A Predictive Model for a Wet-high-intensity-magnetic-separator (WHIMS) using Artificial Neural Networks

C.R.M. Reichel, A.F. van der Merwe & J. Cronje

Abstract—**Materials can be classified into three major categories based on the magnetic susceptibility thereof; the property governing the response of the material subjected to a magnetic field. Chromium has many uses in the industry, with stainless steel production being the most important. Chromite ore in South Africa is mainly mined in the Bushveld complex situated in the central western region of the Highveld. Magnetic separation is the physical separation of discrete particles. Wet high-intensity magnetic separation (WHIMS) is commonly used in the gold, uranium, iron and chromite recovery industries. The WHIMS system is based on the imbalance of forces on particles. These forces are magnetic, gravitational, centrifugal, frictional or inertial, and attractive or repulsive forces in favour of the magnetic forces, all due to the production of a magnetic field. During the experimental procedure, single stage separation was used for the aim of this project. Operational parameters such as magnetic intensity (flux), wash water flow rate, feed flow rate and feed density along with particle size are varied. The primary objectives in this study were to obtain experimental data from a laboratory scale WHIMS and to use this data to construct an artificial neural network (ANN) able accurately predict grade, yield and recovery. Sampling and analysis were used to determine the recoveries, grades and yields for the varied operating conditions. The material used during this study is chromite ore. The ANN's predicted the grade, recovery and yield with high accuracy. The data from experimentation suggest that the WHIMS system recovers best at smaller particle sizes.**

Keywords—Artificial Neural Networks, Modelling, Predictive Model, Wet High Intensity Magnetic Separator, WHIMS

I. Introduction

Ore concentration using magnetic fields is known as magnetic separation. Magnetic separation can be described as the physical separation of discrete particles grounded in the competition of three forces. The first is a magnetic force, secondly is gravitational, centrifugal, frictional or inertial forces and thirdly, inter-particle magnetic attractive or otherwise repulsive forces. These forces are depended on the separator's character and the particle size distribution (PSD), magnetic susceptibility and any other parameters that may have to some extent an effect on these forces. The PSD magnetic susceptibility and parameters are referred to as the nature of the feed. Many types of magnetic separators exist today [1]. Any magnetic separator splits the feed into two or more components [2]. A WHIMS system exploits the magnetic properties of the ore to separate magnetic material from non magnetic material. From previous literature it was found that the WHIMS system experience recovery losses when the particle size drops below 20µm [3]. Capacity, plugging and particle misplacement are the main concerns during WHIMS operation. The WHIMS operates by passing material through a magnetic field inside a rotating matrix. Wash water flushes the magnetic material out of the matrix where it is collected in a launder box [4]. Many different applications for chromium exist and, depending on the application, a different form of chromium is required. These forms include chromite, ferrochrome and chromite acid. Chromite ore is mainly mined in the Bushveld complex situated in the central western region of the Highveld [5]. ANN's are models based on the natural configuration of the brain. Due to some problems outside the scope of current compters, ANN's pose a less technical way for the development of machine solutions to problems. ANN's are non-linear statistical models and the accuracy thereof is highly dependend on the quality of the data used as well as the specific topology [6]. The objective of this project boils down to a proof-of-concept: that ANN's could be used to predict the magnetic product's grade, yield and recovery for a WHIMS system.

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II. Experimental Procedure

Chromite ore samples from two different processing plants in the region were obtained. The ore samples were dried separately prior to sampling for particle size distribution (PSD) analysis and X-ray fluorescence (XRF) analysis. PSD analysis provided information regarding the particle size (d_{50}) and spread of the PSD, often referred to as EPM (Ecart Probable moyen), while XRF analysis provided information regarding

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the chrome content and chrome-to-iron ratio. Operational parameters investigated on the WHIMS include: feed density, feed flow rate, magnetic intensity and wash water flow rate. The material parameters that were varied include PSD (i.e. d_{50} & EPM) and chrome-to-iron ratio. All parameters were kept constant while varying only a single parameter during experimentation. All the operational parameters could be varied via a mechanical adjustment except for the feed density, which was altered manually. The d_{50} value was altered by passing the feed material through a sieve, consequently altering the EPM. After conducting an experiment, both the product and tailings were dried separately, both were then sampled for XRF analysis and only the product sample was subjected to a PSD analysis.

