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Prediction of Final Concentrate Grade Using Artificial Neural Networks from Gol-E-Gohar Iron Ore Plant

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Abstract In this study, the artificial neural networks methods were used to predict the iron, phosphor, sulfur and iron oxide content of final concentrate from the Gol-E-Gohar iron plant, Kerman province, Iran. The particle size (d_{80}), iron, phosphor, sulfur and iron oxide percentages of run of mine (R.O.M) were used as the inputs for the network. Feed-forward artificial neural networks (FANNs), with 5-8-7-7-4 and 5-8-8-6-4 arrangements were used to estimate the final concentrate grade in both wet and dry magnetic separation processes. The outputs of the models were the iron, iron oxide, phosphor and sulfur content of the final concentrate. Satisfactory correlations of $R^2 = 0.98$ were achieved in training and testing stages for the wet magnetic process prediction. The proposed neural network model, as an alternative to the simulation method, can be used accurately to determine the effects of changes in feed and concentrate grade of Gol-E-Gohar iron ore plant in dry and wet magnetic processes.

Keywords: *prediction, FANN, phosphor, sulfur, Gol-E-Gohar*

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1. Introduction

Artificial intelligence tools have been used for many years in a number of mineral processing applications. These networks have been used for different applications such as modeling for particle size analysis [1], simulation for particle shape quantification [2], assessment of flotation experiments [3,4,5] and the modeling of gold liberation from diagnostic leaching data[6].

The Gol-E-Gohar iron ore beneficiation plant is located around 55 km southwest of Sirjan, Kerman province, Iran. This plant is situated at the center of a triangle comprising the cities of Kerman, Shiraz and Bandar Abbas in Iran and is one of the major manufacturers of iron concentrate in Iran with capacity of 3.5 million tons annually [7]. The plant feed was provided from the Gol-E-Gohar iron mine which is also located in Kerman province, Iran. Figure 1 shows location of Gol-E-Gohar beneficiation plant in Iran.

The iron ore, after drilling, blasting, loading the extracted ore, are transported by mining trucks to the plant. Then the extracted ore are transferred to gyratory primary crusher. The maximum feed size to gyratory crusher is 1.5 m (d_{max}) and d_{80} of gyratory crusher product is about 20 cm. After primary crushing, the crushed ore transfers to autogenous mills (AG mills). The maximum size of AG mills product is 3 mm (d_{max}) and d_{80} of product is about 550 microns. The product of AG mills transfers to dry low intensity magnetic separator (LIMS). The LIMS output contains 3 types of products including concentrate, tailings and middlings. The middlings is regrinded in wet ball mills in the next stage and producing the iron concentrate using a wet low intensity magnetic separator. The final concentrate is then transported to a tailings dam after dewatering using filters and thickeners. Finally, dry and wet concentrate are blended together and then ready to send to the customers. Table 1 shows the chemical specification of final iron concentrate produced by the Gol-E-Gohar iron ore plant with a d_{80} of 60 microns and maximum moisture of 2%.

Figure 1. Gol-E-Gohar beneficiation plant location in Iran

The input-output data was obtained from the Gol-E-Gohar iron plant. In order to obtain the most suitable ANN models which predict the final iron concentrate grade, the performances of the models in terms of mean relative error (MRE) and mean absolute error (MAE) were calculated by the following equations:

$$MRE = \frac{\sum_{i=1}^{N} \frac{X_{predicted,i} - X_{observed,i}}{X_{observed,i}}}{N} \times 100 \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{N} \left| X_{predicted,i} - X_{observed,i} \right|}{N} \quad (2)$$

Table 1. Chemical properties of final iron ore concentrate in Gol-E-Gohar iron ore plant

Element or oxide (%)	Amount
Fe	67% min.
FeO	20% min.
P	0.05% max.
S	0.5% max.
CaO	0.6% max.
SiO_2	2% max.
Al_2O_3	0.5% max.

2. Artificial Neural Networks Modeling

In the recent years, artificial intelligence and particularly feed-forward artificial neural networks (FANNs) have provided tools for optimising operations and the problems involving large amounts of information that humans cannot easily solve. Artificial Neural Networks have been successfully applied to a number of pattern classification problems and they are powerful tools, which have the ability to determine the highly complex relationships from input–output data [8].

