DESIGN OF A PREDICTIVE MODEL WITH ARTIFICIAL NEURONAL NETWORKS FOR THE RHEOLOGY OF PULP TAKING CHARACTERISTIC SEDIMENTATION DATA

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ABSTRACT

Most of Chile's mining industries with metallurgical processes have operations that use profuse amounts of water, as in the case of flotation, with the discard of almost 95% of water from this process, so recovery of water is crucial. In this study focused on rheology, an analysis methodology and techniques based for prediction with neural networks will be presented. Various factors affecting and influencing the rheology of a sample previously settled with flocculant were used, seeking the best management and selection of training data for a neural network to help predict the variables of Yield Point Unshear, Yield Point Fully Shear , Viscosity and Yield Stress with an error of 10% to 20% respectively for the ratio of the predicted data and the actual data.

Keywords: Neural networks; Rheology; Rheometer; Viscosity; Yield Stress; Yield Point Unshear; Yield Point Fully Shear.

Introduction

Rheology, the science of physics that studies the relationship between stress and deformation of matter for its flow, is an established engineering discipline with applications in various fields of mining and metallurgy (Aguilar, Sàez, Llorèns, Soler, & Ortuño , 2002). The behavior of the flow impacts on the transfer of mass and energy, for which it is the basis of analysis in metallurgical unit operations of large tonnage and processing under a continuous flow such as mixing, transport, pumping, grinding, filtering and thickening, these operations they are from plants.

The processes that involve liquid-solid physical gravitational separation would be sedimentation, thickening and thickening. As a result, rheology has become an important part of mining programs for metallurgical testing in water recovery projects in thickeners specifically (Méndez, 2016). The type of mineral and the variability within the deposit increases the amount of rheological data necessary for the adequate characterization of the deposit and the subsequent generation of complete design criteria. The rheological data needs of the mining and metallurgical industries will consist of a fluidity assessment and the generation of design criteria.

The parameters of interest that appear in the rheological models are Yield Point Unshear, Yield Point Fully Shear, Yield Stress and Viscosity depend on the properties and characteristics of the mineral (Gilberto & Perdomo, 2002). Being important in the relationship of the specific gravity of the mineral, its solid concentration, mineralogy, type and flocculant doses, clays and pH (Chilean Mining,

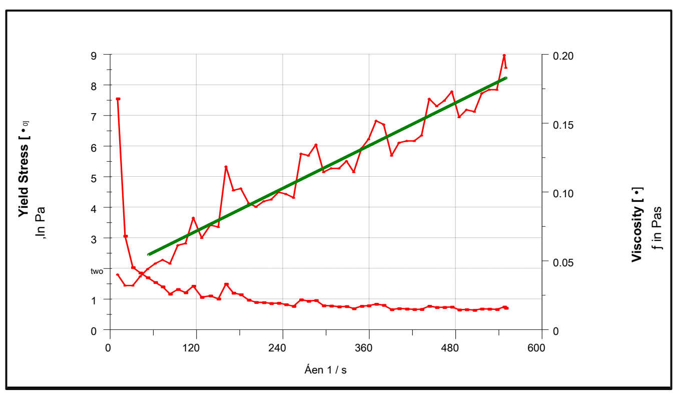
2020). Thus, characterizing the mineral and using constitutive equations that relate the stresses applied to the pulp and the deformations it undergoes, they are measured directly with rheological equipment.

The rheological method has been used for decades by a rheometer, which is a device that can exert a force on a material and measure its response with high precision, by means of coaxial cylinders with angular velocity (Torres García & Valencia, 2014). The device used is known as the Searle model, in which the outer cylinder is fixed, while the inner cylinder can rotate with angular velocity, exerting a torque on the pulp contained between the two (Anton Paar, 2014).

The pulps used are primarily Bingham plastics, being of a pasty type, which when subjected to low stresses behave like a rigid solid but which, passing a certain value of the
effort • 0, they behave like a Newton-type fluid (Raimond & Carraher, 2002).

$$• = •_0 + • (••⁄••) \quad (1)$$

These tests are mostly carried out at room temperature with the VT550 rheometer and MV-DIM rotor through the CUP method (Torres García & Valencia, 2014). In the **Figure 1** An example of rheology is carried out with a concentration by weight 41%, in a Bingham type fluid
(Raimond & Carraher, 2002), the Yield Stress •0 is 1,816 [Pa] and the Viscosity [•] 0.01164 [Pa * s].



F ig or to: Yield stress and Viscosity measurement in a Rheometer (Tapia Hernández, 2020).