III. Model development

After the experimental procedure, the data was processed to obtain the grade, recovery and yield for each experiment. The values of the d_{50}, EPM, chrome-to-iron ratio, feed flow rate, feed density, wash water flow rate and magnetic flux served as inputs to the ANN's. The MATLAB software (with the use of its neural network toolbox) was used to construct the ANN's. The Levenberg-Marquadt (LM) training algorithm was used to train the neural networks [7]. The major advantage of using MATLAB is that the pre-processing of data is done automatically. Pre-processing refers to the normalisation of the input data. All the ANN's constructed consist of a single hidden layer. The technique of pruning was used. The pruning technique is described as a large ANN which is initially trained and consequently trimmed of neurons in the hidden layer until the optimum structure is obtained. "Optimum structure" is commonly defined as the minimum training time required (depended on ANN structure) for a satisfactory error on training [6]. Ten ANN's were constructed in order to simulate each output: grade, yield and recovery. This was done for each ore sample. A combined network containing all three outputs for both ores and three networks for the grade, yield and recovery only with both ores. The mathematical functionality of ANN's is described in section IV.

IV. ANN Mathematical functionality

ANN's characteristically involve multiple layers, with the first layer serving as the input layer, accepting inputs and transmitting them to other neurons. A hidden layer, where most neurons reside, can be termed the hidden part of the ANN. Most of the calculations occur in the hidden layer. The last layer is known as the output layer containing the last (few) neuron(s). Inputs are standardised first before being directed to the network. Inputs are weighted (by the weights) and summed. These are passed through an activation function producing an output. The activation function outputs are weighted and summed again, ready to be sent to the next activation function. This process wherein inputs or outputs (between layers) are weighted and summed before being passed through an activation function unto the (final) output is termed forward propagation. [6]. Fig 1 provides a graphical representation of a neurons mathematical functionality.

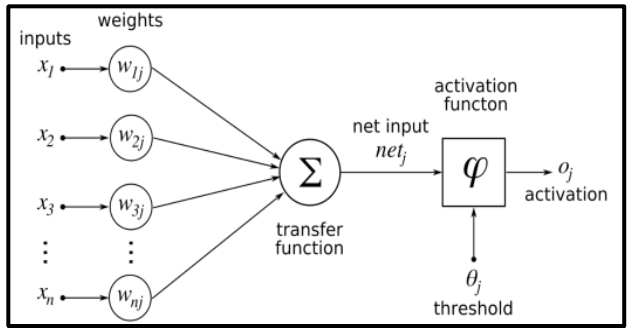

Fig 1: Mathematical functionality of a neuron [10]

V. Results and Discussion

The results obtained from experimentation are summarised and normalised in Table . The data is normalised relative to the maximum of each variable, i.e. a d_{50} value of 55 μm is interpreted as 55 % of the maximum d_{50} value, and 50 feed rate is interpreted as 50 % of the maximum feed rate used. The recovery, grade and yield are the normalised values obtained from using the normalised parameter settings. All flow rates are measured in litre per minute and flux is measured in kilogauss.

