Estimation of Recovery Percentage in Gravimetric Concentration Processes using an Artificial Neural Network Model

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Abstract*—The concentrate process is the most sensitive in mineral processing plants (MPP), and the optimization of the process based on intelligent computational models (machine learning for recovery percentage modelling) can offer significant savings for the plant. Recent theoretical developments have revealed that many of the parameters commonly assumed as constants in gravity concentration modelling have a dynamic nature; however, there still lacks a universal way to model these factors accurately. This paper aims to understand the model effect of operational parameters of a jig (gravimetric concentrator) on the recovery percentage of the interest mineral (gold) through empirical modeling. The recovery percentage of mineral particles in a vibrated bed of big particles is studied by experimental data. The data used for the modelling were from experimental test in a pilot-scale jig supplemented by a two-month field sampling campaign for collecting 151 tests varying the most significant parameters (amplitude and frequency of pulsation, water flow, height of the artificial porous bed, and particle size). It is found the recovery percentage (%R) decreases with increasing pulsation amplitude (A) and frequency (F) when the size ratio of small to large particles (d/D) is smaller than 0.148. An empirical model was developed through machine learning techniques, specifically an artificial neural network (ANN) model was built and trained to predict the jig recovery percentage as a function of operation parameters and is then used to validate the recovery as a function of vibration conditions. The performance of the ANN model was compared with a new 65 experimental data of the recovery percentage. Results showed that the model (R^2 = 0.9172 and RMSE = 0.105) was accurate and therefore could be efficiently applied to predict the recovery percentage in a jig device.

Keywords—Empirical modeling; dynamic gravimetric concentration model; gravimetric concentration; machine learning for recovery percentage modelling; mineral processing

I. Introduction

Recently more and more attention is paid to the methods of increasing the amount (yield) of gold concentrates obtained in separation by gravimetric processes that have an undesired gangue minerals (commercially worthless minerals) content. The purpose of gravity separation processes in jigs is to produce maximum amount of concentrate having desired gold content. This problem has been discussed during fifty last years in many research papers [1]–[32].

The mineral concentrate zone is a highly nonlinear process that requiring control; its parameters vary with time and depend on the mineral feed rate and its size and density composition [30]–[34].

Although the use of neural network models is well established in the literature, it should be noted that such models, that depend on a large amount of data in the mineral processing industry is not very frequent, seeing the need to require such intelligent systems for further planning of design and optimization tasks, with which it is possible to understand, explain and test without the need to intervene in the real process [24], [35]. Machine learning models in general and artificial neural network models in particular, can be used to design and optimize control systems of concentrate discharge in jigs without the need to require a complex model that describes in detail the phenomena involved inside the equipment.

Regretfully, the lack of knowledge about all the phenomena that occur in this type of process is a frequent condition in practice in the mineral processing industry. Such situation occurs due to the low availability of phenomenological studies and due to some difficulties in modeling, inherited from past experiences; insufficient computational power led to the false appreciation that neural network models are complex. In addition, future research is needed to implement advanced control functions through the use of computer vision and multivariate data analysis. Such situations are directly reflected in the low availability of accurate models, which causes, for example, design problems in mining-metallurgical processes that must vary their operating conditions due to the heterogeneity of the ore to be processed. Today, it is possible to overcome such difficulties and use machine learning models such as neural networks to predict and describe the behavior of these processes, exploiting the capabilities of the model to analyze large amounts of data on the operational variables of the process while works with the process itself [32]–[34], [36].

Over the years, DEM and CFD models with a more detailed description of the gravimetric concentration phenomenon are being used more often [16], [29]. However, in spite of that progress, some challenges remain. For instance, one of the main goals that has not been accomplished so far is an agreed mathematical description of the percentage of mineral recovery (%R) and the operational parameters of the equipment (amplitude and frequency of pulsation, water flow, height of the artificial porous bed and size distribution). The %R turns out to be of paramount importance since it is directly related to the amount of grams of gold per tons of ore concentrated (gpt): ideally, the gold percentage recovered from the concentrate stream should be equal to 100%.

Currently, the literature provides different ways to determine the %R, depending on the final application. As mentioned before, in some DEM and CFD models the authors use constant or linear approximations for %R [2], [13], [37]. Some other authors use empirical correlations describing the %R in terms of parameters mainly related to the geometry of the equipment and granulometric distribution of the mineral [31], [32], [38]. In spite of the many available ways to determine the %R in gravimetric equipment , the main observed concern about the above approaches is that they are only useful in the systems from which they were developed [2].