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The greatest difficulty in mathematical development lies in finding an equation that represents the Bingham equation and that also involves the main physical, chemical and mechanical variables that influence the pulp flow behavior in coaxial cylinders. This situation is critical for processes where there is no mineralogical and clay information (Klein & Hurlbut, 1997), so it will consist of sedimentary data to define respectively the importance of how the Bingham influence stress on the concentration of particles Sedimentation influences both the viscosity and the yield stress of the pulp, since, as the concentration increases, the viscosity and the yield stress increase (Merrill Cifuentes, 2016). In the **Figure 2** Companies are illustrated at Solid Percentage Growth for Yield Stress.

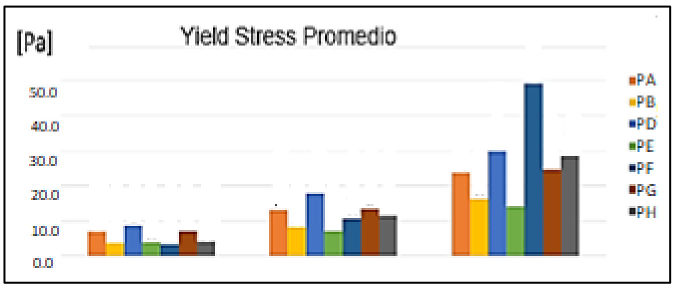

Figure 2: Increase in Yield stress to the increase in solid% (Tapia Hernández, 2020).

So far, no mathematical model or any new approximation has been developed that is capable of representing the rheological behavior without the rheometer in its entirety. Since the rheology process is influenced by a variety of factors in developing a mathematical model to govern the rheometer process, it is complicated to develop and implement.

In

Consequently, statistical models, correlation and factors of importance for the rheology of mineral samples sedimented in a fluid have been successfully implemented. These models have traditionally been used for the functional relationship between the predictor variables and the response variables in what is It will use an artificial neural network (ANN), constituting an alternative for the early and rapid prediction of sedimented mineral tests in the laboratory to be used for the processes where it is intended to know or verify the rheology of these.

Static sedimentation

Due to the great variation that mineral pulps present in terms of factors, the estimation of rheological parameters is uncertain. It is possible to gather information from databases of different similar companies in Chile to estimate values of these parameters, but they must be used carefully since the characteristics of the pulps produced will largely depend on the mineral extracted according to the company's mining plan. In the data analysis towards the mining companies, they must be identified as PA, PB, PD, PE, PF, PG and PH due to the confidentiality of their identity, these data are from the study carried out previously in the analysis of tailings thickeners (Tapia Hernández, 2020).

The companies analyzed will be selected with general restrictions in the databases:

- Speed [m / h] from 0 to 15.% final
- solid from 40 to 60%. Final Volume [ml]
- 200 to 260.
- Unit Area [m2 (24 h) / ton] from 0 to 005. Specific
- Gravity from 0.6 to 3.14. 184g dry weight.
-
- Solid percentage increase 50 to 60 [%] Similar flocculant
- type Type (1,3,4,5,6,7) Flocculant dose 5 to 10 [g / t].
-
- The pH of the sample is between 7 and 9.

In this study, the sedimentation tests have conditions that consist of defining granulometry, reagent, weight (gr), pH and temperature parameters. Carrying out the analysis of 220 sedimentation tests with flocculant, room temperature and a pH of 7 to 10. The data obtained and interest of a sedimentation test are the specific gravity, speed, final volume, percentage of final solid, percentage of solid initial and unit area. The tests do not contain additives from the flotation metallurgical process, such as collectors and foaming agents, being a sample directed to the analysis of tailings thickeners that specifically add the flocculant reagent for the agglomeration of the particles in an aqueous medium and the case that the surface destabilization of the colloidal particles is needed,

The analysis of specific gravity is a factor in sedimentation, since it is the density of a material in relation to water. Since rocks consist of several different phases of mineral and do not have a fixed specific gravity that can be neglected. This type of analysis will be used for the selection of projects, comparing the data as a whole, since many data have different pH, percentage of initial solid and sedimentation rate.

The analysis of the percentage of final solid and the speed in meters per hour of sedimentation shows how fast it finishes compacting and a percentage of final solid is obtained. In the **Table 1** The statistics are illustrated to select only the data grouped between 25 to 75% of the data by company.

Table 1: This statistical of all em dam s for the Veloci dad [m / h]

	PB	PA	P.S.	PE	PG	Pf	PH
25%	2.92	12.54	11.91	4.74	4.42	5.62	9.96
fifty%	8.58	14.34	13.86	13.47	8.22	12.30	11.64
75%	13.02	27.96	14.70	27.99	11.04	25.08	21.90
Average	8.85	18.50	15.28	15.34	7.27	15.31	13.88

The difference in the final solid percentage with the initial one is due to compaction with flocculants and hydration of the sample by the clays, causing an expansion that results in a solid different from the initial one. The percentage of solid greatly influences the rheological behavior of the sample at the time of settling and forming the solid bed, the percentage of solid varies according to the statistics in the analysis of the samples by company. In the **Table 2** The statistics are illustrated to select only the data grouped between 25 to 75% of the data by company.

