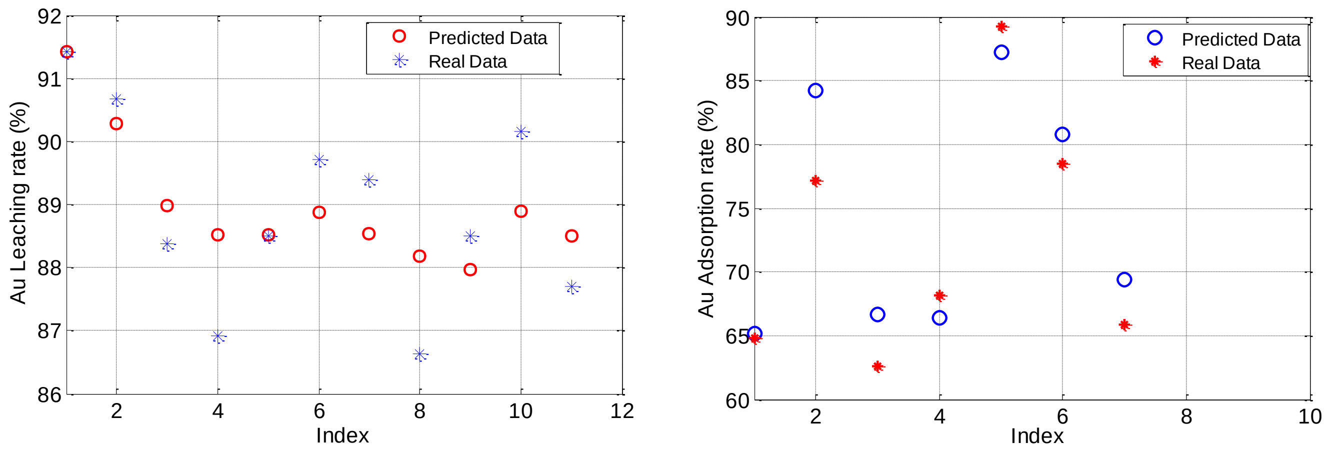
(a) **(b)**

Figure 10: The results of SVM model for training data (a): leaching, (b): adsorption.



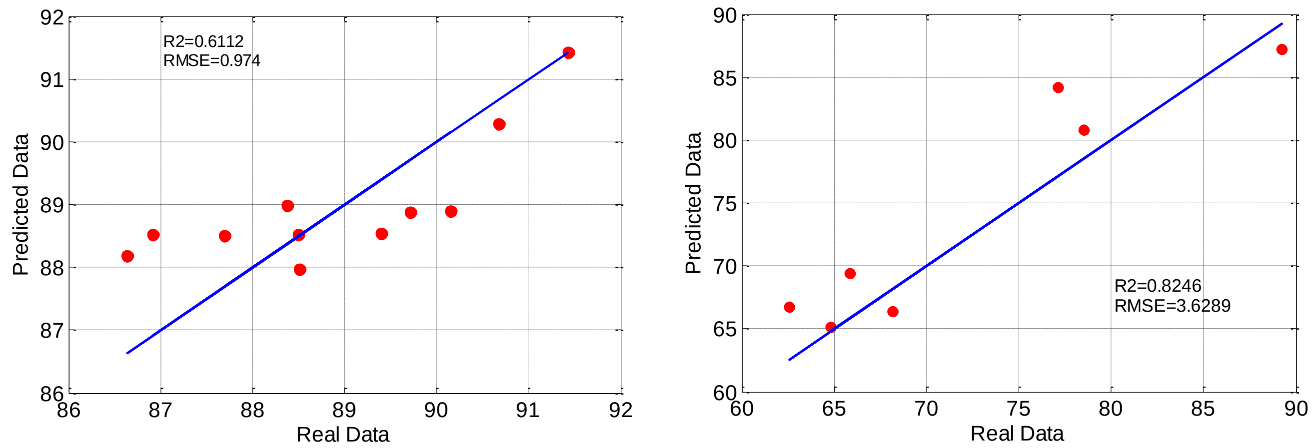
(a) **(b)**

Figure 11: The correlation between real and predicted data based on SVM model for training data (a): leaching, (b): adsorption



(a) **(b)**

Figure 12: The results of SVR model for test data (a): leaching, (b): adsorption.