Table I: Results from experimentation

PSD-d50	EPM	Cr/Fe	Feed Flow Rate	Feed density	Wash Water Flow Rate	Flux	Recovery	Grade	Yield
Ore 1									
55.0	64.8	100	50	100	33.3	90.9	76	79	73
55.0	64.8	100	50	100	100	90.9	66	100	51
55.0	64.8	100	50	100	33.3	100	88	77	88
55.0	64.8	100	100	100	33.3	90.9	67	87	59
55.0	64.8	100	50	66.7	33.3	90.9	74	76	74
55.0	64.8	100	50	66.7	33.3	100	85	79	83
55.0	64.8	100	50	100	100	100	77	97	61
55.0	64.8	100	100	100	33.3	100	74	84	67
55.0	64.8	100	50	66.7	100	100	75	95	60
55.0	64.8	100	100	66.7	33.3	100	76	84	69
55.0	64.8	100	50	66.7	100	90.9	72	99	55
55.0	64.8	100	100	66.7	33.3	90.9	66.7	85.0	60.2
64.4	66.4	99.2	50	100	33.3	90.9	67.5	79.0	65.5
64.4	66.4	99.2	50	100	33.3	100	85	79	83
Ore 2									
100	100	98.3	50	100	33.3	90.9	80.5	79.1	83.7
100	100	98.3	50	66.7	33.3	90.9	88.9	87.4	83.7
100	100	98.3	50	100	100	90.9	75.6	99.1	62.8
100	100	98.3	100	100	33.3	90.9	71.6	88.1	66.9
100	100	98.3	50	100.0	33.3	100	92.3	79.3	95.8
100	100	98.3	50	66.7	33.3	100	93.6	83.5	92.3
100	100	98.3	50	100	100	100	95.5	97.0	80.9
100	100	98.3	100	100	33.3	100	85.5	90.0	78.1
100	100	98.3	50	66.7	100	100	76.9	95.9	65.9
100	100	98.3	100	66.7	33.3	100	80.4	90.1	73.4
100	100	98.3	50	66.7	100	90.9	75.4	100	62.1
100	100	98.3	100	66.7	33.3	90.9	76.5	90.9	69.2
25.9	83.4	99.2	50	100	33.3	90.9	94.0	81.6	94.8
25.9	83.4	99.2	50	100	33.3	100	100	82	100

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The wash water flow rate has an effect which is twofold: an increase in the wash water flow rate reduces the yield, but increases the grade and vice versa. The same effect can be seen on the feed flow rate. The effect of the feed density is yet unclear due to having effects on both grade and yield. It is suspected that there may be a correlation between the feed density and particle size. An increase in the magnetic flux results in an increase in the product yield. Thus for optimal performance of the WHIMS, an equilibrium has to be found between all of the mentioned operating parameters. The benchmark test are the chosen standard operating conditions of the WHIMS machine.

TABLE II: PSD DATA OF FEED AND PRODUCT

Ore and Test	d_{50} of feed (% of max)	d_{50} of product (% of max)
Ore 1 benchmark test 1 (Un-sieved Set)	55.04	30.85
Ore 1 Benchmark Test 2 (Un-sieved Set)	55.04	30.48
Ore 2 Benchmark Test 1 (Un-sieved Set)	100.00	26.67
Ore 2 Benchmark Test 2 (Un-sieved Set)	100.00	26.46
Ore 1 Benchmark Test 1 (Sieved Set)	64.43	72.91
Ore 1 Benchmark Test 2 (Sieved Set)	64.43	72.10
Ore 2 Benchmark Test 1 (Sieved Set)	25.92	72.91
Ore 2 Benchmark Test 2 (Sieved Set)	25.92	54.27

From the data in Table it can be seen that the WHIMS system recovers the smaller particle sizes. This is verified by XRF analysis of the samples, indicating that the majority of the chrome content resides in the smaller size ranges. For ore 2 (sieved set benchmark test 1 and 2) the product d_{50} differs greatly which could be the result of (i) the chrome content spread in the PSD and (ii) the available data of the PSD is outside the particle size range for PSD analysis, resulting in the Rosin-Rammler equation fitted to this PSD data to show a slight offset. Literature states that a WHIMS system experience recovery losses at particle sizes below 20µm, which could also be the conclusion for this PSD d_{50} for the product of ore 2 benchmark test 2 (sieved set) [3]. The results obtained from modelling shows that all ANN's obtained an accuracy of approximately 80% or higher. All the graphs' data are normalised with regards to the maximum of the two data sets. The coefficient of determination and mean square error (MSE) for each of the networks are summarised in TABLE . From the table and the graphs it can be seen that the ANN's are highly accurate models. The model with the lowest accuracy yielded a coefficient of determination of 78%. The reason for the low accuracy might be due to the lack of data to train the specific ANN.