Table 2: This statistical of all em dam s for he% Final Solid

	PB	PA	P.S.	PE	PG	Pf	PH
25%	51.28	55.25	56.22	48.76	57.71	47.53	50.82
fifty%	54.97	57.86	59.28	53.89	62.32	53.52	52.93
75%	58.79	60.67	60.82	58.21	64.79	55.92	54.86
Average	55.11	57.99	58.57	53.69	59.84	51.98	52.67

The Unit Area analysis is to see how much the feed flow would be to the respective thickener design. The area will depend on the sedimentation rate and the concentration of solids in the feed. The most used method for calculating the Unit Area in this project is with the Coe and Clevenger method (Fuerstenau & Han, 2003), which is used with the sedimentation of samples with flocculants, with this the spectator design is carried out. This gives the relation to smaller unit area, greater% of final solid. In the **Table 3**

The statistics are illustrated to select only the data grouped between 25 to 75% of the data by company.

Table 3: This statistical the emp resas for him Unit area [m 2h / ton].

	PB	PA	P.S.	PE	PG	Pf	PH
25%	51.28	55.25	56.22	48.76	57.71	47.53	50.82
fifty%	54.97	57.86	59.28	53.89	62.32	53.52	52.93
75%	58.79	60.67	60.82	58.21	64.79	55.92	54.86
Average	55.11	57.99	58.57	53.69	59.84	51.98	52.67

Mineral rheology

Rheology measurements are made with the rheometer, but different sensor cups must be used. They are classified by two types, to obtain the results of Yield Point Unshear and Full Shear, the Vane method is used, which is the change in deformation per unit of time. and for different types of solid, the cup method is used with the Bingham equation, which can be extrapolated in a trend line to generate a linear equation by finding the Yield Stress, which is the force applied to a product area and the viscosity is the opposition of a fluid when being transported or pushed (García Quesada, 2008).

The rheology results, which are viscosity and Yield Stress, are calculated by the most appropriate sensor to produce the analysis variables from a flow curve operating under stress controlled by the rheometer. The analysis performed with the increase of solid is the main objective to determine the prediction of viscosity and Yield Stress. The Yield Stress measurement by companies have measurements in the same sample with different% solids. Yield Stress occurs because the sample is at rest and shear is generated, causing the particles immersed in the sample to align in the direction of the flow, as is the case of polymer chains that begin to elongate and aggregates or agglomeration of the particles to break. Viscosity is a variable that is determined indirectly by converting the values of effort or torque measured on the sample, taking into account the geometry of the measuring device and is characterized as the resistance to flow in pascals per second. The students of Yield stress and Viscosity to solid increase are illustrated in the

Table 4.

The Yield Point Unshear [Pa] is for how much solid force is needed to move the rotor at rest or to see the force necessary to shear the solid settled in the thickener, this would help to see what the force in pascals is necessary to operate the thickener in the resting state. In the **Figure 3** It illustrates how much effort the sample needs in each company in a state of rest.

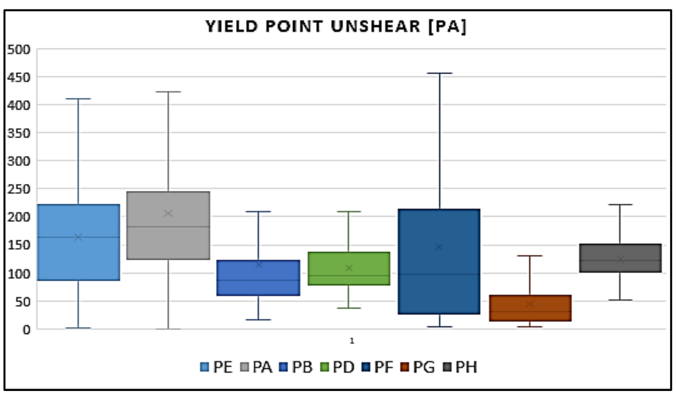

Figure 3: Yield Point Unshear [Pa].

The analysis will be carried out with the data obtained from the samples in the Rheology process. After static sedimentation, obtaining the final solid percentage, the rheology is carried out. It begins with the measurement of the Yield Point Unshear which the sample is at rest and static. This data is also used to obtain a gravity settling analysis without rotor and with only the transfer pump. Yield Point Unshear statistics by company are illustrated in the **Table 5.**

Table 5: Statistics ca Yield Point Unshear [Pa].

