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PREDICTION OF RESULTS OF FLOATATION PROCESS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT – In this paper, the use of artificial neural networks in the flotation process is presented and analyzed. Apart from utilization of flotation in the mineral processing, deinking flotation is used for separation of ink particles from the cellulose fibers. The time of deinking flotation, pH value, reagents such as oleic acid, oleic acid with $CaCl_2$, oleic acid with $AlCl_2$ as well as concentration of reagents were used as input for the network. The recovery of toner particles in froth was used as output data for the network. The neural network demonstrated high correlation coefficients during training (0.97), validation (0.96), and testing (0.94), and subsequent accuracy testing confirmed these results.

Keywords: Artificial neural networks, Machine learning, Flotation, Deinking.

INTRODUCTION

One of the fastest-developing fields in computer science in recent decades is artificial intelligence [1]. Artificial intelligence is a branch of computer science focused on developing programs that enable machines to think and behave in ways that could be considered intelligent. Intelligent thinking represents the ability to reason in accordance with a current, previously unknown situation [2].

Machine learning is a field of artificial intelligence that deals with the development of programs that learn from previously obtained data. Once a solution to a problem is found, the program can remember and apply it in a similar situation. The forms of machine learning can be divided into the following three basic types of learning: supervised learning, unsupervised learning, and reinforced learning [3].

Supervised learning represents an approach to the learning problem in which the learning program receives a set of input data (x_1, x_2, …, x_n) and a set of desired output values, such that for each input data point x_i, there is a corresponding correct output y_i. The task of the program is to learn how to assign the correct output value to a new input data point. Algorithms based on supervised learning include models based on artificial neural networks, decision trees, support vector machines, Gaussian processes, and others [3].

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Artificial Neural Network (ANN) represents a set of interconnected simple processing elements (neurons) whose operating principle is based on the biological neuron. A typical neural network architecture consists of three layers of neurons: input, hidden and output layers [2,3].

The optimal number of hidden neurons depends on multiple factors, including the number of inputs and outputs, number of training pairs, level of noise in the training pairs, complexity of the error function, network architecture, and training algorithm. It can be said that the choice of architecture depends on the type and complexity of the problem being studied. The optimal number of neurons in the hidden layer is very important for the correct functioning of the model. A network with too many neurons will have an excessive number of parameters, making it prone to overfitting. Conversely, a network with too few neurons will not be able to properly approximate the given nonlinear relationships, leading to a problem of underfitting [3].

The flotation process has been used in mineral processing plants to separate valuable minerals from the gangue. This process takes place in a specific environment – flotation pulp – which consists of three phases: solid (mineral particles), liquid (water) and gaseous (air). Separation of mineral particles is made possible due to the differences in their surface hydrophobicity (feature of material characterizing its ability to be wetted with a liquid in the presence of a gas phase) [4].

Compared to mineral flotation, deinking flotation (ink removal from cellulose fibers) is a relatively young process. The basis of deinking flotation is pulp that contains the following components: water, as the carrier medium (approximately 98-99%); fibers, material obtained as a clean fraction (1-2%); fillers (<0.6%), printing ink and other impurities (<0.15%) that need to be removed; and reagents required for the fiber purification process (<0.1%) [5].

The efficiency of the flotation process can be shown through the toner recovery in foam product and cellulose fiber recovery in sink product, effective residual ink concentration in the final product (ERIC), the whiteness and brightness of the fibers.

The main parameters that influence flotation are temperature, pH, toner particle size, air flow, water hardness (concentration of calcium ions in the water), and others. All parameters are interdependent, so the flotation process is defined exclusively by their interaction-i.e., by the mechanism of their combined effect [6,7].

Our understanding of the fundamental physical and chemical processes underlying the deinking processes is growing. But, due to the great variability of the raw material as well as the complexity of the physical processes which occur at the microscopic level, processing problems and process instability remain as challenges [8].