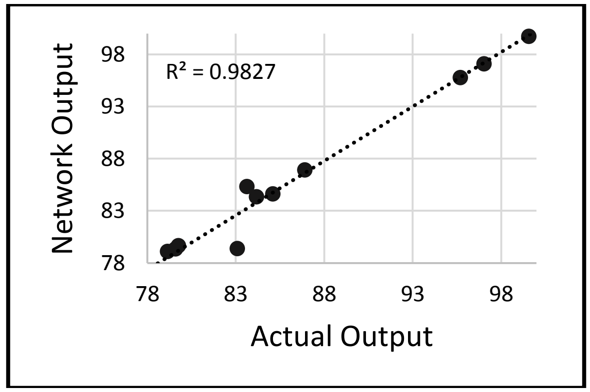

Fig 2: Regression plot for Ore 1 Grade Prediction.

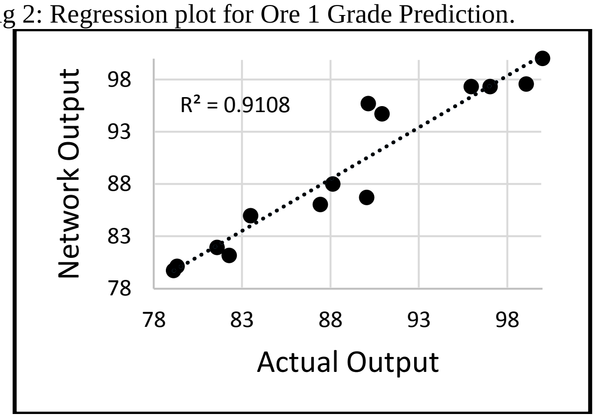

Fig 3: Regression plot for Ore 2 Grade prediction.

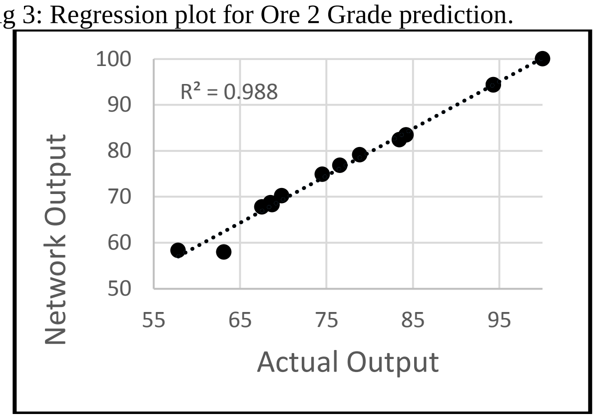

Fig 4: Regression plot for Ore 1 yield prediction.

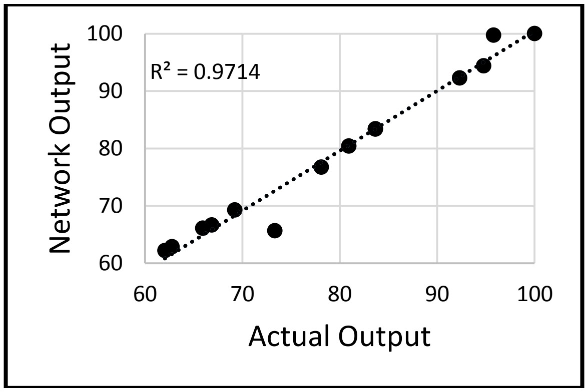

Fig 5: Regression plot for Ore 2 yield prediction.