The fundamental purpose of this work is to apply and promote the use of artificial neural network models (ANN), in the analysis of gravimetric concentration processes for the design and control of equipment. The motivation for a work like this arises from the evident need to include the dynamic behavior of this type of process as fundamental elements in the design tasks in mineral processing engineering. In this regard, there is a large number of computational tools that already offer assistance for CAD (Computer Aided Design) without having written support that justifies such uses. Therefore, the inclusion of the concept of "machine learning" as the foundation of intelligent modeling is imperative, leading to the best use of the model as an analysis tool and support for process design and control tasks [2], [16], [24]. Since the existing works on gravimetric concentration equipment such as the jig, so far focus directly on a statistical analysis and describe the recovery percentages through experimental equations, and the mathematical models that currently describe the phenomenon are highly computationally demanding, making them unattractive for rapid tasks of optimization and control of equipment.

In this work, an accepted methodology for obtaining ANN is used in the modeling of the gravimetric concentration stage in the mineral processing industry. The efficient design and optimization tasks of the jig (which is the main equipment of the concentration stage in a mineral processing plant for gold extraction) require the process model to be able to study its behavior. Therefore, a good effort is dedicated here to the deduction and validation of an ANN model for the jig, counting on data available from a real pilot jig. This paper aims to develop a model to study the %R in a gravimetric pilot plant and its interaction with other internal process variables. First, a artificial neural network model is obtained to describe the dynamic behavior of the pilot plant. Then, the model is tested and assessed in terms of their ability to predict %R in the studied pilot plant.

The rest of the work is organized as follows: in Section II, a review of modeling in mineral processing is presented. In Section III, the ANN model is defined, mentioning the procedure for obtaining it, while in Section IV, said procedure is applied to the jig. Section V shows the simulation results of the obtained model and discusses its qualitative and quantitative validation, ending with a Section VI of conclusions and future work.

II. Related Works

Jig is a gravimetric concentration equipment where mineral particles move in a flow of water pulsating, resulting at the end of the process in a stratification of particles of different densities and sizes. The stratification of the particles inside the jig occurs in a complex multiphase flow field. The particles are subjected to different hydrodynamic forces caused by the movement of the fluid, giving rise to different trajectories that depend on the velocity field of the fluid and particle properties. various variables operations affect the motion of particles among which can be included the flow of food from water and mineral, the amplitude and frequency of pulsation of the fluid, among others [2].

Over the past decades, considerable efforts have been made to design and modify the jigging process to increase gold recovery percentages and optimize processes [1]–[32]. Early in 1970s and late 1990s, mono-size small particles separation through a packed bed of mono-size large particles was studied by physical experiments [18], [39]–[48]. Later numerical models were also employed and the studies were extended to a much wider range of controlling variables on particle separation [3], [5], [9], [11], [15], [16], [19]–[21], [25]–[27], [29], [36], [37].

From the percentage recovery point of view, a jig can be classified as a complex system with multivariable nonlinear dynamics, large uncertainty according to external disturbances and both model structure and parameters, and multiple space and time scales dynamics [4]. Therefore, controlling recovery in jigs is, in general, not a straightforward task. These issues motivated the study of recovery behavior of jig by means of modeling and simulation tools. As pointed out by Dong et al. [4], there are several benefits to modeling jig: plant design and optimization, experimental design, testing research hypotheses, design and evaluation of control strategies, forecasting, analysis of plant-wide performance, and education [4], [28].

For design and optimization purposes of jig, the PET (potential energy theory) [8], [47] and DEM (discrete element method) [25], [38] simulation models are widely used to try understand the gravimetric concentration process in jigs. However, the above contributions don’t address the recovery to the concentration of mineral particles widely distributed in size and density. Therefore, the investigations of Ospina and Usuga [15] and Ospina *et al*. [16] were the starting point. In these previous works, the authors evaluate the sensitivity of the mineral recovery through the variation of the operational parameters of the equipment, from a statistical and numerical analysis, using descriptive models, in the present investigation it is intended to model the jig through predictive intelligent systems.

Intelligent systems are in many places, from vehicles to cell phones and even in some common household appliances such as refrigerators and microwave ovens. This is nothing more than a black box that includes input/output. Among the scopes that can be achieved with this type of systems are the following: System identification techniques applied in real processes, investigating the current methodologies that are being studied; implement parameter estimates by means of neural networks to different systems, taking into account the variables to manipulate and the data collected; validate with experimental data in real time the results obtained with the neural network model against using a mathematical model to confirm if there is a significant decrease in error and general improvements in the automatic control of processes, and encourage research and learning of neural networks for use in different areas of knowledge.

Artificial neural networks arise within the field of artificial intelligence, simulating the behavior of a biological neural network, in order to solve complex problems that would be very difficult to solve using conventional algorithms [49]–[52]. There are different types of artificial neural networks, which are used for different applications depending on their development. These networks are widely used for tasks such as: data classification, pattern detection, obtaining models of the retina of the eye and brain function, probability assessment, optimization, computer vision, and in the case of this research it was used for the prediction of variables in the mining industry.

