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IMPROVING ESTIMATION ACCURACY OF METALLURGICAL PERFORMANCE OF INDUSTRIAL FLOTATION PROCESS BY USING HYBRID GENETIC ALGORITHM – ARTIFICIAL NEURAL NETWORK (GA-ANN)

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Abstract: In this study, a back propagation feed forward neural network, with two hidden layers (10:10:10:4), was applied to predict Cu grade and recovery in industrial flotation plant based on pH, chemical reagents dosage, size percentage of feed passing 75 µm, moisture content in feed, solid ratio, and grade of copper, molybdenum, and iron in feed. Modeling is performed basing on 92 data sets under different operating conditions. A back propagation training was carried out with initial weights randomly mode that may lead to trapping artificial neural network (ANN) into the local minima and converging slowly. So, the genetic algorithm (GA) is combined with ANN for improving the performance of the ANN by optimizing the initial weights of ANN. The results reveal that the GA-ANN model outperforms ANN model for predicting of the metallurgical performance. The hybrid GA-ANN based prediction method, as used in this paper, can be further employed as a reliable and accurate method, in the metallurgical performance prediction.

***Keywords**: artificial neural network, genetic algorithm, prediction, copper flotation*

Introduction

Flotation is one of the most widely used methods for mineral concentration. In the industrial flotation plant, the on-line prediction of metal grade and recovery requires high cost instruments. Also, the investments require a significant amount of maintenance and calibration work. These difficulties have encouraged the approach of estimation of metal grade as an index of control performance. Artificial neural networks (ANNs) are based on the terms called neurons, the duties of which are to estimate complex nonlinear associates existing between ANN input and output

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variables to an arbitrary degree of accuracy. Recently, neural networks (NNs) have been increasingly applied in mineral processing (Nakhaei et. al, 2012; Jahedsaravani et. al, 2015). The NN modeling, a paradigm for computation and knowledge representation is originally inspired by understanding and abstracting the biological structure of neurons and internal operation of human brain. Many researchers have attempted to use NNs for various applications in manufacturing, such as, tool wear prediction, control, grinding process control, flotation process, powder packing density optimization, electrical discharge machining process on-line monitoring etc. (Ezigwu and et al., 1995; Smith and et al., 2000).

ANN modeling can be applied with great benefit for flotation process. Cilek (2002) used ANN to predict the locked cycle flotation test. Labidi et al. (2007) used neural networks for predicting the effect of operational parameters on the efficiency of ink removal from paper by flotation. Chelgani et al. (2010) used ANN to estimate froth flotation and collision probability based on operational parameters. Aldrich et al. (1995) analyzed industrial copper and platinum flotation plants by means of a self-organizing neural net. They have proposed a new method that uses preserving maps of characteristics extracted from digitized images of the froth phase. Gouws and Aldrich (1996) have applied inductive techniques and genetic algorithms (GA) to classify different froth structures from industrial copper and platinum flotation plants that GA outperforms inductive techniques. Jahedsaravani et al. (2015) have studied modeling of metallurgical parameters in the batch flotation process by means of statistical and intelligent techniques. The results of their work indicated that intelligent techniques (i.e. neural network and adaptive neuro–fuzzy method) are more efficient tools than statistical approaches (i.e. non–linear regression). Massinaei et al. (2014) have applied data mining, neural network and time series analysis to evaluate and model the Qaleh–Zari Copper concentrator. The researchers used data mining to select the feed copper grade and particle size among the other operating variables as the most effecting metallurgical performance. Then, modeling and predicting the future trend of copper concentrator was conducted by ANN and time series analysis, respectively. Nakhaei et al. (2013) have studied different techniques (linear regression, non-linear regression, back propagation (BP) neural network, radial basis function) for the estimation of Cu grade and recovery values for flotation column concentrate. Their results indicated that a four-layer BP network gave the most accurate metallurgical performance prediction.

Control and modeling of flotation processes is investigated based on froth features that are obtained from the image analysis technique. The simulation results of flotation process shown that a controller designed by means of the steady-state causal model was satisfactory in achieving froth appearances (Liu and MacGregor, 2008). Moolman et al. (1996) investigated the performance of an industrial precious metal flotation plant based on features extracted from froth images by a machine vision system. They found that this approach is a useful tool for interpretation of the effect of different flotation parameters.