	PB	PA	P.S.	PE	PG	Pf	PH
25%	60.95	124.63	78.40	97.88	27.26	13.54	102.30
fifty%	87.42	182.05	95.60	167.80	95.94	29.89	122.60
75%	121.33	242.53	136.20	223.83	196.78	59.22	151.45
Average	110.40	201.71	107.88	166.47	138.11	44.20	124.74

The analysis of the Yield Point Fully Shear [Pa] is the force that the rotor makes in the sheared sample and it counts the constant force that the thickener breaks. This data is also used to obtain rotor movement sedimentation. In the **Figure 4** It illustrates how much effort the sample needs in each company in a state of rest.

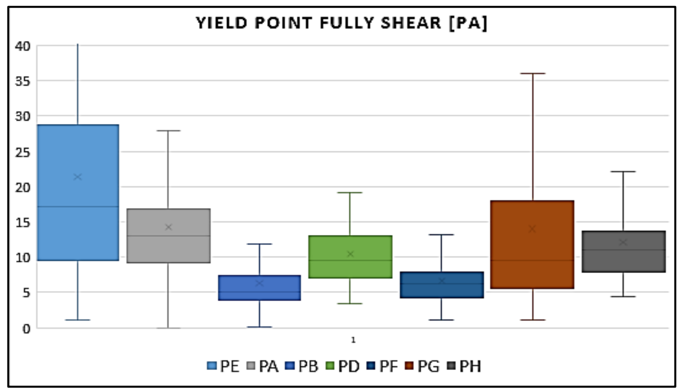

Figure 4: Yield Point Fully Shear [Pa].

After the Yield Point Unshear, the sample is sheared by shaking the sample to make the Yield Point Fully Shear. With this, there are less efforts when shearing the sample, because it has the least rigid compaction due to the rest left by the final solid. Yield Point Unshear statistics by company are illustrated in the **Table 6.**

Table 6: Statistics ca Yield Point Fully Shear [Pa].

	PB	PA	P.S.	PE	PG	Pf	PH
25%	3.96	9.26	7.12	9.45	4.17	5.08	8.03
fifty%	5.08	12.96	9.59	16.75	6.19	9.02	11.10
75%	7.33	16.87	12.97	25.15	7.92	17.48	13.72
Half	6.11	14.25	10.50	18.07	6.63	12.60	12.17

Table 4: Statistics of the companies by percentage of increasing solid in Viscosity [Pas] and Yield Stress [Pa].

	SOLID	VISCOSITY [Pas]							YIELD STRESS [Pa]						
		PA	PB	P.S.	PE	Pf	PG	PH	PA	PB	P.S.	PE	Pf	PG	PH
MAXIMUM	1	0.16	0.14	0.03	1.00	0.09	0.03	0.98	62.84	15.78	25.59	27.72	62.86	26.66	18.22
	two	0.28	0.15	0.07	0.96	0.17	0.06	0.88	70.13	32.33	66.91	53.11	125.4	73.68	71.46
	3	0.82	0.21	0.14	1.00	0.35	0.20	0.99	97.59	56.7	87.69	165	145	112.3	293.5
MINIMUM	1	0.01	0.01	0.01	0.11	0.01	0.00	0.10	0.01	0.01	0.96	0.29	0.13	0.28	0.15
	two	0.01	0.01	0.01	0.10	0.01	0.01	0.11	0.15	0.65	2.63	0.59	1.73	1.05	0.58
	3	0.01	0.01	0.01	0.11	0.01	0.02	0.11	1.33	2.2	6.1	0.86	2.12	4.34	1.51
HALF	1	0.03	0.02	0.02	0.25	0.02	0.02	0.23	6.93	3.72	8.67	3.92	7.15	4.01	3.25
	two	0.05	0.03	0.02	0.28	0.03	0.03	0.40	13.07	8.32	17.93	7.09	13.58	11.54	10.65
	3	0.09	0.04	0.04	0.34	0.05	0.05	0.42	23.78	16.33	30.03	14.24	24.75	28.54	49.31

Artificial neural networks

The development of artificial intelligence is given to the question of the functionality of the brain and that many of the most important concepts have been given. One of the concepts is the paradigm of learning that refers to the mechanisms that allow us to process all the new information that we perceive to transform into knowing. According to the learning paradigm that will be used in this study, it is supervised learning, which is a learning that is based on discovering the relationship between some input variables and some output variables, that means that it learns and modifies its link parameters and errors by neurons alone (Flórez López & Fernandez, 2008).

A neuron is the basic processing unit of neural networks and allows a direct simulation strategy to be developed without having a mathematical model available, which is assumed to be quite complex. This learning arises from teaching algorithms to obtain the result to be generated for a certain value after showing many examples (de la Fuente Aparicio & Calong, 1999). If the conditions are met, the algorithm will be able to give a correct result even with a value that it has not seen before.