Several studies demonstrate the effectiveness of artificial neural networks in modeling and optimizing processes in the pulp and paper industry. Labidi et al. (2007) [9] used an ANN to model ink removal in flotation, finding that higher consistency and airflow rates improved brightness and ERIC in the flotation cell, with strong correlation between ANN predictions and experimental results. Additionally, ANNs have been applied in image analysis, Verikas et al., (2000) [10] employed an ANN, combined with Fuzzy Logic to analyse the colour of dark spots in recycled paper sheets. Pauck (2011) [8] generated nearly 500 deinking runs to form the database for the training neural networks. The models effectively predicted brightness and ERIC, though yield results were slightly less accurate due to process complexity.

In the following study, an algorithm with supervised learning was analyzed, specifically, a model based on artificial neural networks for data obtained by deinking flotation.

EXPERIMENTAL

The Neural Fitting tool from the Matlab software package was used to create and train the network, as well as to evaluate its performance accuracy using mean squared error (MSE) and regression analysis.

The time of deinking flotation (in the range 1-20 min), pH value (in the range 3-12), reagents such as oleic acid, oleic acid with $CaCl_2$, oleic acid with $AlCl_2$ as well as concentration of reagents (0.1 kg/t, 0.4 kg/t, 1 kg/t) were used as input model variables. The recovery of toner particles in froth was used as the output model parameters.

From the total dataset of 225 parameters, 200 (88.89%) were randomly allocated for network training, validation, and testing, while the remaining 25 (11.11%) were reserved for evaluating the trained network's accuracy.

RESULTS AND DISCUSSION

The neural network architecture consisted of 10 hidden neurons (Fig. 1). From the available dataset of 200 parameters, 140 (70%) were used for training, while 30 parameters each (15%) were allocated for validation and testing (Table 1, Fig. 2). Network training was performed using the Levenberg-Marquardt algorithm.

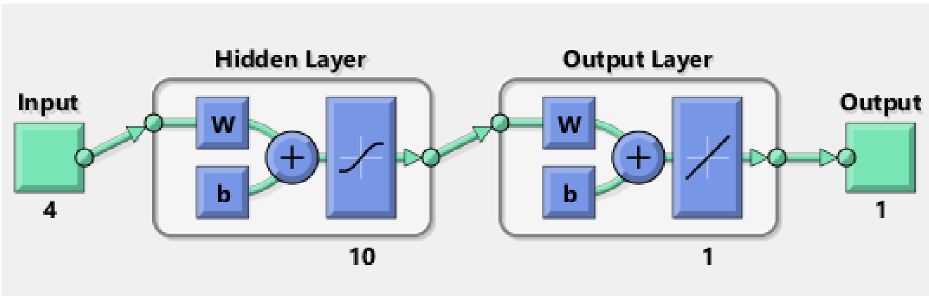

Figure 1 The structure of the created artificial neural network

Table 1 Network performance accuracy criteria obtained using the Levenberg-Marquardt algorithm

Training algorithm		Number of data	Mean squared error (MSE)	Coefficient of correlation (R)
Levenberg-Marquardt	Training	140 (70%)	74.87510	0.977055
	Validation	30 (15%)	192.94061	0.960261
	Testing	30 (15%)	136.83548	0.942087