There is the wide range of ANNs applications for solving a variety of prediction problems. The back propagation learning algorithm is a method of adjusting the weighted connections between nodes using the Widro-Hoff learning method to minimize the error between predicted and target data. Usually, back propagation training is carried out with initial weights in random mode. However, using random initial weights for neural network training may lead to trapping into the local minima and slow converging (Chang et al., 2012). As a result, the NN has been often unable to find a desirable solution. In this research, the genetic algorithm (GA) as a popular technique in evolutionary computation research was applied to optimization of initial weights of ANN to improve the performance of ANN for prediction of metallurgical parameters.

Description of industrial flotation process

The Sarcheshmeh copper ore body located in southeast Iran and contains 1 petagram (Pg) of ore having about 0.80% copper and 0.03% molybdenum. It has been processing 40 Gg/day (old plant since 1982) and 22 Gg/day (new plant since 2002) of ore.

Flow sheet of the Sarcheshmeh flotation circuit is shown in Figure 1. It consists of roughing, cleaning, cleaning-scavenging and re-cleaning stages. In the concentrator plant, to produce 70% of the product finer than 75 μm, output of three stages of crushing is fed to ball mills in the closed circuit with cyclones. The product of the grinding stage is fed to the flotation circuit. The rougher flotation bank consists of eight cells of 130 m^3, the cleaner, scavenger banks, each having three and five cells of 50 m^3, respectively. The coarse portion of the combined rougher and scavenging concentrates (i.e. underflow of secondary cyclone) is ground by using a regrinding mill. The tailings of the rougher flotation are discarded to the final tails, and the concentrate is reground. The copper concentrate is produced by stages of flotation cleaning and re-cleaning. In this flotation circuit, sodium isopropyl xanthate and Nascol 1451 (dithiophosphate and mercaptobenzothiazol) are used as collectors and methyl isobutyl carbonyl and Dow 250 (polypropylene glycol methyl ether) are used as a frother. In this plant, molybdenum is a by-product of process. Collectors used for copper recovery are poor for molybdenite and a small amount of fuel oil is added to the grinding stage to aid molybdenum recovery.

After the flotation stages, a concentrate was produced with an average grade of 28–30% copper and 0.7–0.8% molybdenum. From the previous experience, some factors that have an important role in the flotation of copper ore were selected as the input variables (Banisi et al., 2003).

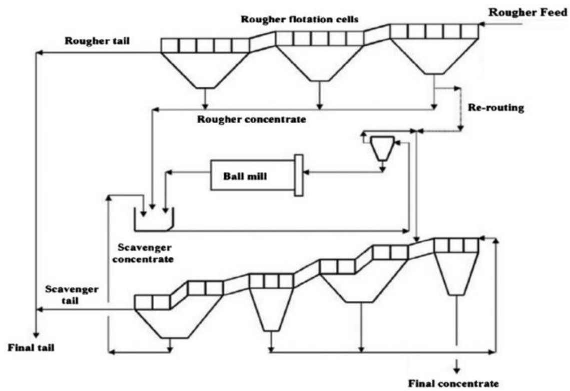

Fig. 1. A simplified flow sheet of Sarcheshmeh flotation circuit (Banisi et al., 2003)

In this study pH, collector, frother and fuel oil concentration, percentage of feed passing 75 micrometer screen, feed moisture content, solid percent, and grade of copper, molybdenum and iron in the feed were considered as the inputs to the network. Table 1 presents the summary statistics for each input variables.

Table 1. The summary statistics for input variables

Variable	Index	Min	Max	Mean	Standard deviation
pH	pH	12.09	12.39	12.3034	0.0559
Collector dosage (g/Mg)	Col	10.5	25.0673	18.5813	2.9573
Frother dosage (g/Mg)	Fr	12	22.5	16.3130	2.0084
Fuel oil dosage (g/Mg)	Fo	1	5.9486	3.3258	0.7240
Solid percent (%)	Sp	25.1106	29.0876	27.4425	0.8253
Moisture percent (%)	Mp	4.4367	5.4665	4.8356	0.2116
Size percent of feed passing 75 (%)	Sd	61.1934	66.7105	63.0652	0.9499
Copper grade in the feed (%)	Cug-F	0.5528	0.8221	0.6674	0.0540
Mo grade in the feed (%)	Mog-F	0.0194	0.0403	0.0270	0.0036
Fe grade in the feed (%)	Feg-F	3.7106	6.5878	4.8260	0.6401

Variables of copper grade and recovery in the final concentrate were used as the network output. Table 2 gives the summary statistics for each output variable.

