Back Propagation Neural Network in Determination of Parameter $d50_C$ of Hydrocyclones

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Abstract: *The $d50_C$, an important parameter of Hydrocyclones can accurately be determined by using Back Propagation Neural Network (BPNN). The BPNN yields in high predictions with good correlated data. The results may be used in generating useful signals for the automatic control of Hydrocyclones.*

1. INTRODUCTION

Hydrocyclones find extensive applications in minerals process industry for classification of solids suspended in fluids. They are manufactured in different shapes and sizes to suit specific purpose of operation. Hydrocyclones normally have no moving parts. The only movement is the slurry passing through it. Inside the cyclone, due to forces experienced by the slurry, particles suspended in the fluid are classified to be discharged either from the vortex finder as overflow or from the spigot opening as underflow. The *d*50 is a parameter which determines the classification efficiency. The *d*50 represents a particular particle size reporting 50% to the overflow and 50% to the underflow streams.

However in practice, the *d*50 is corrected by assuming that a fraction of heavier particles are entrained in the overflow stream which has the same fraction of water in the underflow. This correction of *d*50 is designated as $d50_C$ and the $d50_C$ is accepted as the normal representation of the classification efficiency. Tromp curves, as shown in Figure 1, are used to determine the *d*50 and the $d50_C$.

Under normal industrial applications of Hydrocyclones, any deviation from a desired $d50_C$ value can not be restored without changing the operation conditions or/and the geometry of the Hydrocyclone. Also, sensing the changes in $d50_C$ is a difficult task. It requires external interference by taking appropriate samples from the overflow and underflow streams and conducting lengthy size distribution analysis of these samples. However, in literature, automatic control of Hydrocyclones have been discussed by Gupta and Eren [1]. These authors installed appropriate sensors to monitor the signals generated by the instruments under the normal operating condition of the Hydrocyclone. These parameters were used in a an on-line computer control system to actuate appropriate controllers and servo-mechanisms to reduce the difference between the observed $d50_C$ and the desired values.

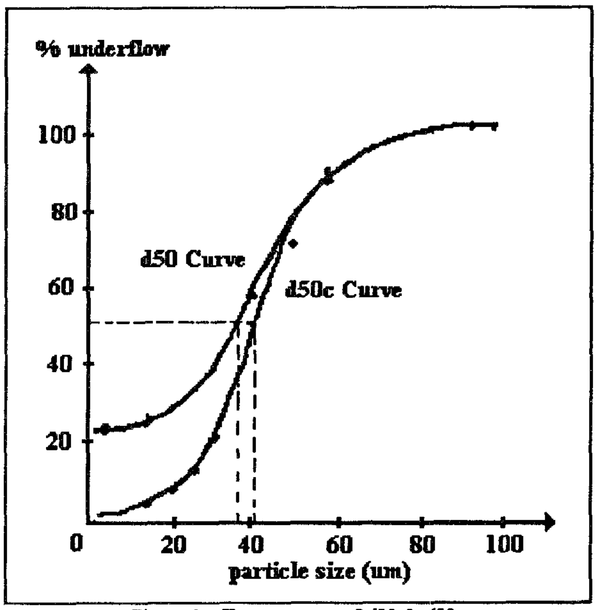

Figure 1. Tromp curves of *d*50 & $d50_C$

In the automatic control of Hydrocyclones the output signal, $d50_C$, can not be sensed or conditioned directly, but needs to be calculated from operation parameter. The correct prediction of the $d50_C$ is essential to generate control signals.

In literature, for the mathematical determination of $d50_C$, a number of variables obtained from the slurry characteristics and cyclone geometry have been used [1], [2], [3], [4], [5]. Most of these models have been derived using multivariate analysis and statistical data which is generated by varying one variable and keeping others constant as exemplified in Figure 2.

The data tested in this paper was obtained from a closed circuit slurry test-rig. The slurry, mixed in a 500 litre reservoir, made from -212 mesh ground silica particles was circulated through the cyclone.