Neural networks have had an impact on the modeling of various processes that show highly non-linear dependence between different variables. After the training stage, the neural network model is capable of predicting the learning data pairs and interpolating between points which have never been observed before [9].

The application processes of an ANN model design include the following steps [10,11,12]:

1. Collecting the whole data in one place.
2. Determining the train and test sets.
3. Converting the data into the ANN inputs.
4. Determining, training and testing the network topology.
5. Repeating the steps 1 to 4 till the optimum model is determined.
6. Applying of the optimal ANN model.

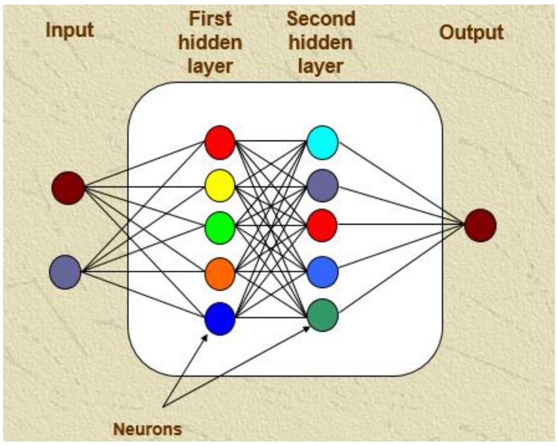

Figure 2. Schematic structure of Multilayer perceptron neural network

The structure of multilayer perception (MLP) is shown in Figure 2. In general, MLP is widely used for many applications such as pattern classification, recognition, prediction and approximation.

An output is the prediction that the neural network will learn to produce. The neural network tries to find the relationship between the inputs and the outputs by calculating their relative importance (weights). It calculates and compares the results with the actual answer in the data. Learning is achieved by adjusting the weights in order to minimize the errors of the outputs [13]. Figure 3 illustrates the working procedure using artificial neural networks modeling in this paper.

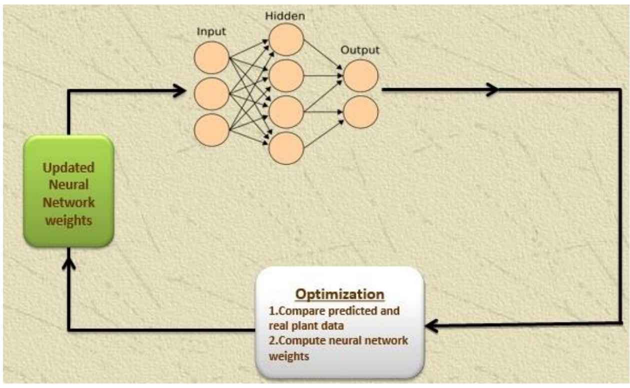

Figure 3. Working Procedure using artificial neural network

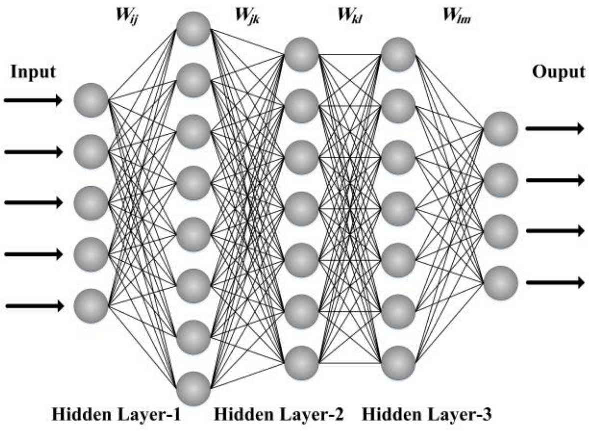

Figure 4. Multilayer perceptron neural network model 1 (5-8-7-7-4)