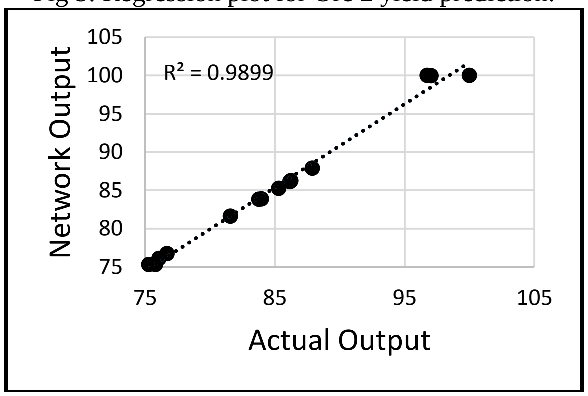

Fig 6: Regression plot for Ore 1 Recovery prediction.

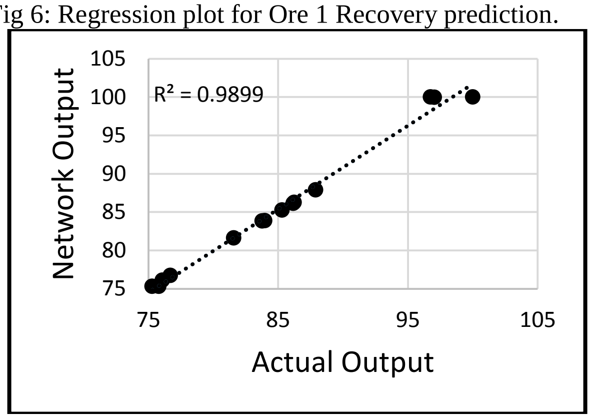

Fig 7: Regression Plot for Ore 2 recovery prediction.

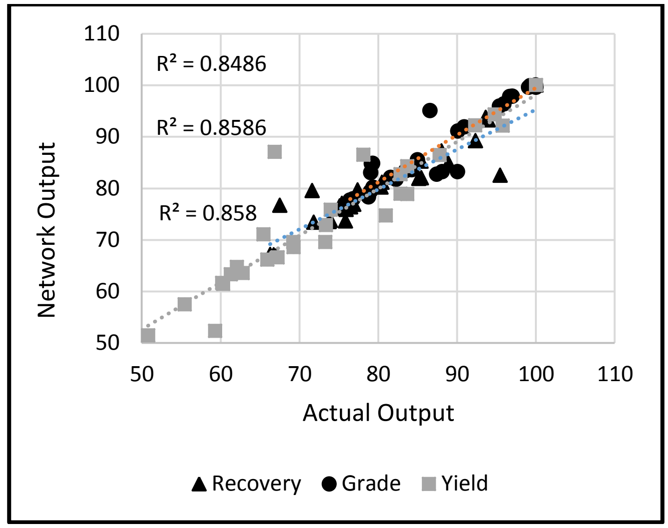

Fig 8: Regression plot for combined neural network.

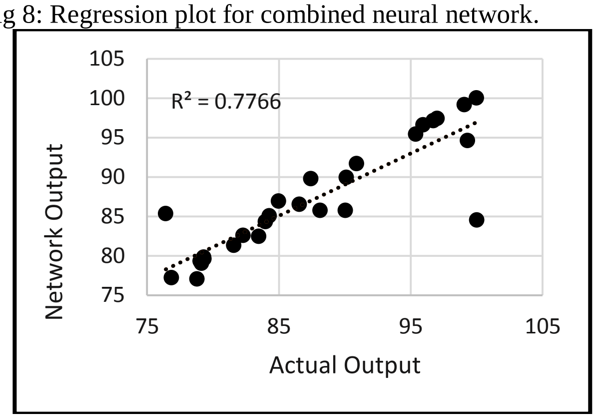

Fig 9: Regression plot for overall grade prediction.