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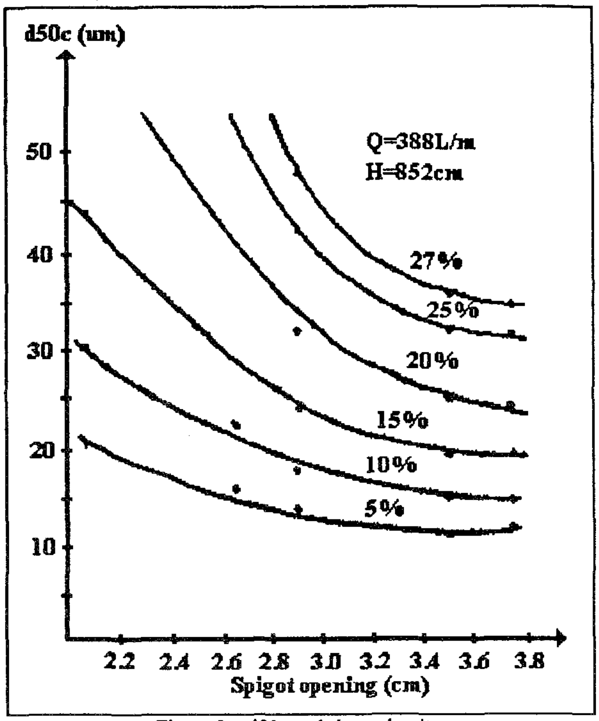

Figure 2. $d50_c$ and slurry density.

Representative overflow and underflow samples of the slurry were taken simultaneously over a fixed time. The samples were then dried and analysed by conventional methods using sieves. Over 200 data points were obtained describing *d*50 and $d50_c$ values. Variables affecting $d50_c$ were manipulated in a controlled and sequential manner. These variables were: input flow rate, input density, vortex finder height, spigot opening and the temperature of the slurry.

In literature, application of Back Propagation Neural Network (BPNN) for the prediction of $d50_c$ has been illustrated [6], [7]. In this paper, the technique is applied with a particular emphasis for the generation of control signals.

In recent years, artificial neural networks (ANN) have been applied to many problems [8]. One of the main contributions is in the area of pattern recognition [9]. Unlike the traditional methods based on empirical formulae or statistical techniques, ANN is trained for a set of known input and output data. Through an iterative learning process, the ANN learns from the given data and becomes a model relating the new set of input/output data. Once it is trained, the network is capable to produce outputs from subsequent inputs. The application of ANN in the estimation of Hydrocyclone parameters is new and the objective of this paper to report the results from such applications.

2. APPLICATION OF BPNN AND THE RESULTS

Five parameters of Hydrocyclone were selected for training of ANN. These parameters were the conventional parameters (inlet flowrate, inlet density, spigot opening, vortex height and temperature of slurry) on which the classical formulae approach was based on. The results are given in Figure 3.

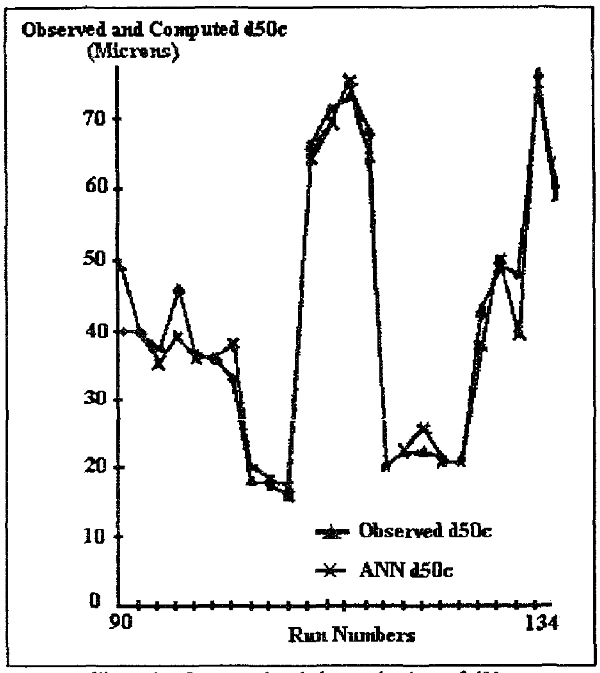

Figure 3. Computed and observed values of $d50_c$

The regression analysis, between the observed $d50_c$ and that calculated by using ANN, has been illustrated in Figure 4.

Results indicate the fitness of the predictions giving a correlation coefficient of 0.986 with r-squared value of 97.17%.

