Use of Artificial Neural Networks in Estimation of Hydrocyclone Parameters with Unusual Input Variables

Halit Eren, Chun Che Fung, Kok Wai Wong and Ashok Gupta

Curtin University Technology,
School of Electrical and Computer Engineering
Kent Street, Bentley, WA, Australia.
Tel: (61-9-351 7903) Fax: (61-9-351 2584) E-Mail:terenh@cc.curtin.edu.au

Abstract - The accuracy in the estimation of Hydrocyclone parameter, \(d_{50C}\), can substantially be improved by application of Artificial Neural Network (ANN). With ANN, many non-conventional Hydrocyclone variables such as: water and solid split ratios, overflow and underflow densities, apex and spigot flowrates can easily be incorporated in the prediction of \(d_{50C}\). Selection of training parameters are also shown to affect the accuracy.

I. INTRODUCTION.

Hydrocyclones are used in industry for classification and separations of solids suspended in fluids. The separation efficiency of Hydrocyclones are determined by the parameter \(d_{50}\) which represents the partitioning of a particular particle size reporting 50% to the underflow and 50% to the overflow. In order to determine \(d_{50}\), tromp curves are used to provide the relationship between the weight fraction of each particle size in the overflow and underflow streams. In practical applications, the \(d_{50}\) curve is corrected by assuming that a fraction of the heavier particles are entrained in the overflow stream which is equivalent with the fraction of water in the underflow. This correction of \(d_{50}\) is designated as \(d_{50C}\). The correct estimation of \(d_{50C}\) is important since it is directly related to the efficiency of operations and also it leads to computer control of Hydrocyclones as illustrated by Gupta and Eren [1]. The computer control of Hydrocyclones can be achieved by manipulation of operational parameters such as: diameter of the spigot opening, the vortex finder height, the inlet flowrate, the density and the temperature of slurries for a desired \(d_{50C}\).

The \(d_{50C}\) depends on the dimensions of Hydrocyclones and operating conditions. Mathematically, the \(d_{50C}\) has been estimated from empirical models derived from analytical and statistical techniques. Some of the typical of conventional formulae can be found in literature [1], [2], [3] and [4]. These models are hard to derive, since the effect of each variable must separately be identified and incorporated in the formula. Because of the difficulties, all the models are restricted to few estimation variables. Also, the empirical models may not be applicable universally since experimental conditions can change from one operation to another. Even within the same experimental set up it is difficult to keep consistent operation conditions, such as particle size distribution, over a period of time. In order to give a wider applicability to the models, incorporation of additional estimation parameters are necessary, but difficult to do so and also time consuming.

To illustrate the inconsistency between the models some comparisons can be made. For example, the data obtained in an experimental set-up correlated with Gupta and Eren's model [1] well, giving a correlation coefficient of 0.963 with an r squared value of 96.66%. When Plitt's model [2] was applied to same data, somewhat poorer results were obtained, with a correlation coefficient of 0.895 and an r-squared value of 80.14%. Nevertheless, it is worth highlighting that Plitt's model might have yielded in better results on the data obtained in their test rig.

In order to eliminate discrepancies between the models, modern techniques such as Artificial Neural Network (ANN) can be applied to estimate the \(d_{50C}\). In this case, in addition to conventional variables e.g. inlet flowrates, inlet density, spigot opening, vortex height and temperature of slurry, other variables can also be included for the prediction of \(d_{50C}\). In this paper, it will be shown that by the application of ANN the fitness of the data can be improved. The results obtained by ANN do not only yield to better correlation but also are much with the measured values.
quicker and flexible to apply in comparison to empirical models.

The ANN used in this study is the Back Propagated Neural Network (BPNN) [5],[6],[7]. The BPNN is widely used as supervised ANN. Supervised Learning requires a set of training data which consists of a number of desired outputs and the corresponding input data. The BPNN has a number of layers; one input layer; one output layer; and a few hidden layers. The objective of training BPNN is to adjust the weights between the layers such that application of a set of inputs produce the desired set of outputs. Calculations are done to obtain the output sets by processing through the input layers to the output layer, and then propagated back through the network. Although, BPNN is known to have some limitations, in literature it has been demonstrated to work successfully in many applications.