(a) **(b)**

Figure 13: The correlation between real and predicted data based on SVM model for test data (a): leaching, (b): adsorption

Table 3
Performance comparison of ANFIS and SVM to predict the leaching and adsorption rate of Au.

Model		Cyanide leaching		Adsorption	
		R^2	RMSE	R^2	RMSE
ANFIS	Train	0.9802	0.2057	0.9887	1.1012
	Test	0.8602	0.5589	0.9621	1.738
SVM	Train	0.9975	0.739	0.9398	2.5457
	Test	0.6112	0.974	0.8246	3.6289

Performance comparison of SVM and ANFIS models: The effectiveness of SVM and ANFIS models and their ability to make accurate predictions was evaluated by two statistical parameters including R^2 and RMSE as the results are listed in table 3. As can be observed from the results, the ANFIS model gave the much better performance of predictions with the higher R^2 and lower RMSE both leaching and adsorption. The differences between the performances of the SVM and ANFIS are due to the theoretical background and the used principles of these two methods.[37] Additionally, the ANFIS prediction results for cyanide leaching rate of gold were compared against the ANN (developed BPNN model) and MLR prediction results reported by Azizi et al.[47]

The findings proved that the ANFIS model had slightly better results than the ANN model and was significantly better than the MLR model. The R^2 value of the ANFIS model was 0.9802 for training stage and 0.8602 for the testing set against 0.9803 and 0.8213 for the ANN model and 0.5561 and 0.6705 for MLR model. Additionally, the SVM and ANFIS predictions for adsorption rates of gold were compared with the results estimated and modeled by response surface methodology (RSM) based on the central composite design (CCD), which is a powerful statistical technique[4].

The findings showed that the ANFIS model had a greater R^2 value (0.9887 at the training stage and 0.9621 for the testing set) from RSM-CCD model with R^2 of 0.8354. Meanwhile, the ANFIS model gave better estimations compared to the predicted leaching recoveries of gold by RSM-CCD model[47]. Therefore, it can be concluded that the ANFIS methodology can be successfully used for predicting and simulating the cyanide leaching and adsorption rates of gold in hydrometallurgy industry.

Conclusion

This study dealt the application of two computational intelligence techniques including ANFIS and SVM for modeling and predicting the leaching efficiency of gold as a function of particle size, pH, leaching time, NaCN concentration and solid content and also adsorption rate of Au onto activated carbon as a function of the agitation speed, pH, adsorption time and activated carbon concentration. ANFIS and SVM models were trained and constructed based on 80% experimental data with the values of high R^2 of 0.9802 and 0.9975 for cyanide leaching rate and R^2 of 0.9887 and 0.9398 for adsorption rate respectively. The SVM model predicted the leaching rate of gold with the values of R^2 and RMSE of 0.6112 and 0.974 while for adsorption process, values were 0.8246 and 3.6289 respectively.

Also, the simulation results demonstrated that ANFIS model had a much better performance than the SVM in the predictions with R^2 and RMSE of 0.8602 and 0.5589 for the leaching efficiency and 0.9621 and 1.738 for the adsorption rate of gold respectively. Meanwhile, the ANFIS predictions showed an excellent agreement with the experimental values. Ultimately, the findings proved that the ANFIS model could be considered as a cost-effective, powerful and easy technique to simulate and model the cyanidation and adsorption processes of gold as a function of influential factors.

