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Developing a Generalised Neural-Fuzzy Hydrocyclone Model for Particle Separation

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Abstract *- Development of a neural-fuzzy model for an operational hydrocyclone is reported in this paper. The model integrates the benefits of the Artificial Neural Network (ANN) and the fuzzy-logic techniques. It preserves the generalisation capability of an ANN while expressing the final model in fuzzy rules. These rules can be modified and examined by the user. This will in turn control the interpretation ability of the system. Results from a case study have shown that the new proposed neural-fuzzy hydrocyclone model produces comparable results as those from the ANN model but with an added advantage of the use of linguistic fuzzy rules.*

I. INTRODUCTION.

Hydrocyclones are used in mineral processing industry for separation and declassification of solids suspended in fluids. The separation efficiency is determined by the parameter *d50c* which represents the partitioning of a particular particle size reporting 50% to the underflow and 50% to the overflow. However, an exact model of a hydrocyclone is difficult to derive due to the highly non-linear operational characteristics and the vast amount of parameters involved [1, 2]. As the efficient operation of a hydrocyclone is important, an accurate model providing non-linear functional matching of the multi-dimensional inputs-outputs is necessary in order to improve the system performance.

Traditionally, mathematical models based on empirical methods and statistical techniques in describing the performance of the hydrocyclones have been used [2]. Although these approaches have long been employed in the industry, they do have their shortcomings. For example, these approaches have the limitation on the number of variables that can be handled at one time. Besides, the experimental conditions can change from one operation to another, these models therefore may not be applicable universally.

In recent years, Artificial Neural Network (ANN) is an emerging technology that has been applied to the problem of hydrocyclone modeling [3,4,5,6]. The most commonly used ANN configuration is the Backpropagation Neural Network (BPNN). In many applications, it has been shown that the neural network method is an improved alternative approach as compared to the traditional techniques. BPNN has the advantages that the network can learn from the given input-output data and the ability of handling a large number of variables. Although the technique has proven to be useful for the prediction of the *d50c* control parameter, the main disadvantage is its inability to convey the acquired knowledge to the user. As a trained network is represented by a collection of weights, the user will have difficulty to understand and to modify the model. In most cases, the system may not even gain the confidence of the user.

On the other hand, a fuzzy-rule-based system using linguistic terms is more meaningful and user-friendly. However, establishing the fuzzy rule-base is a difficult task unless some form of automatic rule generator is available [7]. In addition, the rules generated from limited data may have no assurance of the generalisation ability of the model.

Fuzzy Logic Systems (FLS) and Artificial Neural Networks (ANN) are complementary technologies in designing intelligent systems. The objective of the proposed generalised Neural-Fuzzy hydrocyclone model is to combine the advantages of the two techniques and at the same time to reduce their disadvantages. This proposed approach makes use of the BPNN to learn and generalise from the available data. After the BPNN has learned the underlying function, it is used to generate training data to cover the whole universe of discourse of the fuzzy variables in accordance to the number of memberships. This generated training data are then used by a self-generating fuzzy rules inference system [7] to build a fuzzy rule-base. In this way, the fuzzy rule-base will incorporate the generalisation ability of the trained BPNN. As the data generated by the BPNN cover the whole universe of discourse of the fuzzy system, the rules in the final system can be used to interpret any data that are different from the original training data. Hence, the proposed generalised Neural-Fuzzy hydrocyclone model has preserved the generalisation ability of the BPNN, but with the added advantage that the user can modify and examine the interpretation function. The user can also include their knowledge and experience into the fuzzy rule-base to modify the behaviour of the hydrocyclone model. A case study is presented in this paper to demonstrate the features of the new approach. The results have shown to be comparable to those obtained from the BPNN but with the advantage of the use of linguistic fuzzy rules.