However, in the field of modeling systems for mineral processing (grinding, classifying and concentrating), artificial neural networks are relatively recent, but their use is increasing in this type of systems due to the efficiency of the results that they can generate, avoiding the implementation of complex calculations with better performance [16], [24]. Currently, the intelligence systems by means of artificial neural networks can be summarized into four structures: i) supervised learning: the neural network learns a set of inputs and the desired outputs to solve the problem [53]–[56], ii) direct inverse learning: the neural network learns from the feedback of a system, so that, when the signal is obtained, it determines the parameters to be performed [52], [57]–[60], iii) utility backpropagation: this structure optimizes the mathematical equation that represents the system, where its main disadvantage is that it requires a model of the system to be analyzed [61]–[65] and iv) adaptive critical learning: similar to the utility backpropagation structure, but without the need for a model of the plant [66]–[68]. Although this type of structures are present and well accepted in different industrial processes, it is evident that in mineral processing applications and especially in the prediction of variables of interest such as mineral recovery, the existing studies of this type of design are based on simulations, this research being a starting point for the implementation of intelligent systems in gravimetric concentration equipment where experimental data obtained from a pilot scale jig is worked on.

This paper aims to use an ANN model to study the recovery percentage (yield) in a pilot jig and its interaction with other internal process variables (pulsation amplitude and frequency, water flow, particle size distribution and height of the artificial porous bed.). First an ANN model is obtained to predict recovery percentage by experimental data from the pilot jig. Then, the model is tested and assessed in terms of their ability to predict recovery with 65 other experimental tests different from those used for training the neural network.

III. Methodology

Mineral processing is considered fundamental to the mining industry. Classically, the term mineral processing or mineralurgy is used to describe the transformation operations involved in the upgrading and recovery of minerals [69]. These operations are carried out sequentially to obtain a raw material useful in subsequent processes or a final product desirable in the market. The operations that are grouped under the name mineral processing can be divided into four groups: size reduction, classification, concentration, and refining. Each stands out within a mineralurgical process, according to the mineralogical characteristics of the feed and the specifications of the final product. In a gravimetric concentration equipment a stream called feed is divided into two: a stream called concentrate, which has a high content of the species of interest and another stream called tails, in which this content is substantially decreased [2], [19]–[21]. Different operational parameters such as amplitude and frequency of water pulsation, bed thickness and feed flow characteristics affect the stratification process. In the following, the methodological application to obtain an artificial neural network model of a pilot-scale jig is shown.

The following methodology was proposed and followed step by step. This methodology attempts to bring together the theoretical component, the practical component, and the planning of the work.

1) Approach of an Experimental Design. Development of the Experimental Design. Assembly of jig at laboratory scale.

2) According to the proposed experiment design, the procedures to carry out the experimental tests on the laboratory scale jig and the data collection are planned.

3) Conducting tests in the jig at laboratory scale with alluvial ore sample suspensions to observe the concentration process in jigs, varying the proposed conditions. Sample collection and characterization.

4) Analysis of the results of the tests carried out.

5) Formulation of the ANN model that better predict the recovery percentage in jigs.

6) Validation of the obtained model with jig data at laboratory scale. The model was simulated in MATLAB®9.11(R2021b) using own code installed in a computer with an 8-core processor and 12GB of RAM. We used 216 samples (with sampling time T s = 0.1 s) for model identification and validation.

The aim is to estimate the percentage recovery of high-density minerals from low-density minerals in a jig according to a stratification of the particles present in a feed stream (F_a) whose solids load is less than 10% in volume. The stratification is produced by the transmission of mechanical energy which is generated by the movement of a plunger that exerts pressure on the water (F_{h2o}) in the internal chamber of the jig in a harmonic way, generating a movement in pulses (ascent and descent) of the particulate system that enters the separation chamber of the jig, so that a stratification of the bed formed by the particles is obtained, which is later used to produce the separation of the minerals. The separation chamber of the jig is open to the atmosphere. Inside it there is a screen where a bed of particles is deposited with an intermediate density with respect to the minerals to be separated. The particle bed has an initial height H_0 (packed bed) that rises to a height H_{max}, (fully fluidized bed) according to the upward and downward movement of F_{h2o}. The F_{h2o} current contains water at a flow rate greater than or equal to the minimum fluidization velocity of the particles to be separated. The anharmonic motion of F_{h2o} generates a hydrodynamic interaction between the two phases present in the process (solid-solid, solid-liquid interaction). This interaction alters the movement of the mineral particles in the separation chamber of the jig. The upward movement of water and mineral particles is called the fluidization stage. In this stage the mineral particles rise from a height H_0 to a height H_{max}, initiating the stratification of the particles. At the beginning of stratification, the mineral particles with higher density and larger size tend to be deposited in the lower part of the bed, while the particles with lower density and smaller size are in the upper part of the bed. When the descent stage begins, the denser particles have a higher sedimentation velocity than the less dense particles, this allows that before the compaction of the bed, the heavier mineral particles are deposited quickly below the screen, obtaining after several cycles of pulsation, a complete separation of the mineral particles in two streams: $F_{rejection}$ and $F_{concentrated}$. The process is carried out under ambient temperature conditions and no chemical reaction is present. A diagram of the general process is shown in Fig. 1. The jig from which actual data were taken to train and validate the model has the conditions reported in Table I.