References

1. Das N., Recovery of precious metals through biosorption—a review, *Hydrometallurgy*, **103(1-4)**, 180-189 **(2010)**

2. Morcali M.H., Zeytuncu B., Ozlem E. and Aktas S., Studies of gold adsorption from chloride media, *Materials Research*, **18(3)**, 660-667 **(2015)**

3. Wojnicki M., Luty-Błocho M., Socha R.P., Mech K., Pędzich Z., Fitzner K. and Rudnik E., Kinetic studies of sorption and reduction of gold (III) chloride complex ions on activated carbon Norit ROX 0.8, *Journal of Industrial and Engineering Chemistry*, **29**, 289-297 **(2015)**

4. Khosravi R., Azizi A., Ghaedrahmati R., Gupta V.K. and Agarwal S., Adsorption of gold from cyanide leaching solution onto activated carbon originating from coconut shell—Optimization, kinetics and equilibrium studies, *Journal of Industrial and Engineering Chemistry*, **54**, 464-471 **(2017)**

5. Martens E., Zhang H., Prommer H., Greskowiak J., Jeffrey M. and Roberts P., In situ recovery of gold: Column leaching experiments and reactive transport modeling, *Hydrometallurgy*, **125**, 16-23 **(2012)**

6. Sayiner B., Modeling of the carbon in pulp (CIP) process in gold cyanide leaching plants using the plant data, *Physicochemical Problems of Mineral Processing*, **50(2)**, 841-851 **(2014)**

7. Sayiner B. and Acarkan N., Effect of silver, nickel and copper cyanides on gold adsorption on activated carbon in cyanide leach solutions, *Physicochemical Problems of Mineral Processing*, **50(1)**, 277-287 **(2014)**

8. Kondos P., Deschênes G. and Morrison R., Process optimization studies in gold cyanidation, *Hydrometallurgy*, **39(1-3)**, 235-250 **(1995)**

9. Yang L., Jia F., Yang B. and Song S., Efficient adsorption of Au $(CN)^{2-}$ from gold cyanidation with graphene oxide-polyethylenimine hydrogel as adsorbent, *Results in Physics*, **7**, 4089-4095 **(2017)**

10. Ladeira A., Figueira M. and Ciminelli V., Characterization of activated carbons utilized in the gold industry: physical and chemical properties and kinetic study, *Minerals Engineering*, **6(6)**, 585-596 **(1993)**

11. Bryson A.W., Gold adsorption by activated carbon and resin, *Mineral Processing and Extractive Metallurgy Review*, **15(1-4)**, 145-151 **(1995)**

12. Ho L.H., Feng S.Y., Lee Y.C. and Yen T.M., Using modified IPA to evaluate supplier's performance: Multiple regression analysis and DEMATEL approach, *Expert Systems with Applications*, **39(8)**, 7102-7109 **(2012)**

13. Lee J., Kim J. and Hyeon T., Recent progress in the synthesis of porous carbon materials, *Advanced Materials*, **18(16)**, 2073-2094 **(2006)**

14. Soleimani M. and Kaghazchi T., Adsorption of gold ions from industrial wastewater using activated carbon derived from hard shell of apricot stones–An agricultural waste, *Bioresource Technology*, **99(13)**, 5374-5383 **(2008)**

15. Poinern G.E.J. et al, Adsorption of the aurocyanide, Au $(CN)^{2-}$ complex on granular activated carbons derived from macadamia nut shells–A preliminary study, *Minerals Engineering*, **24(15)**, 1694-1702 **(2011)**

16. Yu H., Zi F., Hu X., Nie Y., Chen Y. and Cheng H., Adsorption of gold from thiosulfate solutions with chemically modified activated carbon, *Adsorption Science and Technology*, **36(1-2)**, 408-428 **(2018)**

17. Habashi F., Principles of extractive metallurgy, Routledge (**2017)**

18. Ellis S. and Senanayake G., The effects of dissolved oxygen and cyanide dosage on gold extraction from a pyrrhotite-rich ore, *Hydrometallurgy*, **72(1-2)**, 39-50 **(2004)**