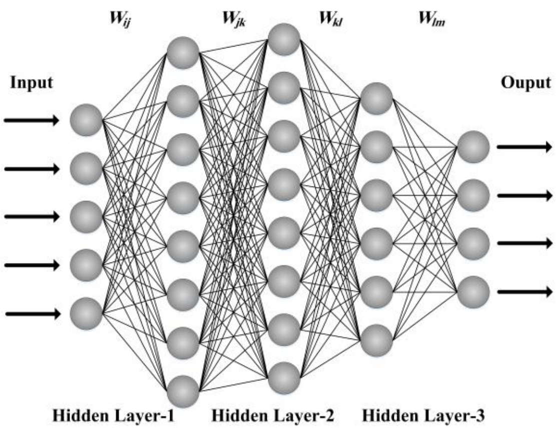

Figure 5. Multilayer perceptron neural network model 1 (5-8-8-6-4)

In this study, the MLP neural networks have 3 hidden layers. Five neurons in the input layer correspond to the percentage of Fe, FeO, P, S and d_{80} of the iron ore feed, and four neurons in the output layer correspond to Fe, FeO, P and S content for the final iron ore concentrate. Figure 3 and Figure 4 depict the models 1 and 3 of feed-forward network with one input layer, three hidden layers, and one output layer, which were used for the prediction of final iron ore concentrate grade.

3. Results and Discussions

Data used to test the proposed approach are taken from the Gol-E-Gohar plant chemical analysis daily database. The database consists of the percentage of Fe, FeO, P, S and d_{80} of the feed (iron ore) and also Fe, FeO, P, S content of the final iron ore concentrate. A total of 219 sets of data were used in the predictions by ANN; 200 data sets for training and 19 sets for testing the network were used. The training process was stopped after 200 epochs (Figure 6). In each epoch, the entire training set was presented to the network and errors were calculated and used to adjust the weights in the network using sigmoid transfer function.

Modeling was carried out in five stages according to the feed of different mills (wet or dry mills) and also the mixture of wet and dry iron ore concentrate. This was done in order to have a convenient comparison between the results and reliable prediction for the quality of final iron ore concentrate with the least error.

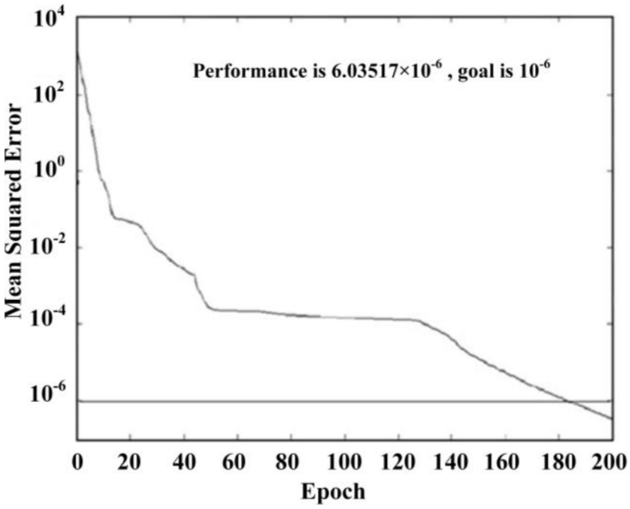

Figure 6. Parity plot for epoch and mean square error for training sets

Table 2. The different stages of modeling and obtained correlation coefficients

Model	Products	Network structure	Correlation Coefficient			
			Training	Test	Validation	Prediction
1	Feed to the wet mill (wet concentrate)	5.8.7.7.4	0.99978	0.99544	0.89471	0.98121
2	Feed to the wet mill (wet tailing)	5.8.7.8.4	0.99373	0.92943	0.65774	0.88849
3	Feed to the dry mill (dry concentrate)	5.8.8.6.4	0.99990	0.99908	0.99341	0.99846
4	Feed to the dry mill (dry tailing)	5.4.5.8.4	0.98149	0.93472	0.86349	0.94411
5	Mixture of wet and dry concentrate (final concentrate)	5.10.8.9.4	0.99367	0.87127	0.86167	0.93923

Table 2 shows the different stages of modeling according to the network structure and also the obtained correlation coefficients. As it can be seen, the highest correlation coefficient was observed in models of 1 and 3 for all training, testing, validating and prediction stages. The correlation coefficient value for the training set on both of models 1 and 3 were equal to 0.99. The correlation coefficient for testing sets was 0.99 in both models of 1 and 3. The coefficient of determination value for the training set on both of models of 1 and 3 were 0.98. The test set that actually determines how good the model is shows that the models can estimate the outputs quite satisfactorily. The satisfactory correlation of 0.99 for prediction of iron concentrate grade was achieved. The satisfactory coefficient of determination 0.98 for prediction of iron concentrate grade was also achieved. It was observed that the final concentrate grade could be predicted using the ANN model satisfactorily.