Table 2. The summary statistics for output variables

Variable	Index	Min	Max	Mean	Standard deviation
Cu grade in the final concentrate (%)	Cug-C	18.6122	28.8488	24.5525	1.7797
Cu recovery in the final concentrate (%)	Cur-C	82.6762	90.1167	86.3908	1.8602

Model Description

Artificial neural network

The artificial neural network, similarly to the brain, consists of a large number of neurons. A neuron is a basic information processing unit which forms the basis for designing the artificial neural network. These neurons in the ANN are connected by weight links passing signals from one neuron to another. Each neuron is a summing element followed by a transfer function. The output of each neuron is fed as the input to all of the neurons in the next layer.

Genetic algorithm

In the field of artificial intelligence a genetic algorithm (GA) is a search heuristic algorithm based on biological evolution. This heuristic is used to generate useful solutions to optimization and search problems (Sivanandam and Deepa, 2008). In GA, an array of variables to be optimized were defined that are called a chromosome. If a chromosome has *N* variables, GA meets the N-dimensional optimization problem. This chromosome is written as an *N* element row vector. The GA commenced optimization with several chromosomes that is called a population. A fitting function was evaluated for all the chromosomes in each generation (iteration). Individuals which have the best value of fitness function, are selected. After parents are selected, new chromosomes are produced by two main operators, crossover and mutation. A crossover is a process of taking more than one parent and producing offsprings from them. Some of the chromosomes are mutated to get out of the local minima. Then, the offsprings are accumulated and their fitness value is evaluated. Finally, the children are inserted into the population to replace worse individuals of the current population. Reproduction is continued until a stopping criterion is met.

Architecture of ANN model

For developing a nonlinear ANN model of a system, multilayer perceptron neural network (MLP) is used. This network, usually consists of a structure of three layers described as input, hidden, and output layers. The most popular ANN is the feed forward multilayer ANN which uses the back propagation learning algorithm. In this work, two hidden layers are used as the hidden layer between input and output layers of ANN. Back propagation learning works by adjusting weight values starting at the output layer, then moving backward through the hidden layers of the network. This training procedure essentially aims at obtaining an optimal set of network connection weights that minimizes a pre-specified error function (Rumelhart et al., 1986).

Data pre-processing can be effective in the process of training the neural network (Demuth and Beale, 2002). To have a successful training process, all of data were normalized and then fed to the NN for the training phase. Finally, these data are changed in the range of -1 and 1. The normalized value (X_N) for each raw input/output dataset was calculated using the following equation:

$$X_N = 2\frac{X - X_{\min}}{X_{\max} - X_{\min}} - 1 \quad (1)$$

where X_N is the normalized value of each input or output variable, X is an original value of a variable, and X_{max} and X_{min} are maximum and minimum original values of the variables, respectively.

A total of 92 datasets were used in the predictions by ANN; 69 and 23 datasets were applied for training and testing the network, respectively for estimation of copper grade and recovery. Usually, the optimum number of hidden layers and neurons in each layer is found via a trial and error method (Anderson and McNeill, 1992).

The proposed model of hybrid GA-ANN

Howbeit the NN should reduce the mean square error (MSE), the ANN may yield poor performance, because the initial weights are efficiently not chosen. Some researchers combined the genetic algorithm and neural network to improve the learning process of ANN (Sexton and Gupta, 2000; Montana and Davis, 1989). In this work, a GA is applied to optimize the initial weights of the network because of improving of the ANN performance for metallurgical parameters prediction. The GA parameters in this work are given in Table 3.

Table 3. GA parameters

Parameters	Value
Crossover probability	0.5
Mutation probability	0.02
Population size	50
Number of generations	100

In recent years, ANN has become a very powerful and practical tool for modeling of very complex nonlinear systems, and the genetic algorithm can be found in various research fields for system parameter optimization. Thus, GA was applied to initialize and find the optimal connection weights of ANN. The outline of combining GA and ANN algorithms is shown in Fig. 2.

In this study, the real coded method for describing the chromosomes was used. The population size in this study was 50 chromosomes and each chromosome composed of 220 weights and 22 biases was represented by one gene. Since all of the NN weights fell in the range of between -2 and 2 after the back propagation training, the range of initial population was selected in this range. The objective function was the mean square error of target and output values attained from the built model by ANN technique. In fact, the ANN approach created a model for mapping a complicated nonlinear relationship between flotation process conditions and copper grade and recovery of flotation. The chromosomes in the mating pool are arranged in a descending order of decreasing fitness function. Part of the population was selected for mating (N_{sel}) and the remaining population that have the lowest fitness function is discarded to make space for the new offspring (N_{dis}). Couples are selected from this population by the roulette wheel selection function. Roulette wheel selection, also known as the fitness proportionate selection, is used in the genetic algorithm for selecting potential solutions for recombination.