Training

Artificial neural network training is the learning process, which is carried out through repeated processing of validated examples in the same training with a robust database. Giving you the network's ability to learn and memorize large amounts of information without apparent connection. Additionally, the algorithm is capable of making predictions from the data in the database with which the same artificial neural network has been trained (Jones, 2019). To determine the architecture of the neural network, it is not determined by mathematical methods, but by trial and error they determine which is the most appropriate architecture. An artificial neural network is made up of the input layers,

The input-hidden-output layers topology of the neural network for the prediction of the Yield Stress will be 6-13-3 for the prediction of the three types of solids 50, 55 and 60 percent. Viscosity prediction will be 6-12-3 for prediction of the three types of solids

50.55 and 60 percent. For the last prediction of the neural network, it will be a more forceful neural network, since through trial and error it was possible to choose the architecture of 6-22-10-7-2-2 to the prediction of the Yield Point Unshear and Fully Shear on the same neural network. The neural network data is illustrated in **Table 7.**

The internal processing of the hidden layers of artificial neural networks are made up of algorithms that represent simple units of computation, interconnected in a topology defined by the validation tests carried out, giving rise to continuous learning processes and with information synthesis. Their outputs have the advantages of not being subject to a specific mathematical model, they are tolerant to localized failures of the input data and they do not require conditions external to the data itself. Unless it's for normalization and ranking.

The training of the neural network will be with the Feed Forward Backpropagation method, which is able to approximate any non-convex function (Annema, 1995), generating an analytical solution with a certain degree of precision. Being an automatic forward propagation, to later validate the predicted result, which is propagated backwards as a chain of responsibilities throughout the network, layer by layer. This is due to the fact that the previous layers depend on the later layers and with that we can recursively find the neuron that was to blame for the error and penalize it (Jayne, Yue, & Iliadis, 2012).

For the use of the Feed Forward Backpropagation method, the Levenberg Marquardt equation is used, updating the weights and parameters of the neurons (Kumar Shukla, 2010). This algorithm is fast in training neural networks, but you must have normalized and standardized data. In the event that they are not, it will only predict data that was used to train the artificial neural network. Being capable of developing functional relationships between data autonomously and providing a functional precision tool in non-linear and multidimensional interpolation planes, artificial neural networks have been used mainly in solving problems that involve prediction and pattern identification tasks. automatically.

Once the parameters have been modified, the same validation process will automatically be generated again until the error decreases to obtain a minimum error in the prediction of the neural network, the gradient descent method will be used (Anderson,

1997), which is the vector that contains the slopes of each dimension and is used because it is an algorithm for non-convex functions, which do not have a single global minimum value. The minima are found with the derivative indicates the slope, which can be measured by the steepness of each point of the non-convex function. The drift is set equal to zero to find where it is zero, deriving multiple equations since non-convex functions have multiple minimum numbers.

To accelerate the convergence of the mean squared error, the Hyperbolic tangent sigmoid activation function and the Pure linear one are used (Anderson, 1997). Which in simple words are responsible for distorting the plane like the one in the figure to find the optimal result with the descent of the gradient. The transfer functions help at the time of training, since the sums of all the functions generate the non-convex plane, helping the descent of the gradient to converge faster (Pérez Lépez & Santín Gonzáles,

2007)

Table 7: Neural network layers for architecture and training.

	RANK	VARIABLE	INDICATOR
ENTRY	0 - 15	Speed	[m / h]
	0 - 005	Unitary Area	[m2h (24hrs) / ton]
	0.6 - 3.14	Specific gravity	[Gs]
	40 - 60	Final Solid%	[%]
	200 - 260	Final Volume [ml]	[ml]
	184g (dry)	Initial Solid%	[%]
EXIT	RNA 1	Yield Stress	[Pa]
	RNA 2	Viscosity	[Pa * s]
EXIT	RNA 3	Yield Point Fully Shear Yield	[Pa]
		Point Unshear	[Pa]

RNA results

The neural network will consist of input variables, hidden layers and output. The six input variables will be Speed [m / h], Unit Area [m2h (24hrs) / ton], Specific Gravity [Gs],% Final Solid [%], Final Volume [ml] and% Initial Solid [%] . These six input variables will be for all artificial neural networks shown below.

The prediction of the Yield Stress was tested in the neural network with a number of 30 samples external to the database, these tests have the sedimentation input data to validate the precision. For this artificial neural network it will have two hidden layers, the neural network with the activation function will be Hyperbolic tangent sigmoid, the hidden layer will have 13 neurons and the output layer will have 3 neurons. The output will be the Yield Stress to three types of solid increasing of 50, 55 and 60 percent illustrated the architecture in the **Figure 5.** The results of the artificial neural network can be visualized in the **Figure 6,** which has an average prediction of a **82.1%** precision, being the relation of the prediction data of the artificial neural network and the data that were made with the respective rheometer.