Table 3 shows the prediction errors. Negative values of errors in Table 3 indicate that the prediction values and compared with actual values. The performance of used function is the mean absolute error (MAE), the average absolute error between the networks predicted outputs and the target outputs, that was 0.02, -0.23, 0, 0 for testing data in Fe, FeO, P and S % predictions for model 3, respectively.

Table 3. Error determination of the mean absolute values and mean relative error values available for five models

Model	MAE				MRE(%)			
	S	P	FeO	Fe	S	P	FeO	Fe
1	-0.0653	0.0015	1.0034	-0.3277	7.36	-3.66	-4.2	0.48
2	0.00	0.05	-0.24	-0.53	0.15	-17.42	9.4	2.22
3	0.00	0.00	-0.23	-0.02	-0.38	8.04	0.99	-0.04
4	0.48	0.09	1.27	-0.48	-14.15	-40.28	-58.87	1.81
5	-0.18	0.00	-0.05	-0.34	24.21	-0.65	0.18	0.50

Figure 7-Figure 10 illustrate the predicted data using FANN versus actual data in the plant process. The R^2 values for the testing sets were 0.96, 0.96, 0.90 and 0.94 in Fe, FeO, P and S % predictions, respectively. It was observed that the grade of final iron concentrate could be predicted using the ANN model satisfactorily.

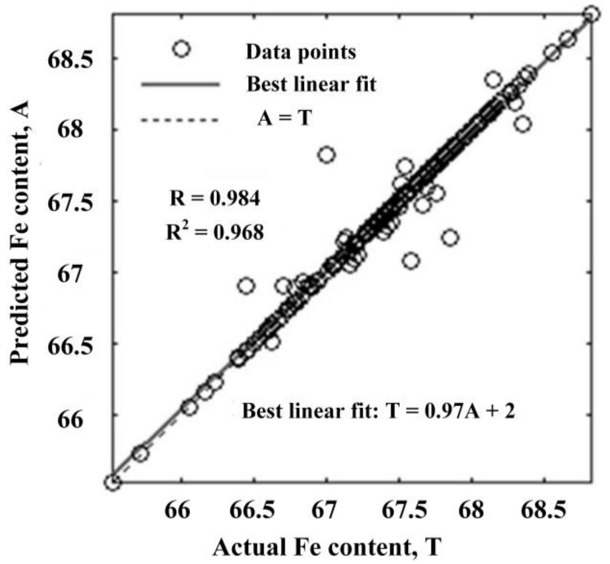

Figure 7. Linear regression predicted Fe content versus actual Fe content in final iron ore concentrate

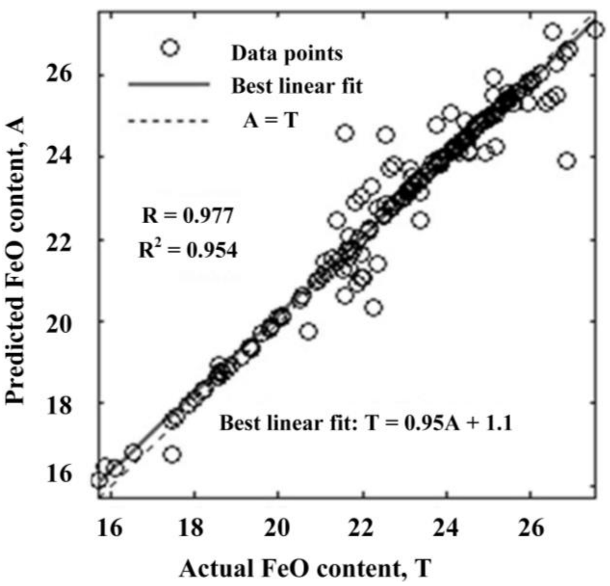

Figure 8. Linear regression predicted FeO content versus actual FeO sulfur content in final iron ore concentrate