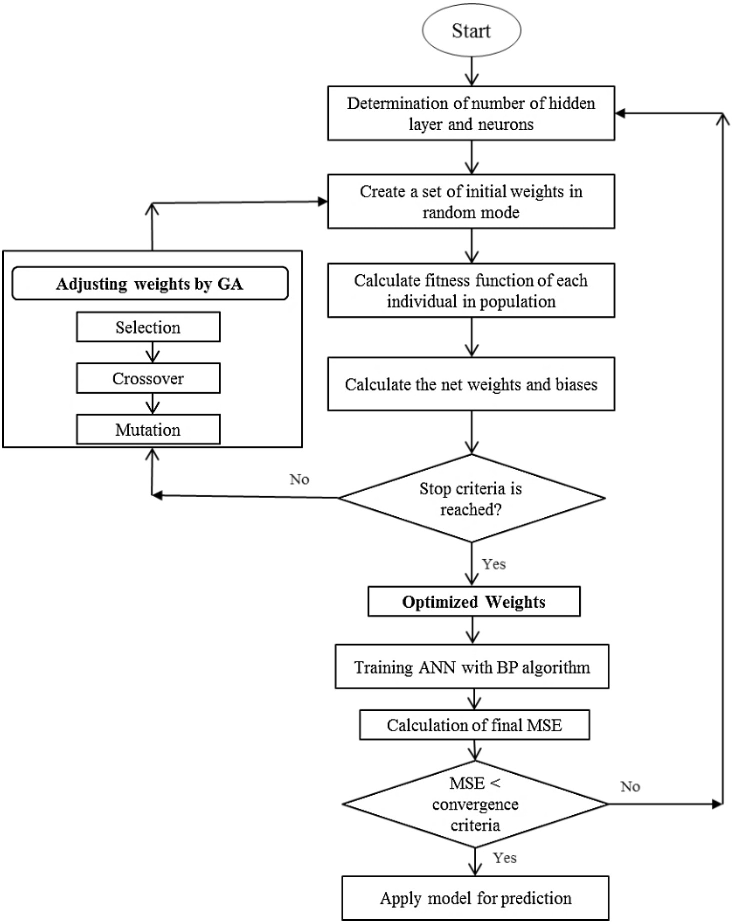

Fig. 2. Algorithm of combining GA-ANN

In the roulette wheel selection function, the fitness assigns a fitness to possible chromosomes. This fitness level is used to associate a probability of selection with each individual chromosome. If f_i is the fitness of its individual in the population, its probability of being selected is $p_i = \frac{f_i}{\sum_1^N f_i}$, where N is the number of individuals in the population (Sivanandam and Deepa, 2008).

Two chromosomes are selected from the initial population and offspring produced by the crossover operator. In this study, the single point crossover for producing offspring are used, where the two mating chromosomes are cut once at corresponding points and the sections after the cuts are exchanged. The crossover point of the chromosomes takes place in random mode to generate new offsprings. After crossover, the chromosomes are subjected to mutation. If crossover is searched, the current solution to find better ones, mutation is assumed to help in the exploration of the whole search space. Mutation is done by randomly changing few genes (factor values) in the remaining good chromosomes. Reproduction is continued until the stop criteria is met. The algorithm is run for a defined number of iterations. The number of iterations was 100 generations, because algorithm had almost converged.

Results and Discussion

Results of ANN

The ANN model has been developed by considering two hidden layers in the MLP architecture and with training using the back propagation algorithm. The best structure and geometry of the ANN model is 10-10-10-2 (Fig. 3), which adequately recognized the effects of different operating conditions and feed characteristics of flotation process and can predict copper grade and recovery. As mentioned above, the network based on four layers is selected to estimate the copper grade and recovery. Linear (purelin), tangent sigmoid (tansig) and tangent sigmoid (tansig) functions were applied to the output layer, second hidden layer and transfer inputs at the first hidden layer, respectively. The optimum number of neurons was selected via a trial and error procedure (Anderson and McNeill, 1992).