A full factorial experimental design was developed involving the variables that exert the greatest control in the operation of the equipment (water flow, pulse amplitude, pulse frequency, granulometry, APB height) by means of an experimental matrix. This factorial design consists of five factors where the frequency, water flow and granulometry each have three levels (high, medium, low) and the amplitude and APB height each have two levels (high and low) resulting in a total of 108 tests plus replicates, a total of 216 tests. Table II summarizes the values considered for the different operating parameters. The response variable is the main metallurgical index (Recovery percentage (%R)).

Regarding the method of data collection and analysis. Primary data were used, which were collected through each of the ore samples generated from the experimental design (see Table I) by quantifying the gold mineral content in each of the 151 samples for identification and the 65 samples for validation, through two methods known as fire assay and time sequence analysis [7]. The effect of the operational parameters (see Table 2) on %R could be predicted from a sequential order of recovery percentage values (trend at equal time intervals).

The neural network method was selected because of its great capacity to adapt to different types of problems, the previous experience with the use of neural networks [70]–[73], and the ease of implementation of this type of technique, in addition to being a technique with great potential that is causing a revolution by proving to be the future of technology.

An artificial neural network (ANN) is an automatic learning and processing paradigm inspired by the functioning of the human nervous system [58], [59], [65]–[67], [74]. A neural network is composed of a set of neurons interconnected by links, where each neuron takes as inputs the outputs of the preceding neurons, multiplies each of these inputs by a weight and, by means of an activation function, calculates an output. This output is in turn the input of the neuron it precedes. The union of all these interconnected neurons the artificial neural network [50], [51], [54], [55].

Fig. 1. Jig Diagram.

TABLE I. PILOT SCALE JIG CHARACTERISTICS

Feature	**value**
Mineral Feed Flow (**F_a**)	200 g/min
Water flow (**F_{h2o}**)	[1.5-2.5] gal/min
Mineral size (granulometry)	[125-850] µm
Artificial porous bed height (APB)	[2.5-3.75] cm
Pulse amplitude	[5-7] mm
Pulse frequency	[5-9] Hz
APB particle diameter	3 mm

TABLE II. OPERATING PARAMETERS AND RESPECTIVE OPERATING LEVELS

Levels	**High**	**Medium**	**Low**
Frequency (Hz)-**F**	9	7	5
Pulse amplitude (mm)-**A**	7	-	5
Granulometry (mesh series Tyler)-**T**	+50 (1)	-50 +100 (2)	-100 (3)
Water flow (gal/min)-**H**	2,5	2,0	1,5
Artificial porous bed height (cm)	3,75	-	2,5

The artificial neural network as well as biological networks learn by repetition, and the more data you must train and the more times you train the network the better results you will get [62], [63], [67]. Training an ANN is a process that modifies the value of the weights associated with each neuron, so that the ANN can generate an output from the data presented in the input [52]. The weights are really the way the neuron learns. These weights will be modified in a certain way to adapt the value of the output in such a way as to minimize its error with respect to the real result that the artificial neuron should produce [55], [75].

Based on the above arguments, the following questions arise for this methodological development: What data are relevant for the management of the problem to be addressed?, which variables are relevant to address and manage this problem?, where can the data be obtained?, how to prepare and encode the data?, what type of network should be chosen?, how many hidden layers and how many neurons are necessary to manage the possible solution to the proposed problem?, what learning rule to choose?, and what initialization is given to the weights?. These data will be acquired by means of experimental tests using the pilot plant of the jig. The data obtained from the experimental tests will be organized in a spreadsheet to be later entered into the software that will be used to code the neural network (Matlab®(R2021b)). The network to be designed will be initially selected with a configuration of one hidden layer with 13 neurons in each layer, five inputs, one output and a learning coefficient of 0.3 and random weights. However, once implemented, several tests will be performed to determine if a change in any of the parameters is necessary to obtain better results. The structure intended to be implemented for this proposed model is shown in Fig. 2. This structure has the possibility of being changed if a better alternative is discovered in the future during the process of development, research, and implementation.

As regards the activation functions, several functions were tested, among them the logsig, the ReLu, the softplus, the hardlim and the tansig, choosing in the end the logsig since it is the function that reaches a low margin of error in the shortest time for this specific process with the input data obtained.