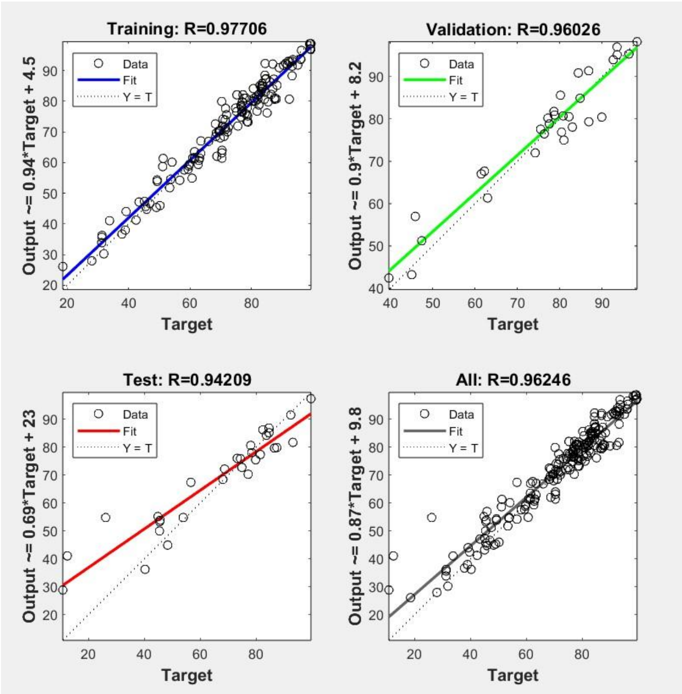

Figure 2 Plot of network's target values versus predicted outputs based on trained parameters, using the Levenberg-Marquardt training algorithm

Testing of the model demonstrates that the neural network achieves good results, as shown by a correlation coefficient of 0.94209. The excellent agreement between experimental data and ANN outputs, evidenced through both graphical representation and quantitative correlation analysis, validates the model's satisfactory prediction accuracy.

Since 88.89% of the data (200 parameters) were used for training, validation, and testing in the previous part, the remaining 11.11% (25 data points) that were not used for model training were preserved for prediction purposes, in order to determine the model's accuracy. The following Fig 3 present graphical comparisons between the values obtained from the network and the actual values obtained experimentally.

Figure 3 shows that the network modeling was successfully implemented, with the neural network accurately capturing the trend of experimental result curves.

Based on these results, it can be concluded that the artificial neural network architecture, comprising an input layer, a single 10-neuron hidden layer, and an output layer, is effectively applicable to this dataset type.

The number of required neurons was supposed to be determined by iteration. The greater the number of neurons, the more complex is the function which can be approximated. On the other hand, more neurons require more data which can also lead to overfitting of a function. At this point the training information and the neural network can be saved and inputted with other real data to produce a predicted output. If the performance of the network is not adequate, several corrective measures are available [8]: the network can be reset or initialized with new initial weights and biases and retrained; the number of neurons can be increased or decreased; expand the training dataset; change the number of input values; the ratio of data in training, validation and test sets can be changed; try alternate learning and training algorithms, and pre-processing of inputs and outputs.

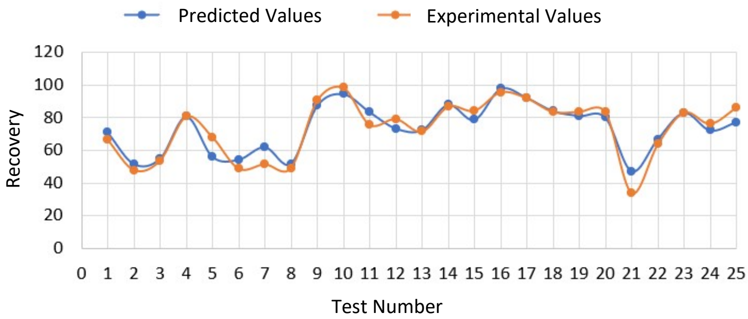

Figure 3 Comparative values obtained experimentally and using the ANN model with the Levenberg-Marquardt training algorithm

CONCLUSION

In this study, an algorithm with supervised learning was analyzed, specifically an artificial neural network model for data obtained by deinking flotation.

The neural network architecture consisted of a single hidden layer with 10 neurons. Network training was performed using the Levenberg-Marquardt algorithm.

The inputs of the models were time of deinking flotation, pH, reagents such as oleic acid, oleic acid with $CaCl_2$, oleic acid with $AlCl_2$ as well as concentration of reagents, while the output values were recovery of toner particles in froth.

The neural network demonstrated high correlation coefficients during training (0.97), validation (0.96), and testing (0.94). Subsequent accuracy testing confirmed these results, showing that the network effectively modeled laboratory processes with strong correlation.

Based on these results, it can be concluded that the artificial neural network architecture, comprising an input layer, a single 10-neuron hidden layer, and an output layer, is effectively applicable to this dataset type.

Since this study employed 10 hidden neurons in the neural network architecture, determining and utilizing the optimal number of neurons for this specific dataset could potentially yield even better results.

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