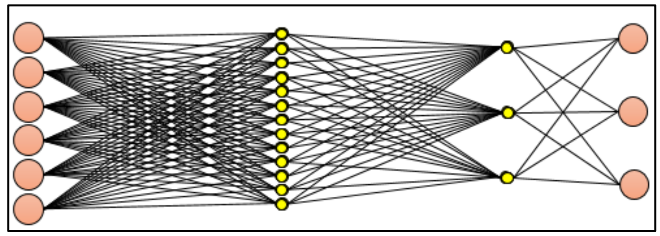

Figure 5: Neural network architecture for Yield Stress prediction for each solid.

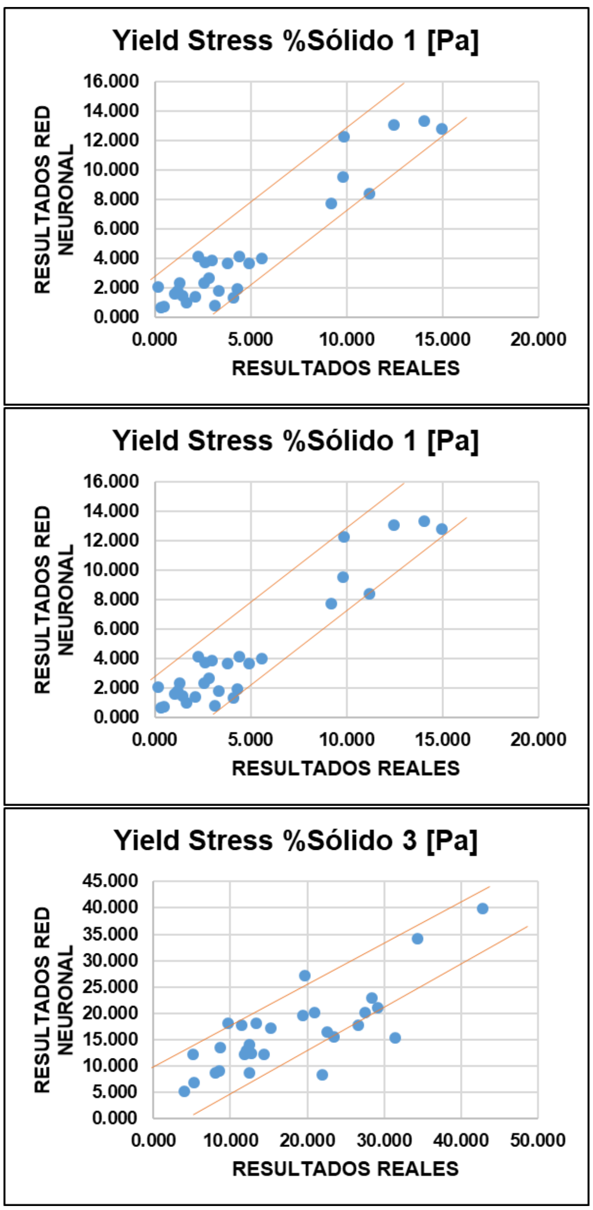

Figure 6: The Yield Stress results for the prediction in the neural network for each solid