Finally, it is possible to observe that the neural network was developed with its own code (the Matlab library was not used) along with the database with which it would be trained. The Matlab program consists of three parts: i) Network configuration: This is the main part, where the neural network is configured and trained. This was done using arrays of cells, so that it was possible to store arrays of different sizes in a single variable. Each row of the network variable is a different type of data, such as the weights of each layer, biases, errors, and so on, ii) Feedforward: In this file the forward propagation stage of the network was performed, where all the elements of the database are passed through the neural network, obtaining an output, and iii) Backpropagation: The backpropagation algorithm implemented for this network was gradient descent, where the aim is to minimize the error by calculating the partial derivatives of the error or cost function (mean squared error in this case), in terms of the weights of each neuron, modifying them in order to reduce the error in the output.

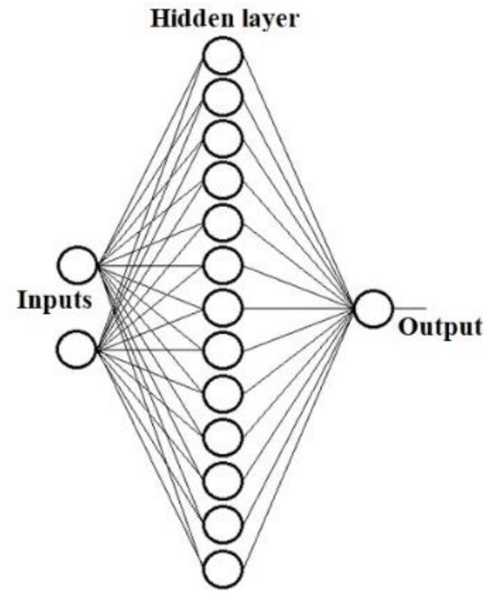

Fig. 2. Neural Network Configuration for Intelligent System.

Several tests were performed to verify the learning of this network and that the data delivered by it were consistent even with parameters that it had not received in the training stage, obtaining more than acceptable values, and thus proceeding to the implementation stage.

To assess the performance of ANN model, was followed the procedures suggested by Cruz et al.[58]. After visual evaluation and tests for fitting the behavior, the two criteria: Root Mean Square Error (RMSE), and coefficient of determination (R^2) were applied [31], [32], [34] (see Eqs. (1) and (2)):

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(x-x_t)^2}{n}} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x-x_t)^2}{\sum_{i=1}^{n}(x-\bar{x})^2} \quad (2)$$

where x is experimental data of the recovery percentage, x_t is ANN output, n is the sample size and $\bar{x}$ is the mean of experimental data for the recovery percentage.

IV. Results

This section presents the results obtained in this research, which includes the description of the intelligent implementation. The neural network was trained from plant experimental data, using the database "JigRNA.xlsx", which have 151 rows of data, the first column being the pulsation frequency value, the second the pulse amplitude value, the third the ore size, the fourth the water flow value, the fifth the APB value, and the sixth to the mineral recovery percentage value (output). Table III shows a portion of the recorded data.

Once the results of the experimental tests were obtained, the variables values were normalized in the interval 0 to 1, this in order to work with less uncertainty the data that would be entered into the neural network and have a free response of engineering units. Eq (3) shows how the data were normalized and Table IV shows a portion of the normalized data.

$$Normalized_{value} = \frac{(Value_{real} - Value_{mim})}{(Value_{max} - Value_{min})} \quad (3)$$

After normalization, a multilayer perceptron ANN with five inputs (corresponding to the five parameters used in Table IV) was created using proprietary code in a Matlab® script. The program identifies the five input and the output (%R). From the simulations performed, errors of less than 2% were obtained with 13 neurons in the hidden layer and starting the training process for 200 epochs. The results of the network without training and the training performance are shown in Fig. 3 and 4 respectively.

Fig. 3 shows the unsorted distribution of the data for the untrained neural network, once the training algorithm is started, it converges in only 40 epochs (see Fig. 4), making the network follow the input patterns that have been provided.

The performance of the ANN model was compared in two stages. In the first stage (Fig. 5), the identification data are shown with the absolute errors (maximum, average and minimum) that are reported in Table V.