II. GENERALISED NEURAL-FUZZY HYDROCYCLONE MODEL

The objective of this proposed technique is to set up a hydrocyclone model that is meaningful to the human users. At the same time, the linguistic fuzzy rules involved should best describe the underlying function of the training data. BPNN and Fuzzy Logic System have their strong and weak points. To ensure the network possesses generalisation ability, the Self-organising Map (SOM) data-splitting and early stopping validation method are used to establish the neural network model from the available training data [8]. The trained network is capable to reject noise while preserving the underlying function of the system. However, once the network is trained, it is difficult to relate to the operational characteristics of the hydrocyclone. The user cannot include additional knowledge or modify the way that the model behaves. Another alternative is to use a fuzzy system. Using a self-generating fuzzy rules system [7], the fuzzy rules can be extracted from the training data. However, there is no validation process to ensure that the rules extracted are describing the generalised underlying function of the training data. Besides, as the rules are extracted for all training points, noise and outliers will also be included in the fuzzy rule-base.

The proposed generalised neural-fuzzy hydrocyclone model combines the two approaches. Establishment of the model is basically divided into two parts. The first part involves the training of a generalised BPNN. The second part involves the setting up of the self-generating fuzzy rules system. The following procedures outline how the system is established.

Step 1. Train a BPNN using SOM data-splitting and early stopping validation.

Step 2. After the network has been trained, determine the number of memberships for the fuzzy system.

Step 3. Generate input variables for all possible memberships.

Step 4. Apply the generated input data to the BPNN and obtain outputs for the corresponding inputs.

Step 5. Use the self-generating fuzzy rules algorithm to establish fuzzy rules based on the input and output data generated from the neural network.

Step 6. The extracted rules form the fuzzy rule-base of the generalised fuzzy interpretation system. The final system uses the centroid defuzzification technique.

III. CASE STUDY AND RESULTS

Data collected from a Krebs hydrocyclone model D6B-12°-839 describing *d50c* have been used. There are total 95 training samples used in establishing the hydrocyclone model. Another 44 testing samples are used to benchmark the prediction accuracy of the system. These testing data are not used in anyway during the training process. Although the initial ANN model is capable to handle 14 input variables, only three input variables are selected after performing the significant input contribution measure [6]. The input contribution measure basically identified the significant inputs that are important in predicting the hydrocyclone parameter. In this case, it was found that overflow density (R_o), solid percentage (ρ_i) and spigot opening diameter (D_u) are dominate in predicting the *d50c* parameter. They in turn determine the separation efficiency of the hydrocyclone.

For comparison purpose, two hydrocyclone models have been built. The first one is the normal BPNN hydrocyclone model, while the second one is the proposed generalised Neural-Fuzzy hydrocyclone model. Different numbers of membership function for the neural-fuzzy model have been used. The number of fuzzy membership functions tested are 5, 7 and 9. Fig.1 shows the cross-plots of the predicted *d50c* values from the two models with respect to the measured *d50c* training data set.

Figure 2 shows the cross-plots of the BPNN and neural-fuzzy model outputs against the measured *d50c* testing data set. The testing data are not used in the training process. They are used to "blind test" and for the evaluation of the performance of the model. From these figures, it can be observed that the prediction results from the BPNN and neural-fuzzy models are comparable to one another.

Table 1 shows the correlation between the predicted and the measured values of the *d50c* parameters. The prediction accuracy of the models are very close to one another. For the training data, the correlation is 0.992 for the BPNN model, and 0.964, 0.987, and 0.988 for the neural-fuzzy models with 5, 7 and 9 membership functions respectively. In the case of the testing data, the correlation between the test-data and prediction model outputs are: 0.993, 0.972, 0.986 and 0.991 for the BPNN and the neural-fuzzy models with 5, 7 and 9 memberships respectively. It is obvious that the accuracy increases with the number of membership functions. This is due to an increased resolution of the fuzzy variables. However, this will lead to an exponential increase in the number of fuzzy rules.