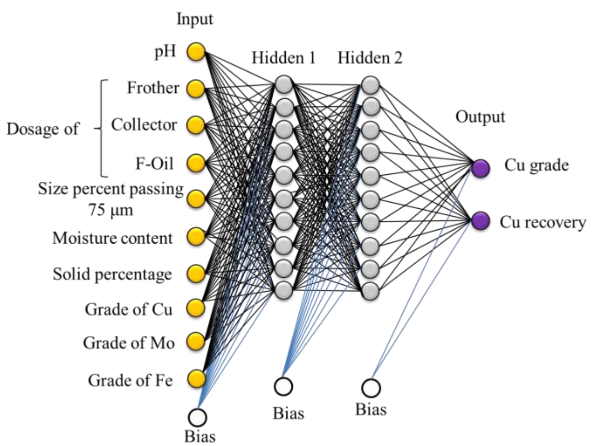

Fig. 3. Architecture of ANN

The determination coefficient (R^2) and the mean square error (MSE) values in the training and testing stages are given in Table 4.

Result of GA-ANN

The result of fitness optimization via GA-ANN as the function of generation is depicted in Fig. 4, in which mean and best fitting values are converged after 30 generations. The best fitness of the objective function for the GA-ANN model is 0.1484. The chromosome of the best individual (weights and biases) in the last iteration is saved for the back propagation training.

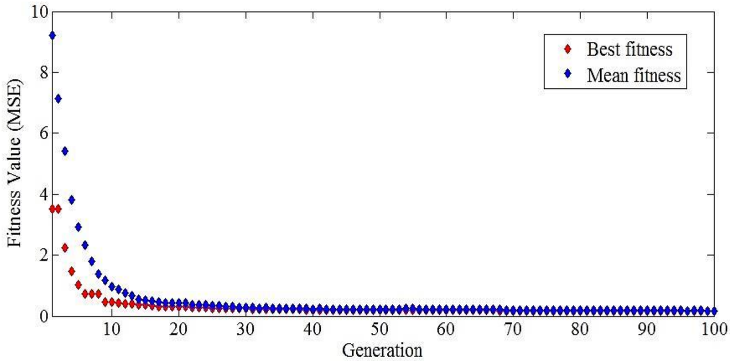

Fig. 4. Best fitness convergence of the problem

The attained results of R^2 and MSE values from two models for training and test stages are given in Table 4, respectively.

Table 4. Comparison of MSE and R^2 values of ANN and GA-ANN in training and testing stages

Method	Traning stage				Testing stage			
	Copper Grade		Copper Recovery		Copper Grade		Copper Recovery	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
ANN	0.9155	0.7242	0.9108	6.6552	0.8908	6.6552	0.8983	9.3753
GA-ANN	0.9995	0.0029	0.9913	1.2097	0.9793	1.2097	0.9791	0.9586

As can be seen, among the two methods used in the present study, the GA-ANN one provides the smallest MSE and the best correlation coefficient for all of the training and test datasets. Apparently, it has been observed from Table 4 as well as Fig. 5 that the GA-ANN model is more accurate than the random ANN model to predict the metallurgical performance of the industrial flotation process. However, by improving the initial weights using a GA, the accuracy of the ANN can be significantly improved. The difference between MSE of the ANN and that of the GA-ANN shows that setting appropriate initial weights are critical for the performance of the ANN. It can be concluded that the GA-ANN model provided a robust tool for prediction the error which varied slightly and smoothly.

Today, the development of sensors for measuring the grades plays an important role in optimizing and controlling flotation processes. These approaches not only contribute to the reduction of the required experimentation, but also reduce the problem associated with empirical models that involve the evaluation of large number of constraints. The on-line estimation of grade usually requires a significant amount of work in maintenance and calibration of on-stream analyzers, in order to maintain good accuracy and high availability. These difficulties and the high cost of investment and maintenance of these devices have encouraged the approach of improving the estimation accuracy of metal grade and recovery as indices of control performance. Therefore, advanced new methods such as GA-ANN must be employed.

In the literature, many studies have been done on metallurgical performance prediction based on the ANN, and there have been a number of investigations on the application of GA for optimization. The NN with using random initial weights for neural network training has been often unable to find appropriate solution for predicting process output. Therefore, in this research we combined the genetic algorithm (GA) with ANN for improving the performance of the ANN to model and predict flotation process for any given operating conditions and feed characteristics.