TABLE III. RANDOM DATABASE USED TO TRAIN THE ANN

F	A	T	H	APB	%R
5	7	1	2	3,75	68,69
7	5	3	2,5	3,75	6,8
5	7	2	2,5	2,5	13,7
9	7	2	2	3,75	31,1
7	5	3	1,5	2,5	93,5
5	5	2	2	3,75	14,64
5	7	3	1,5	3,75	50,08

TABLE IV. NORMALIZED DATABASE USED TO TRAIN THE ANN

F	A	T	H	APB	%R
0	1	0	0,5	0	0,6905
0,5	0	1	1	1	0,0683
0	1	0,5	1	0,5451	0,1376
1	1	0,5	0,5	1	0,3126
0,5	0	1	0	0,545	0,9399
0	0	0,5	0,5	1	0,1471
0	1	1	0	1	0,5034

TABLE V. ERRORS IN IDENTIFICATION

Model	Max. Error	Mean Error	Min. Error
ANN	0,4449	0,0630	3,4382e-06

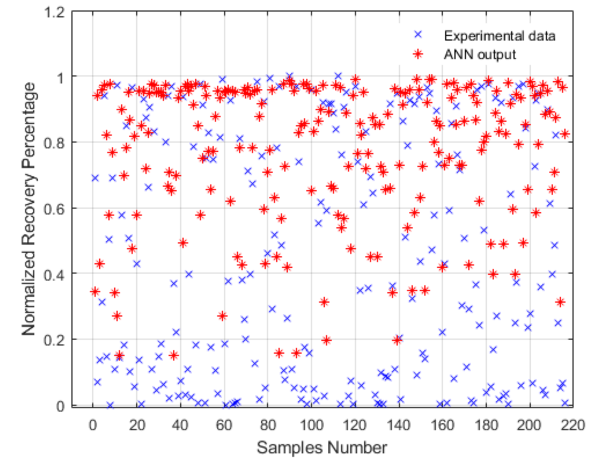

Fig. 3. ANN Response without Learning.

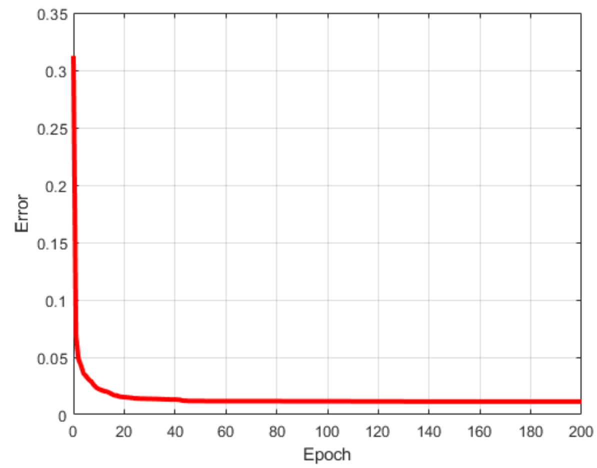

Fig. 4. Training Performance.

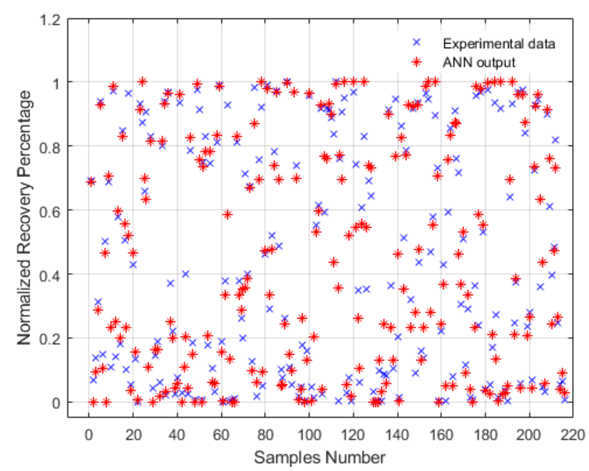

Fig. 5. ANN Performance.

In the second stage the model is compared by means of the validation data (Fig. 6) with their respective R^2 and RSME presented in Table VI. Additionally, Fig. 7 shows the histogram of the errors made by the Neural Network for the validation data.

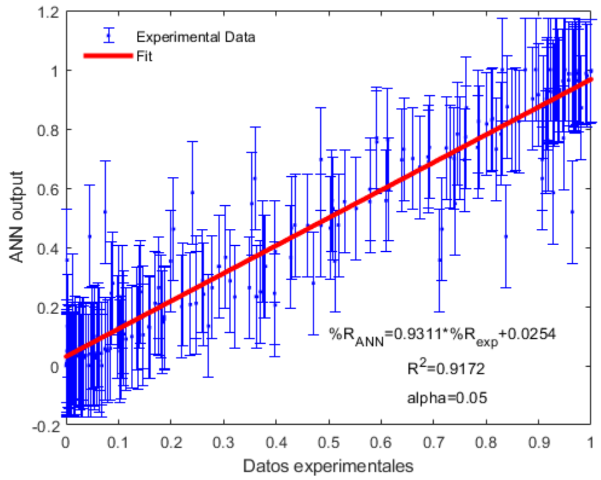

Fig. 6. Relationship of the Validation Data with the ANN Output.