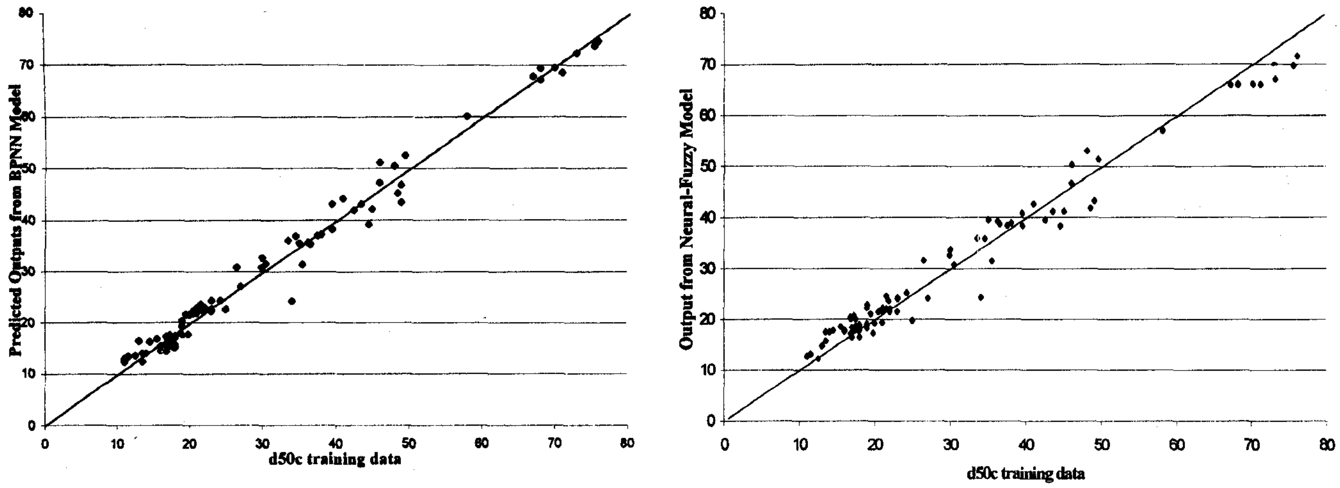

Fig. 1 Comparison of Outputs from BPNN and Neural-Fuzzy models for training data set

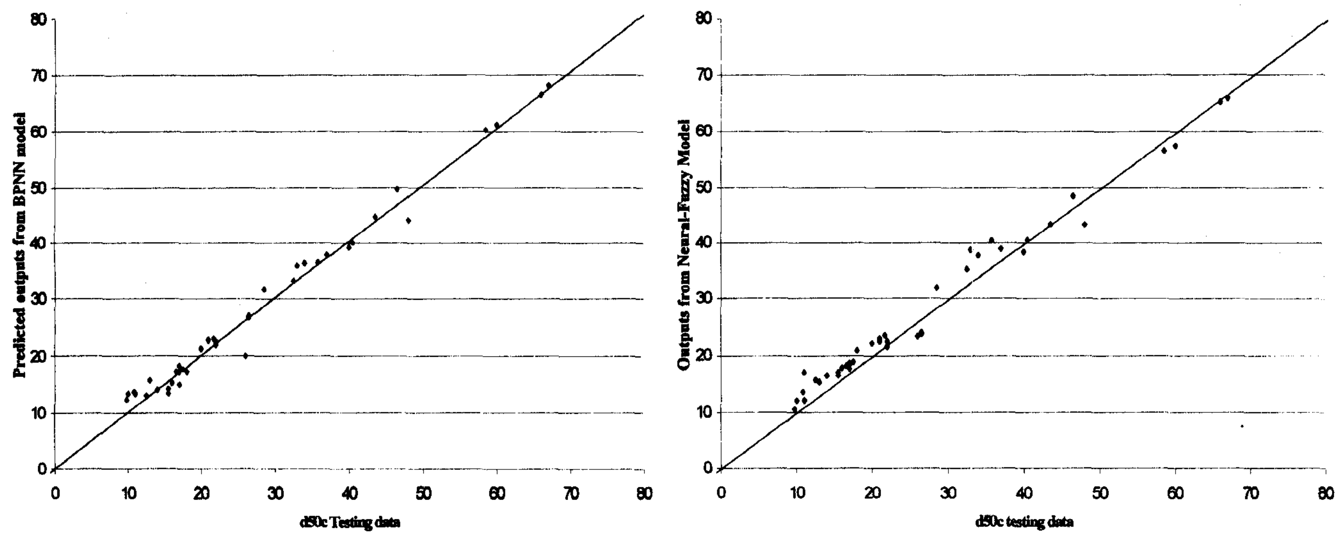

Fig. 2 Comparison of Outputs from BPNN and Neural-Fuzzy models for testing data set

Table I: Correlation between results.