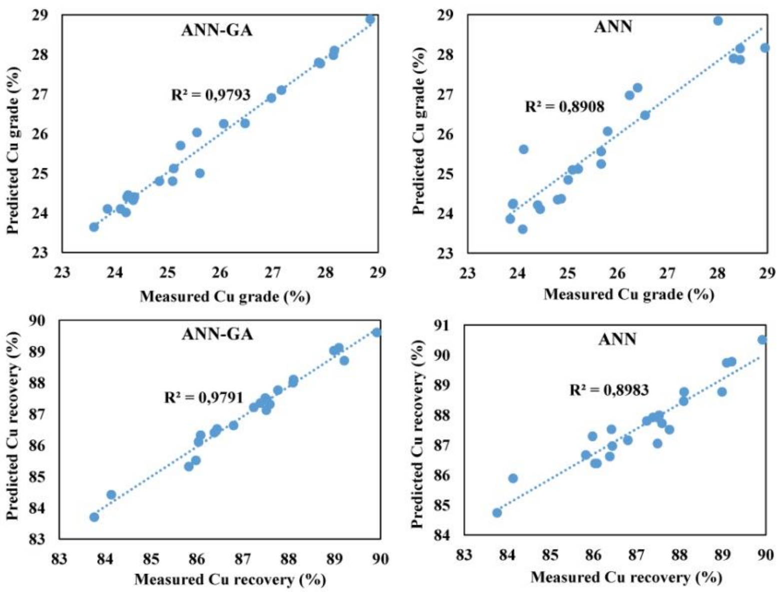

Fig. 5. Comparison of predicted and measured values for ANN and GA-ANN models in testing stage

Table 5 shows a comparison of prediction accuracy of the ANN in flotation processes under different operating conditions (i.e. batch or industrial conditions) and number of input and output parameters. As shown in Table 5, the prediction accuracy of the hybrid GA-ANN for copper grade and recovery is higher than that of other ANN models such as BPNN, adaptive neuro–fuzzy etc. It can be concluded that the hybrid GA-ANN performs significantly better than AAN. Genetic algorithm with optimizing the initial weights of ANN can be applied to predict metallurgical performance.

Table 5. Comparison of prediction accuracy of ANN under various operating conditions of copper flotation process (BPNN: back-propagation neural network, RBFNN: radial basis feed forward neural network)

Type of ANN	Operating condition	Number of input parameters	Number of output parameters	The correlations between the observed and predicted values		Ref.
				Cu grade	Cu recovery	
BPNN	Pilot plant	8	2	0.90	0.86	Nakhaei et al. 2012
BPNN	Pilot plant	3	1	0.93	-	Nakhaei et al., 2010
BPNN	Pilot plant	8	2	0.92	0.92	Nakhaei and Irannajad, 2013
RBFNN	Pilot plant	8	2	0.91	0.90	Nakhaei and Irannajad, 2013
BPNN	Batch	5	4	0.91	0.88	Jahedsaravani et al., 2015
Adaptive neuro-fuzzy	Batch	5	4	0.92	0.84	Jahedsaravani et al., 2015
BPNN	Industrial	5	2	-	0.80	Massinaei et al., 2014
Hybrid GA-ANN	Industrial	10	2	0.97	0.97	In this study

Conclusion

In this research, the ANN and GA-ANN capabilities for predicting metallurgical performance for industrial copper flotation were investigated. Operational conditions such as pH, collector, frother and fuel oil dosage, size of feed passing 75 micrometers, moisture content in feed, solid percent, grade of copper, molybdenum and iron in the feed were applied to predict the copper grade and recovery by using the ANN and GA-ANN models. The performance of each of the two models was tested by using new data sets. From the obtained results (Table 4) it is clear, that the GA-ANN model shows absolutely lower error measure when compared to the ANN model. Based on the obtained results, the GA-ANN indicates superiority in assessing the quality in terms of accuracy.

In this paper, a genetic algorithm has been described which can be applied to optimize the initial weights of the feed forward neural network for modeling and prediction of the industrial flotation process. Genetic algorithms are an optimization method which are suited for exploring complex space in an intelligent method to find values close to the global optimal values. These results demonstrate the improvements gained by using a genetic algorithm coupled with the ANN in comparison with ANN alone, because in the GA-ANN method, the weights are optimized quite satisfactory. This work is extended to optimize the training and performance of the ANN that can also be achieved by using the GA. By optimizing the initial weights, the GA-ANN performs significantly better than AAN.

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