TABLE VI. ERRORS IN VALIDATION

Model	R^2	RSME
ANN	0,9172	0,105

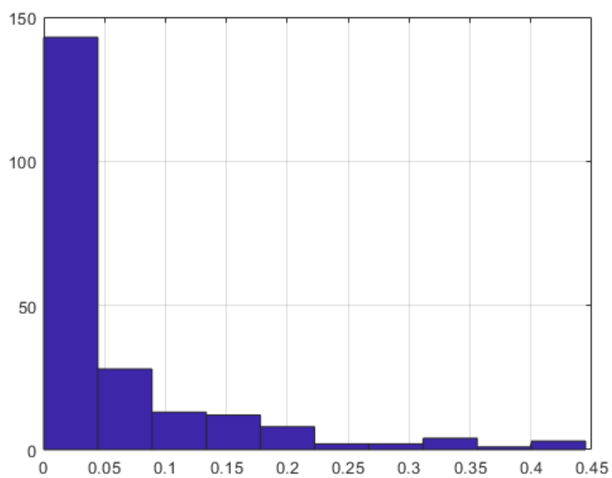

Fig. 7. Histogram of ANN Errors with Validation Data.

It can be seen from Fig. 5 to 7 and Tables V and VI that the performance of ANN model may be suitable for prediction of recovery percentage in gravimetric concentration equipment in the mineral processing industry, both in identification and validation, yielding errors of less than 2%, which is adequate for engineering purposes, especially to implement an optimization strategy for the jig concentration process.

The ANN model result in its matrix form can be expressed according to Eqs. (4) to (9). In the hidden layer Eq. (6) the inputs to the network $X_{5\times1}$were shown one by one (see Table 4). These result in an output $Y^1_{13\times1}$ (Eq. (7)) for each neuron from applying the activation function $f^1(a^1_{13\times1})$ (logsig). Subsequently, the outputs of the neurons of the hidden layer are fed to the neuron of the output layer (Eq (8)) to obtain the output of the whole network or each input supplied (Eq. (9)).

$$a^k_{n\times1} = W^k_{n\times p} \cdot Y^{k-1}_{p\times1} + b^k_{n\times1} \quad (4)$$

$$Y^k_{n\times1} = f^k(a^k_{n\times1}) \quad (5)$$

$$a^1_{13\times1} = W^1_{13\times5} \cdot X_{13\times1} + b^1_{13\times1} \quad (6)$$

$$Y^1_{13\times1} = f^1(a^1_{13\times1}) \quad (7)$$

$$a^2_{1\times13} = W^2_{1\times13} \cdot Y^1_{13\times1} + b^2_{1\times1} \quad (8)$$

$$Y^2_{1\times1} = f^2(a^2_{1\times1}) \quad (9)$$

In Eq. (4) to (9), the W^k are the weights of each of the connections of the neurons with the upstream and downstream layers and the $b^k$are the biases of each of the neurons. These two parameters are trained for each input supplied to the network and are updated epoch by epoch until the neuron output is as close as possible to the experimental data. The values of these parameters after training and validation are shown in Tables VII to IX.

TABLE VII. INPUT-NEURON WEIGHT MATRIX HIDDEN LAYER ($W^1_{13\times5}$)

Neuron	F	A	T	H	APB
1	13,169	-8,118	9,593	-14,15	-7,127
2	13,338	23,438	14,351	6,829	-39,237
3	-2,497	-8,079	2,932	-1,547	-8,782
4	25,019	2,770	-40,937	3,161	2,032
5	2,287	5,335	1,892	3,824	3,860
6	-21,545	7,757	-12,758	-5,941	-14,059
7	-12,903	11,024	-9,002	0,628	8,4
8	9,771	-0,809	-20,987	-0,855	-1,302
9	13,742	-8,853	-6,582	-6,028	19,347
10	0,271	3,452	1,864	3,541	0,165
11	-7,925	5,39	2,966	7,421	-1,126
12	41,617	24,659	-23,697	-48,221	71,691
13	13,914	8,624	3,308	7,510	13,214

TABLE VIII. WEIGHT MATRIX NEURONS HIDDEN LAYER-NEURON OUTPUT LAYER ($W^2_{1\times13}$)

Neuron Hidden Layer	Output Neuron
1	6,5676
2	-4,5756
3	-6,4016
4	-12,4363
5	-20,2859
6	6,5559
7	-5,5759
8	15,4027
9	-10,4933
10	18,7184
11	-6,7827
12	5,4746
13	4,9074

In Table VII, each row represents a neuron of the hidden layer, and each column represents the connection to each of the inputs (corresponding to the five operational variables of the jig). Similarly in Table VIII, each row corresponds to an output of the hidden layer neurons, and each column is the connection from the hidden layer to the output neuron of the network. Finally, Table IX can be interpreted as follows: each row corresponds to the bias of each of the hidden layer neurons. The bias value for the output layer neuron was $b^2_{1\times1}$=6,4373.