In the implementation of BPNN, for a single hidden layer, the total time of training had a typical value of 815 seconds, approximately 30,000 iterations, with five variables and 200 input data points. The maximum individual error was 26%.

Normally, to utilise the ANN, once the network is trained the learning of the network is assumed to be holding for any new data. To verify it, in this project the network was trained by using 50% of the data. Other half set of the data was testing the fit as illustrated in Figure 5. In this case, the correlation coefficient has reduced to 0.97 with an r-squared value of 94.07%.

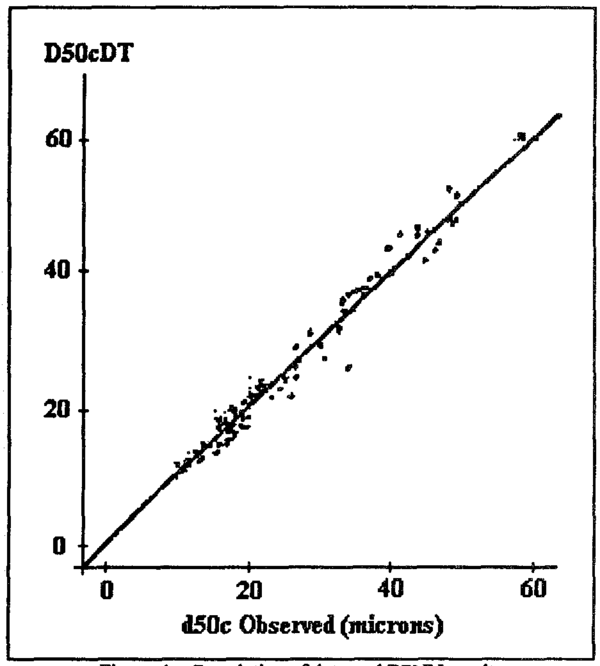

Figure 4. Correlation of data and BPNN results

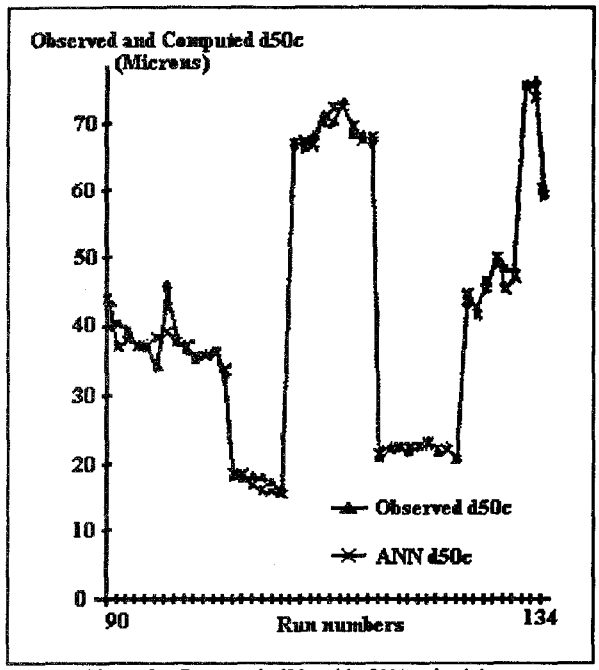

Figure 5. Computed $d50_C$ with 50% trained data.

3. SIGNAL PROCESSING and ON-LINE CONTROL

The automatic control strategy for the on-line control of Hydrocyclones has been discussed by Eren and Gupta [10], [11]. In their application the $d50_C$ was set to desired value. The signals from the instruments were processed to calculate the present value of $d50_C$ using the conventional models. To minimise the differences between the set value and the present value the operating parameters such as spigot opening and, vortex height and the flowrates were changed sequentially until the desired value of $d50_C$ was obtained. The operating parameters were physically altered by suitable servomechanism systems.

This research is continuing on the implementation of ANN for the on-line control of the Hydrocyclones. Evidence indicates that the desired values of the $d50_C$ can still be obtained using ANN instead of conventional methods. In this application, once the network is trained the values of $d50_C$ can be pulled up estimated from the present values of the parameters. Any deviation between the desired set value and the predicted value can be compensated by adjustment of one or more operational parameters. Say, if one variable is adjusted to achieve the set value, the corresponding $d50_C$ needs to be pulled up from the network to be compared again with the set value. A possible control is suggested in Figure 6.