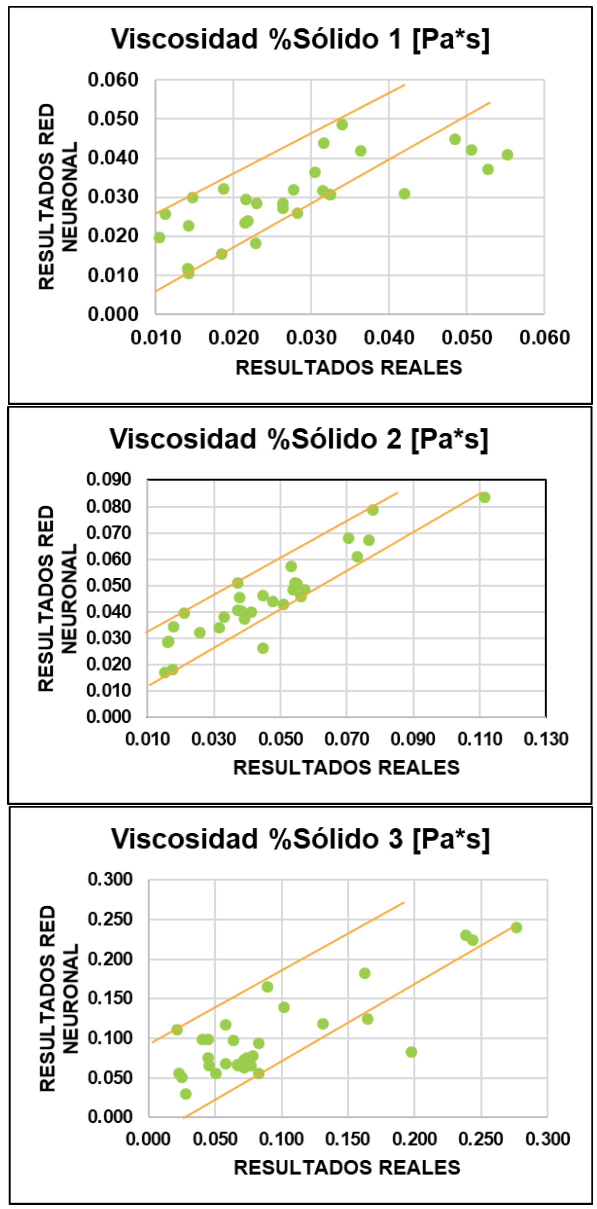

Figure 7: Viscosity results for prediction in the neural network for each solid

Viscosity prediction was tested in the neural network with a number of 30 samples as well as Yield Stress, being external to the database. For this artificial neural network, it will have two hidden layers of processing, with the Hyperbolic tangent sigmoid activation function, the hidden layer one will have one less than that of Yield Stress, with 12 neurons, and the output layer will have 3 result neurons. The output will be the Viscosity at three types of increasing solid of 50, 55 and 60 percent illustrated the architecture in the **Figure 8.** The results can be viewed in the **Figure 7,** which has an average prediction of a **80.7%** precision, being the relation of the prediction data of the artificial neural network and the data that were made with the respective rheometer.

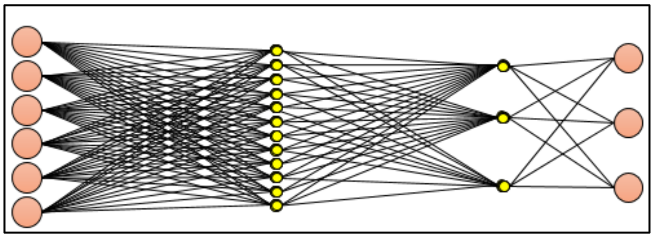

Figure 8: Neural network architecture for Viscosity prediction for each solid.

For the last prediction of the Yield Point Unshear and Yield Point Fully Shear the architecture of the artificial neural network was chosen consisting of input variables, hidden layers and output, but with more layers. The six input variables will be the same, being the Speed [m / h], Unit Area [m2h (24hrs) / ton], Specific Gravity [Gs],% Final Solid [%], Final Volume [ml] and% Solid Initial [%]. For the architecture of the neural network, there will be three hidden layers, the neural network with the Hyperbolic tangent sigmoid activation function and the last one for a better convergence in the result will be that of Pure linear.

Layer one will have 22 neurons, layer two will have 10 neurons, layer three will have 7 neurons, and layer four will have 2 neurons for output. The output layer will be the result Yield Point Fully Shear and Yield Point Unshear illustrated in the architecture in Figure 8.

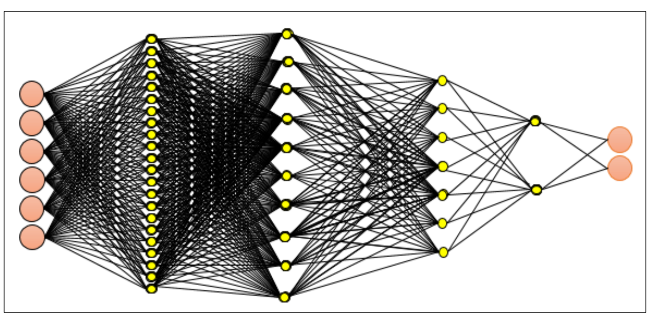

Figure 8: Neural network architecture for Viscosity prediction for each solid.

The prediction results that have the same inputs for the two rheology outputs, Yield Point Unshear and Yield Point Fully Shear. The prediction of Yield Point Unshear and Yield Point Fully Shear artificial neural network was tested with a number of 4 samples external to the database, these tests have the sedimentation input data to validate the precision.