One advantage of BPNN is that it does not require much knowledge of the system before it can generate the desired output. BPNN can learn from the training examples such that the learning can be applied to new input data generated under similar operating conditions. Although, the training of BPNN is slow, once it has learned the outputs can be generate in a very short time. However, the selection of parameters for BPNN, such as the number of hidden neuron in the hidden layer, may require many tests to determine the best configuration.

II. ADDITIONAL HYDROCYCLONE ESTIMATION PARAMETERS and THE RESULTS.

In this application, ANN was first applied with the conventional five Hydrocyclone variables, namely: the inlet flowrate and inlet density, the vortex finder height, the spigot opening diameter and the temperature. Figure 1 illustrates the results obtained. In order to enable direct comparisons with the conventional models, two of the classical formulae have been selected. These being Gupta and Eren's model [1] and Plitt's model [2] and they are also plotted in the same figure. it can be seen that ANN results are superior for most values of $d_{50}$,. Further statistical analysis of this figure gave the following information: for Gupta and Eren's model the correlation coefficient 0.963 with r-squared value of 96.66%, for Plitt's model correlation coefficient 0.895 and an r-squared value of 80.14%. These can be compared with the results obtained by ANN which yielded in a correlation coefficient of 0.986 with an r-squared value of 97.17%.

Fig. 1. The data and predicted results obtained using five parameters
In Figure 2, three further parameters are included as the input variables. The additional parameters were the underflow and overflow flowrates and the ratios of the two flowrates. In this case, statistical analysis indicated that the correlation coefficient of trained results has increased to 0.995 giving an r-squared value of 98.9%.

Fig. 3 depicts the trained ANN results with 14 input variables with the addition of water and solid split ratios, the overflow and underflow densities and the pressure difference between the inlet and the overflow streams. In this case, the correlation coefficient has further improved to 0.995 with an r-squared value of 98.97%.
To fully utilize ANN, once the network is trained the learning of the network is assumed to be holding for any future data generated under the same operational conditions. In order to verify this the network has been trained with some arbitrarily selected 50% of the data and the other 50% has been used for testing. The input variables were selected as in those in Figure 1. Typical results are illustrated in Figure 4. In this example, the correlation coefficient was found to be somewhat reduced to 0.97 with an r-squared value of 96.67%. However, these results are still better compared to those predicted by classical formulae. In this figure it can be seen that there is a wide discrepancy in some of the results which can be observed in run number 94 and 175, suggesting that the prediction error in training is large. In obtaining this figure the following BPNN parameters were selected: hidden layer=1, hidden neurons=4, initial upper weight limits=+1, initial lower weight limits=-1, tolerance error 0.01 and maximum number of iterations=5000.

The training parameters were slightly modified to obtain the results in Figure 5. The hidden neurons were increased to 6, initial weight limits were reduced to ±0.5 and the tolerance error was reduced to 0.0001. As it can be seen, the results improved considerably for a maximum iteration of 50,000. This indicates that the prediction accuracy of the BPNN is directly affected by the selection of parameters such as number of hidden neurons, the threshold training errors and the number of iterations.

In this application only one hidden layer has been selected in obtaining all the results. In general, as a result of this study, it is found that the training time increases with number of input variables. In Figure 1, the training time was 4 minutes, and the mean square error per unit was 0.001317. In Figure 2, training time was around 14 minutes with a mean square error per unit of 0.000707. As expected the time taken for Figure 3 was the longest, 20 minutes. However the mean square error per unit was 0.000249, which was the smallest among the three figures.

Figure 4. The results with large prediction error.
III. CONCLUSIONS

In the prediction of Hydrocyclone parameter, $d_{50c}$, the results of two best known conventional models have been compared with those results obtained by application of Artificial Neural Network. It is shown that ANN yields to superior results which fits better with the original data. Unlike conventional models, ANN can easily incorporate additional Hydrocyclone operational variables to improve the fit. Performance of ANN can further be enhanced by careful selection of training parameters. It is indicated that the use of ANN can lead to more effective and efficient automatic control of Hydrocyclones.

REFERENCES