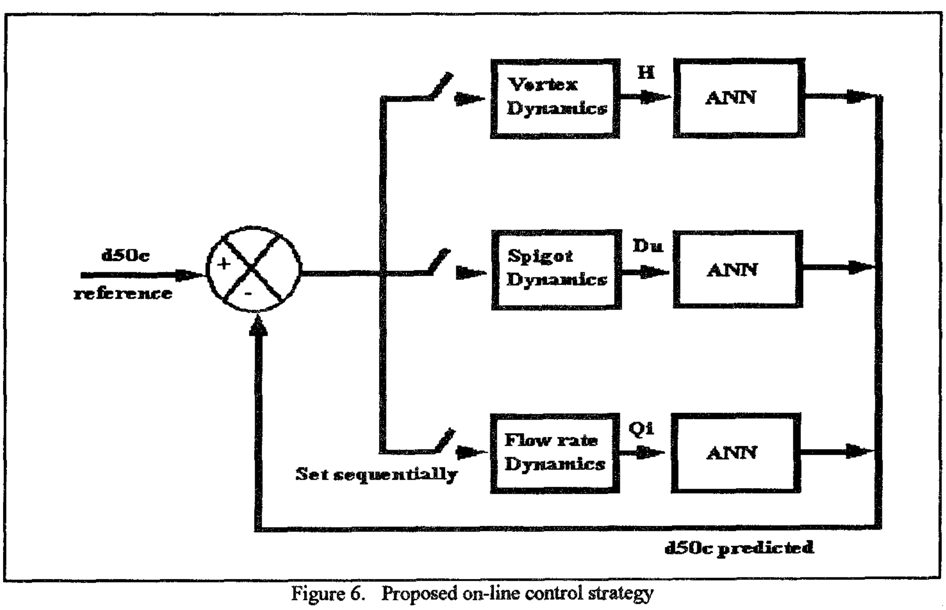

Figure 6. Proposed on-line control strategy

4. CONCLUSIONS

Back Propagation Neural Network has been applied to determine the $d50_C$ of a Hydrocyclone classifier. It is shown that BPNN gives good fit with a high correlation coefficient of 0.986. A method of using ANN results for on- line control of Hydrocyclones has been suggested. The evidence indicates that BPNN can be implemented as a part of control strategy.

5. REFERENCES

[1] Gupta, A and Eren, H, "Mathematical modelling and on-line control of Hydrocyclones", *Proceedings Aus. IMM,* 295 (2), 1990, pp. 31-41.

[2] Lynch, A J and Rao, T C, "Modelling and scaling up of Hydrocyclone classifiers", in *Proceedings Eleventh International Mineral Processing Congress,* Cagliari, 1975, pp. 245-270.

[3] Lynch, A J, *Mineral Crushing and Grinding Circuits,* Elsevier Scientific Publications, 1977.

[4] Mizrahi, J and Cohen, E, "Studies of Some factors influencing the action of Hydrocyclone", *Inst. Min. Met.,1966, pp.* C318-330.

[5] Plitt, L R, "A Mathematical Model for Hydrocyclone Classifier", *C.I.M. Bulletin,* 69 (776), 1976, pp. 114-122.

[6] H. Eren, C. C. Fung and A. Gupta, "Application of artificial neural network in estimation of Hydrocyclone parameters", AusIMM conference Proceedings, Perth, March 1996, pp. 285-290.

[7] H. Eren, Gupta A, C. C. Fung and K.W. Wong "Use of Artificial Neural Networks in estimation of Hydrocyclone parameters with unusual input variables" Submitted to IEEE IMTC/96 Con., Belgium, June 1996.

[8] Rumelhart, D E and McClelland J L, *Parallel Distributed Processing: Explorations in the microstructure of cognition,* MIT Press, Cambridge MA, 1986.

[9] Westead, S. T., *Neural Network and Fuzzy Logic Applications in C/C++,* John Wiley & Sons Inc., Canada, 1994.

[10] H. Eren and A. Gupta, "Instrumentation and on-line control of Hydrocyclones", IEE Control Conf., Cambridge, UK, 1988, pp. 301-306.

[11] H. Eren and A Gupta, "Automation in hydrocyclone operation", IFAC, MMM Symposium, Buenos Aires, Argentina, 1989, pp. 95-100.