Model	Training Set Correlation	Testing Set Correlation
BPNN	0.992	0.993
Neural-Fuzzy 5	0.964	0.972
Neural-Fuzzy 7	0.987	0.986
Neural-Fuzzy 9	0.988	0.991

Figure 3 shows the division of the membership functions over the universe of discourse used by the Neural-Fuzzy model. Nine membership functions are shown in the diagram. The fuzzy membership terms used are Extreme Low (EL), Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium High (MH), High (H), Very High (VH) and Extreme High (EH). In the case of 5 membership functions, the fuzzy terms are: VL, L, M, H and VH. As for the case of 7 membership functions, the fuzzy terms are: VL, L, ML, M, MH, H and VH. Triangular functions are used in this study and each term occupies equal fuzzy space over the universe of discourse. Although other functions and distributions have been tested, it is difficult to determine the optimum configuration applicable to all situations. Further studies are required to determine these parameters.

An example of the linguistic rules from the fuzzy rule-base is shown in Figure 4. The rules are expressed in fuzzy variables and fuzzy membership terms as defined by the user. By examining the rules, the user may relate the performance of the model to a more meaningful representation. However, the number of rules generated by the system increases exponentially with the number of variables and fuzzy membership functions. Further reduction of the number of rules is necessary to bring it to a manageable level.

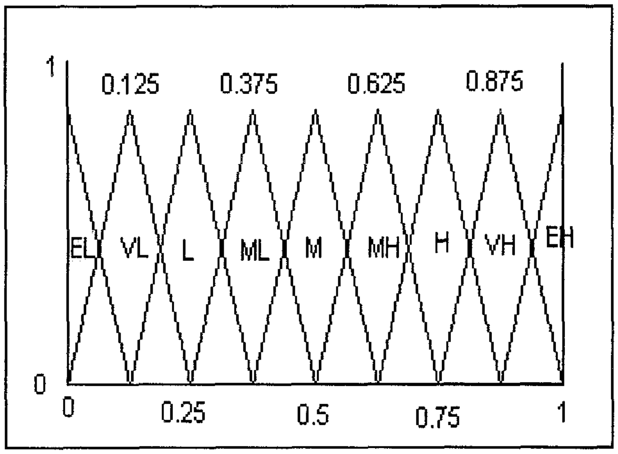

Figure 3. Membership functions over the universe of discourse.

If R_o = VL	and ρ_i = EH	and D_u = EH	then $d50c$ = EL
If R_o = L	and ρ_i = EL	and D_u = EL	then $d50c$ = M
If R_o = L	and ρ_i = EL	and D_u = VL	then $d50c$ = M
If R_o = L	and ρ_i = EL	and D_u = L	then $d50c$ = ML
If R_o = L	and ρ_i = EL	and D_u = ML	then $d50c$ = ML
If R_o = MH	and ρ_i = M	and D_u = MH	then $d50c$ = MH
If R_o = MH	and ρ_i = M	and D_u = H	then $d50c$ = MH
If R_o = MH	and ρ_i = M	and D_u = VH	then $d50c$ = M
If R_o = MH	and ρ_i = M	and D_u = EH	then $d50c$ = M
If R_o = MH	and ρ_i = MH	and D_u = EL	then $d50c$ = VH
If R_o = MH	and ρ_i = MH	and D_u = VL	then $d50c$ = VH

Figure 4. Example rules in the Fuzzy rule-bsae of the neural-fuzzy model.

IV. CONCLUSIONS

This paper proposed a new technique to combine the advantages of the ANN and the Fuzzy Logic System in building a Neural-Fuzzy hydrocyclone model. This proposed system can learn and generalise from the given training data. At the same time, it produces human understandable fuzzy rules to describe the underlying function of the prediction model. With these fuzzy rules, the user can examine and modify the model. This will be a useful tool for an experienced user, as previous knowledge and experience can now be incorporated into the final model. Further studies are currently carried out to determine the optimum configuration of the fuzzy system. In addition, the number of rules in the established system also has to be reduced in order to avoid overloading the user. A compromise has to be reached between the degree of accuracy and the complexity of the final system.

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