19. Brent Hiskey J. and Atluri V., Dissolution chemistry of gold and silver in different lixiviants, *Mineral Procesing and Extractive Metallurgy Review*, **4(1-2)**, 95-134 **(1988)**

20. Marsden J. and House I., The chemistry of gold extraction, SME **(2006)**

21. Navarro P., Vargas C., Alonso M. and Alguacil F.J., The adsorption of gold on activated carbon from thiosulfate-ammoniacal solutions, *Gold Bulletin*, **39(3)**, 93-97 **(2006)**

22. De Andrade Lima L. and Hodouin D., Simulation study of the optimal distribution of cyanide in a gold leaching circuit, *Minerals Engineering*, **19(13)**, 1319-1327 **(2006)**

23.Senanayake G., A review of effects of silver, lead, sulfide and carbonaceous matter on gold cyanidation and mechanistic interpretation, *Hydrometallurgy*, **90(1)**, 46-73 **(2008)**

24. Karimi P., Abdollahi H., Aslan N., Noaparast M. and Shafaei S., Application of response surface method and central composite design for modeling and optimization of gold and silver recovery in cyanidation process, *Mineral Processing and Extractive Metallurgy Review*, **32(1)**, 1-16 **(2010)**

25. Fleming C., Mezei A., Bourricaudy E., Canizares M. and Ashbury M., Factors influencing the rate of gold cyanide leaching and adsorption on activated carbon and their impact on the design of CIL and CIP circuits, *Minerals Engineering*, **24(6)**, 484-494 **(2011)**

26. Shi D. and Gindy N.N., Tool wear predictive model based on least squares support vector machines, *Mechanical Systems and Signal Processing*, **21(4)**, 1799-1814 **(2007)**

27. Sha W. and Edwards K., The use of artificial neural networks in materials science based research, *Materials and Design*, **28(6)**, 1747-1752 **(2007)**

28. Liu D., Yuan Y. and Liao S., Artificial neural network vs. nonlinear regression for gold content estimation in pyrometallurgy, *Expert Systems with Applications*, **36(7)**, 10397-10400 **(2009)**

29. Li Q.C., Li D.X. and Chen Q.Y., Prediction of pre-oxidation efficiency of refractory gold concentrate by ozone in ferric sulfate solution using artificial neural networks, *Transactions of Nonferrous Metals Society of China*, **21(2)**, 413-422 **(2011)**

30. Svalina I., Galzina V., Lujić R. and ŠImunović G., An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: The case of close price indices, *Expert Systems with Applications*, **40(15)**, 6055-6063 **(2013)**

31. Shahbazi B., Rezai B., Chelgani S.C., Koleini S.J. and Noaparast M., Estimation of diameter and surface area flux of bubbles based on operational gas dispersion parameters by using regression and ANFIS, *International Journal of Mining Science and Technology*, **23(3)**, 343-348 **(2013)**

32. Ghaedi M., Hosaininia R., Ghaedi A., Vafaei A. and Taghizadeh F., Adaptive neuro-fuzzy inference system model for adsorption of 1, 3, 4-thiadiazole-2, 5-dithiol onto gold nanoparticales-activated carbon, *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, **131**, 606-614 **(2014)**

33. Khalaj G. and Khalaj M.J., Application of ANFIS for modeling of layer thickness of chromium carbonitride coating, *Neural Computing and Applications*, **24(3-4)**, 685-694 **(2014)**

34. Rafiee R., Ataei M., KhaloKakaie R., Jalali S. and Sereshki F., A fuzzy rock engineering system to assess rock mass cavability in block caving mines, *Neural Computing and Applications*, **27(7)**, 2083-2094 **(2016)**

35. Gong Y., Zhang Y., Lan S. and Wang H., A comparative study of artificial neural networks, support vector machines and adaptive neuro fuzzy inference system for forecasting groundwater levels near Lake Okeechobee, Florida, *Water Resources Management*, **30(1)**, 375-391 **(2016)**