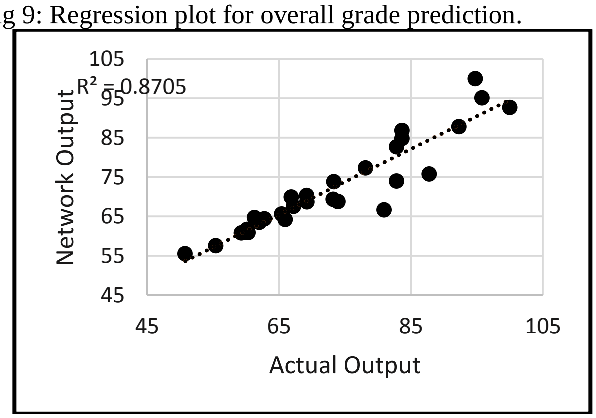

Fig 10: Regression plot for overall yield prediction.

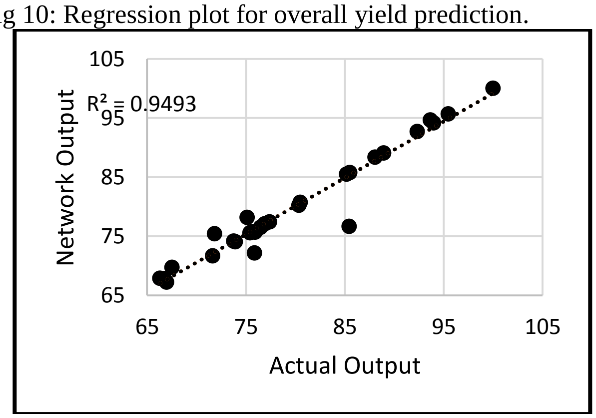

Fig 11: Regression plot for overall recovery prediction.

TABLE III: SUMMARY OF COEFFICIENT OF DETERMINATION AND MSE FOR EACH GRAPH

Figure	Coefficient of determination	Mean square Error
2	0.98	0.20
3	0.91	0.20
4	0.99	0.29
5	0.97	0.29
6	0.99	0.38
7	0.99	0.38
8	0.86	3.49
9	0.78	2.07
10	0.87	4.87
11	0.95	1.55

VI. CONCLUSION AND RECOMMENDATIONS

From the results obtained from modelling, it can be seen that neural networks with a single output performs better than a neural network with multiple outputs. This is in line with the work published by Labbe et al 2009, where the conclusion shows that multiple-input-single-output (MISO) neural networks perform better than multiple-input-multiple-output(MIMO) neural networks. The conclusion is thus that it would be a better choice to use MISO ANN's rather than MIMO ANN's. The coefficient of determination for the separate neural networks for the different ores are remarkably high, with the MSE being relatively low. The ANN models that predict overall grade yield and recovery have a high coefficient of determination and MSE, resulting in a less accurate model. The same is true for the model predicting grade yield and recovery simultaneously. This leads to the conclusion that using artificial neural networks to predict the grade, recovery and yield of a given feed separately from other feeds will result in a highly accurate model. For determining the grade and recovery a large ANN (many neurons in the hidden layer) is required, whilst a small ANN is required to predict the yield. The overall grade, yield and recovery networks performed well, except for the grade network which has a low accuracy with an R^2 of 78% and a MSE that is very high. This performance could be improved upon with the use of a wider as well as larger data set for training of an ANN. The use of these models can lead to optimised control for the WHIMS system. The data obtained from experiments shows improved recoveries at the lower particle sizes, which was indicated by the analysis-by-size. The operational parameters are all clearly intertwined with not only each other but also with properties of the ore to be processed. Flux appears to only have a significant effect on the yield, whilst having little to no effect on the grade when compared to the influence of the feed and wash water flow rates. The wash water flow rate (if increased) decreases the yield whilst increasing the grade - thus having twofold effect as mentioned in Section 5. Equilibrium should therefore be found amongst the operating parameters for the WHIMS system to operate optimally. For this reason a two-stage separation model is used in industry. The feed density is connected to the PSD of the ore: at a low d_{50} value it doesn't appear to have an effect while at larger d_{50} values there is a significant increase in the grade. Feed flow rate has the same effect as that of the wash water. An increased wash water flow rate would decrease the yield but increase the grade. For further studies the tailings of WHIMS system could be studied in order to improve our understanding of the separation taking place. Computational Fluid Dynamics(CFD) may also be used in further studies.

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