TABLE IX. BIAS MATRIX NEURONS HIDDEN LAYER

Neuron Hidden Layer	**Bias ($\boldsymbol{b^1_{13\times1}}$)**
1	-11,6266
2	-4,9026
3	11,9266
4	-0,1623
5	-7,4530
6	23,4868
7	-4,3211
8	4,6968
9	0,7725
10	-3,1677
11	-6,9047
12	-16,4843
13	-20,1379

V. DISCUSSION OF RESULTS

In this paper we proposed as a contribution an ANN model for the estimation of the recovery percentage in a gold gravimetric concentration equipment known as a jig, which was based on the development of its own code in Matlab®, based on experimental data from a laboratory-scale jig (see Figure 1). With respect to traditional empirical and DEM-CFD modelling [15], [16], [20], [25], [26], artificial intelligence applications can become more efficient than the conventional techniques still used in the mineral processing industry as the ones proposed in this research and supported by [24] where is emphasized that in the ANN model, the input variables can include other controlling variables, such as other particle properties and system dimensions, feature that is very similar to phenomenologically based models.

Comparing both the identification and validation errors. It can be said that the performance of the ANN model adequately predicts the response variable (RSME=0.105), despite the great dependence and sensitivity of the recovery percentage with respect to variability. Of the five main operational parameters of the equipment (frequency and amplitude of pulsation, water flow, height of the artificial porous bed, and size of the mineral to be separated). The error in the ANN model could be decreased by two orders of magnitude if more delve into the number of neurons and hidden layers in the network that give a better fit with respect to the data provided. The above was evidenced in [58] where it is ratified that the use of different neural networks, whether they use the gradient method or the convolutional ones, converges to a global minimum of the error.

The prediction performance of the model is compared by experimental data (see Fig. 5 and 6). Note that, since the validation data were recorded from laboratory-scale jig, It is necessary to be able to validate the model taking into account more ore samples and on a full-scale jig, as there could be a significant lag between the result of the pilot plant and the data recorded on an industrial-scale jig [3]. This type of inconvenience can be easily compensated with the application of scaling techniques, integrating the total plant and control design [3], [32].

The average prediction errors that were estimated using the validation data sequence for the model, are shown in Tables V and VI. We see that the ANN model fits well, but one of the limitations of these prediction errors is that a significant number of dynamics (Particle-particle interaction and particle-fluid interaction) remains unmodeled. This may be since when employed models that depend heavily on data (empirical), built through experimentation and observation, the interpretability of many other phenomena that occur in this type of process is limited to the little knowledge that this type of structures present, in addition to other effects that can only be adequately modeled in a phenomenological mathematical structure.

This paper has shown that the modeling framework based on ANN models may give models that are as useful, accurate, and reliable as with phenomenological modeling, even if the system is well understood. Such models may serve as an alternative that may be attractive especially for systems that are not well understood, as in the case of jig. Moreover, we believe ANN model developed in this framework has significant advantages over many other non-linear empirical modeling frameworks. The reason is that it admits interpretability of the model through the intuitive and easily understandable operating regime concept, and the fact that the machine learning models can be interpreted independently.

VI. CONCLUSIONS

In this work, ANN model was developed, and their performance was evaluated by means of absolute errors. It can be said that the application of this type of model in real mineral processes can guarantee an adequate optimization of highly dynamic processes, since the expected results can be obtained in a shorter time without the need to use complex mathematical models, which are often difficult to obtain, or the phenomena involved in most of them cannot be understood in depth.

ANN models have a wide use in present day engineering. In this contribution, special attention is paid to control oriented models. As is well known, chemical, biochemical, and mining-metallurgical models are complex and nonlinear due to the multiple interacting phenomena, making them hard to implement in process control tasks. Although an ANN model (a type of black-box model) is not able to capture and predict the essential phenomena (mass, energy, and momentum transfer), gives significant rapid response with respect to the variables that are intended to intervene, thus providing strategies to rationally optimize and to control industrial scale jigs since in this type of process a large amount of data can be obtained from both input and output variables.

With the implementation of this type of advanced modeling strategy, there was a significant reduction in the error when comparing the conventional empirical data against the experimental data using neural networks and, in turn, a better response to the operational variability of the processes was evidenced. Considering the results obtained, it can be affirmed that neural networks can be the pillar of the so-called fourth industrial revolution, proving to be useful in multiple fields, offering high efficiency and reliability in the optimization of industrial processes.

It is concluded from the identification and validation performed that the ANN model is very sensitive to the data provided. Further simulations on the ANN model, changing the number of neurons in the hidden layer could show very significant changes in the errors of both the identification and validation data.

As a future work derived from the present research, it is intended to complement the architecture of the proposed system by including other artificial intelligence models for the analysis of recovery percentage, using, for example, fuzzy logic, in order to enable the implementation of early warning systems and particle-particle interaction and particle-fluid interaction for monitoring recovery percentage.

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