36. Rafiee R., Khalookakaie R., Ataei M., Jalali S., Sereshki F. and Azarfar A., Improvement of rock engineering system coding using fuzzy numbers, *Journal of Intelligent and Fuzzy Systems*, **30(2)**, 705-715 **(2016)**

37. Najafi G., Ghobadian B., Moosavian A., Yusaf T., Mamat R., Kettner M. and Azmi W., SVM and ANFIS for prediction of performance and exhaust emissions of a SI engine with gasoline–ethanol blended fuels, *Applied Thermal Engineering*, **95**, 186-203 **(2016)**

38. Dindarloo S.R. and Siami-Irdemoosa E., Data mining in mining engineering: results of classification and clustering of shovels failures data, *International Journal of Mining, Reclamation and Environment*, **31(2)**, 105-118 **(2017)**

39. Tuntas R. and Dikici B., An ANFIS model to prediction of corrosion resistance of coated implant materials, *Neural Computing and Applications*, **28(11)**, 3617-3627 **(2017)**

40. Ali D., Hayat M.B., Alagha L. and Molatlhegi O.K., An evaluation of machine learning and artificial intelligence models for predicting the flotation behavior of fine high-ash coal, *Advanced Powder Technology*, **29(12)**, 3493-3506 **(2018)**

41. Franco D.S., Duarte F.A., Salau N.P.G. and Dotto G.L., Adaptive neuro-fuzzy inference system (ANIFS) and artificial neural network (ANN) applied for indium (III) adsorption on carbonaceous materials, *Chemical Engineering Communications*, **206(11),** 1452-1462 **(2019)**

42. Araghi M. and Khatibinia M., Modeling of flow number of asphalt mixtures using a multi–kernel based support vector machine approach, *Iran University of Science and Technology*, **9(2)**, 233-250 **(2019)**

43. Gill J. and Singh J., Energetic and exergetic performance analysis of the vapor compression refrigeration system using adaptive neuro-fuzzy inference system approach, *Experimental Thermal and Fluid Science*, **88**, 246-260 **(2017)**

44. Vapnik V., The nature of statistical learning theory, Springer science and business media **(2013)**

45. Liu L., Yang F., Zhang P., Wu J.Y. and Hu L., SVM-based ontology matching approach, *International Journal of Automation and Computing*, **9(3)**, 306-314 **(2012)**

46. Harrington P.D.B. and Wang X., Spectral representation of proton NMR spectroscopy for the pattern recognition of complex materials, *Journal of Analysis and Testing*, **1(2)**, 10 **(2017)**

47. Azizi A., Ghaedrahmati R., Ghahramani N. and Rooki R., Modelling and simulation of the cyanidation process of Aghdareh gold ore using artificial neural network and multiple linear regression, *International Journal of Mining and Mineral Engineering*, **7(2)**, 139-154 **(2016)**

48. Jang J.S.R., Sun C.T. and Mizutani E., Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review], *IEEE Transactions on Automatic Control*, **42(10)**, 1482-1484 **(1997)**

49. Vapnik V. and Chervonenkis A., A note on class of perceptron, *Automation and Remote Control*, **25**, 103-109 **(1964)**

50. Gong Y., Wang Z., Xu G. and Zhang Z., A comparative study of groundwater level forecasting using data-driven models based on ensemble empirical mode decomposition, *Water*, **10(6)**, 730 **(2018)**

51. Lashkenari M., KhazaiePoul A., Ghasemi S. and Ghorbani M., Adaptive Neuro-fuzzy Inference System Prediction of Zn Metal Ions Adsorption by γ-Fe2o3/Polyrhodanine Nanocomposite in a Fixed Bed Column, *International Journal of Engineering*, **31(10)**, 1617-1623 **(2018)**.

(Received 28th March 2020, accepted 26th May 2020)