For the result of the first output, we have the Yield Point Unshear that has a prediction of the four samples that were related to the real result, developed in the rheometer. It is illustrated in the relationship and difference that the real data have with those predicted in the **Figure 8.**

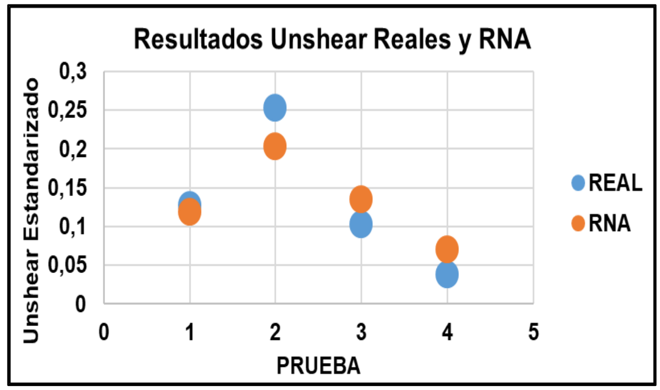

Figure 8: Yield Point Unshear results of output 1 of the neural network.

The precision of the artificial neural network of output 1 is a **75.8%**
In the Yield Point Unshear prediction, although this prediction level is similar as a fairly biased value, it can be analyzed that the data are in an apparent relationship and a similar behavior Illustrating the results in the **Table 8.**

Table 8: Mean squared error (MSE) of the Fully Shear and Unshear for each neuron.

Proof	1	two	3	4
RNA	0.118	0.202	0.134	0.070
REAL	0.127	0.253	0.102	0.038

For the result of the second output, we have the Yield Point Fully Shear that has a prediction of the four samples that were related to the real result, developed in the rheometer. It is illustrated in the relationship and difference that the real data have with those predicted in the **Figure 9.**

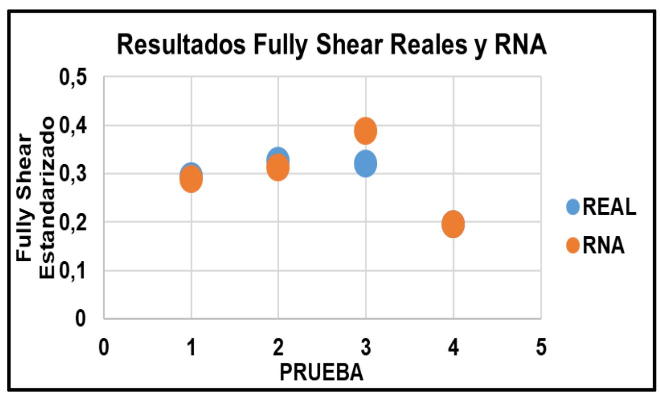

Figure 9: Yield Point Fully Shear results of output 2 of the neural network.

The precision of the artificial neural network of output 1 is a **94.1%**
In the Yield Point Unshear prediction, the unbiased prediction confirms this result, being a favorable result when predicting with sedimentation variables in the input layer and obtaining rheological data in the output layer. Illustrating the results in the **Table 9.**

Table 9: Mean squared error (MSE) of the Fully Shear and Unshear for each neuron.

Proof	**1**	**two**	**3**	**4**
RNA	0.2873	0.3121	0.3863	0.1937
REAL	0.293	0.325	0.320	0.195

Conclution

The data were analyzed for their selection and the results obtained in the prediction proposal could be compared in a more unbiased way, as well as it was possible to identify a series of rheology comparisons seen in various metallurgical plants of the analyzed mining companies, due to mainly to the type of sample that is presented in each mining company, with the underestimation or how to face the influencing and viscosity efforts that end up hampering the mineral treatment capacity by imposing a concentration of solids in the tailings slurry to be treated. In the selection of companies, it was decided to take only the companies that had all the necessary data to be compared and the filters developed in the analysis variables,

The analysis of the companies with the tool is able to establish a wide database for the understanding of the physical rheological phenomena associated with each mining company with their respective tests in the laboratory. The main variables that had incidence and importance for the stress of Yield Point Unshear, Yield Point Fully Shear, Yield Stress and Viscosity were identified.

The architectures and algorithms used in the network presented a linear regression model with an adjustment of • ·> •. • and an Actual / Predicted Data error with a [**95-70]%** in more than one company analyzed in the Yield Point Unshear and Fully Shear rheology tests. The level of prediction accuracy in the neural network is considerable because the laboratory tests that have a level of error already standardized in the metallurgical laboratory tests in the sampling, being a prediction with the least bias or a prediction that has a behavior similar to the real one.

For the Yield Stress or Viscosity results, a neural network was created to predict the increase of the three types of solid per sample, obtaining a favorable result of predicted data with a successful error bias in the data of lower value and acceptable for those of greater value because by standardizing them they are too close to 1 since the maximum number of data for that variable was divided. The graphs of the two companies selected for having similar laboratory parameters and classifications are analyzed that the results of the neural network of Yield Stress or Viscosity compared to real have a successful linear trend.

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