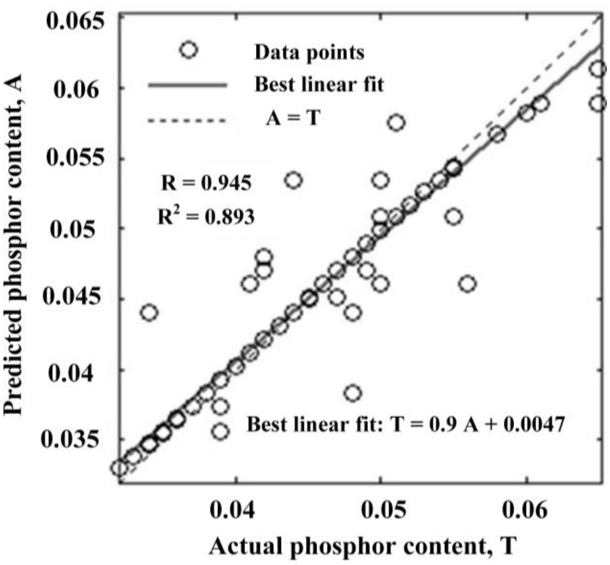

Figure 9. Linear regression predicted phosphor content versus actual phosphor content in final iron ore concentrate

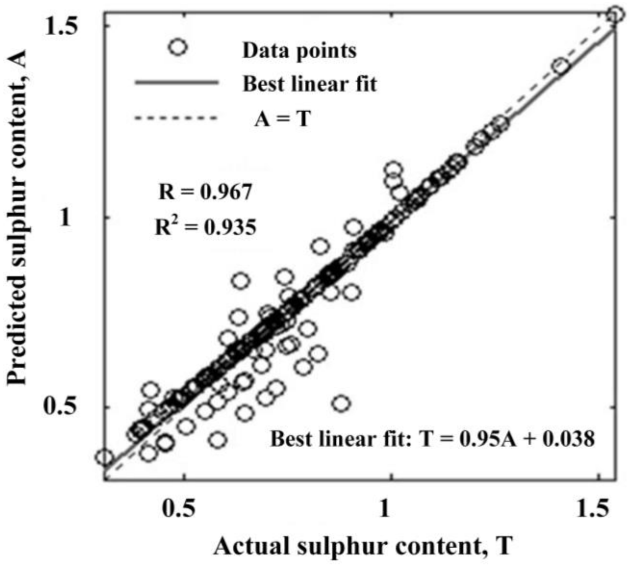

Figure 10. Linear regression predicted sulfur content versus actual sulfur content in final iron ore concentrate

However, the above mentioned results suggest that ANNs owing to their excellent nonlinear modeling ability are better alternative to the linear models for the prediction of final iron concentrate grade.

4. Conclusions

The following conclusions were obtained from the present research:

1. The present study shows that ANN can predict the elements assays very close to the actual assays of output in real plant.
2. The Feed-forward artificial neural networks with 5-8-7-7-4 and 5-8-8-6-4 arrangements were used to predict the grade of final iron concentrate of Gol-E-Gohar iron ore plant.
3. The neural network was trained using early-stop training to acquire a good generalization property. Prior to neural network modeling, the data set was divided into training, validation and test subsets.
4. Based on the results from this modeling, the three-hidden-layer ANN model is capable of predicting the grade of some elements assays for the final iron concentrate subject to different conditions.
5. The predictions from the trained model were in agreement with the actual data with an overall regression value for the neural net model of all elements assays.
6. The accuracy of the models was enhanced by the selection of better network structures instead of selecting a larger data set.
7. Regression analysis reveals that the reproduced and predicted grades by the trained neural network were in close proximity to the actual results of final iron concentrate grade ($R > 0.95$ and $R^2 > 0.90$).
8. The proposed approach can be useful to the geologists, mining engineers and also plant engineers for predicting the grade of different iron ore types and also for suggesting suitable blending of feed materials to achieve the maximum recovery. It can also be used to determine the most advantageous operational conditions for the expected concentrate assay.

9. Since this approach for forecasting the grade of final iron concentrate is an unexamined model at Gol-E-Gohar iron ore plant, it is suggested to assess it in the real conditions to predict effectively the assays of the final iron concentrate.

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