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HYBRID FUZZY MODELLING USING MEMETIC ALGORITHM FOR HYDROCYCLONE CONTROL

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Abstract:

The use of a hybrid fuzzy modeling can act as a good alternative in establishing a hydrocyclone control model in the estimating the hydrocyclone parameter, d50c. In most control and engineering applications, the use of fuzzy system as a way to improve the human-computer interaction has becoming popular. The main advantage of this proposed hybrid fuzzy system used for hydrocyclone control is that it only presents a small amount of fuzzy rules. It uses memetic algorithms to optimize the fuzzy parameters of the system to yield in a more accurate hydrocyclone control system.

Keywords:

Hydrocyclone; d50c; fuzzy system; parameter identification; memetic algorithms; hybrid fuzzy model

1. Introduction

In mineral processing engineering, hydrocyclones have been used for classification and separation of solids suspended in fluids [1]. Hydrocyclones (see Figure 1) basically use the principle of centrifugal separation to remove or classify solid particles suspended in fluids. They perform this separation based on size, shape, and density. Hydrocyclones are manufactured in different shapes and sizes to suit specific purposes as classifiers or separators. Hydrocyclones normally have no moving parts. The feed slurry containing all sizes of particles enters the hydrocyclone through the inlet. Inside, due to centrifugal force experienced by the slurry, the heavier particles become separated from the lighter ones. After the particles suspended in the fluid are classified, they are discharged either from the overflow (vortex finder) or from the underflow (spigot opening). Due to the complexity of the separation mechanism in the hydrocyclone, the interpretation of the physical behavior and forces acting on the particles is not clear but studied extensively.

The separation efficiency of hydrocyclones is determined by the parameter *d50* that represents the partitioning of a particular particle size reporting 50% to the underflow and 50% to the overflow. In order to determine *d50*, tromp curves (as shown in Figure 2) are used to provide the relationship between the weight fraction of each classified particle sizes in the overflow and underflow streams. In practical applications, the *d50* curve is corrected by assuming that a fraction of the heavier particles are entrained in the overflow stream that is equivalent with the fraction of water in the underflow. This correction of *d50* is designated as *d50c*. The correct estimation of *d50c* 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 [2]. 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 *d50c*.

Typically, the *d50c* depends on the dimensions of hydrocyclones and operating conditions. Mathematically, the *d50c* has been estimated from empirical models derived from analytical and statistical techniques. Some of the typical of conventional formulae can be found in literature [2], [3], [4] and [5]. 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

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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 empirical models, incorporation of additional estimation parameters are necessary, but difficult to do so and also time consuming.

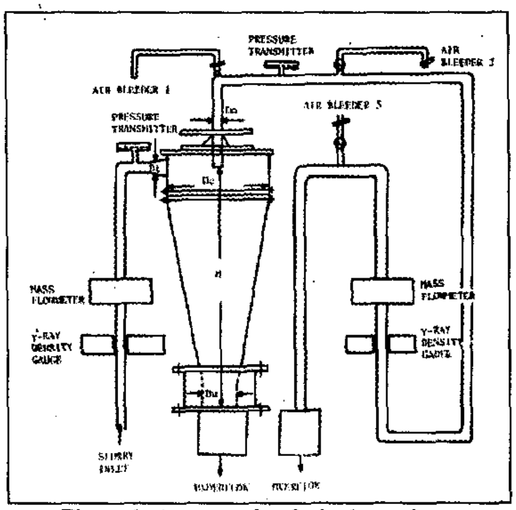

Figure 1. An example of a hydrocyclone.

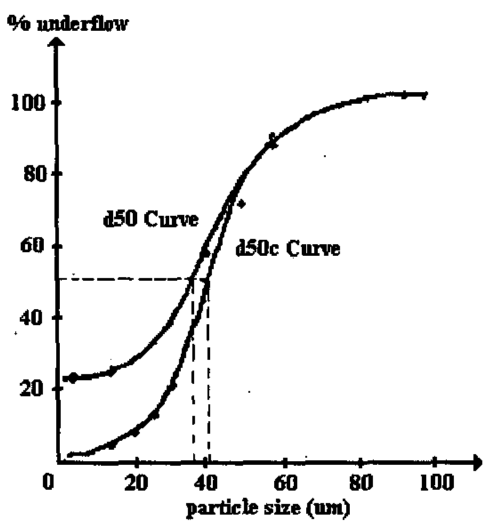

Figure 2. A typical tromp curve.

In recent years, intelligent techniques such as Artificial Neural Network (ANN) [6, 7], Neural-Fuzzy [8] and fuzzy [9] have been applied. Although ANN techniques have proven to be useful for the prediction of the d50c, the main disadvantage is their 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. The Neural-Fuzzy approach shown to be better than the ANN approach as it can generate fuzzy rules for the user to manipulate. However, the fuzzy rules generated to cover the whole sample space are too tedious for the user to examine. In [9], the authors have reported the use of a self-generating fuzzy rules technique [10] to extract fuzzy rules directly from input-output data. As these fuzzy rules do not cover the whole sample space, they have proposed a fuzzy rule interpolation technique to perform inference for spaces that have no fuzzy rule can be found. However, this self-generating fuzzy rule technique also generates quite a number of fuzzy rules.

In this paper, a hybrid fuzzy modelling technique has been proposed such that it will generate minimum fuzzy rules required for the control law, and at the same time incorporate memetic algorithm to improve the fuzzy parameters to further improve the fuzzy model. The advantages of using this hybrid fuzzy modelling system for the control are as follows. Firstly the control model can be constructed in a short period of time using efficient computation intelligence techniques. Secondly with the minimum fuzzy rules extracted from the experimental data, human analyst can understand, modify and update the control function easily.

This paper will be structured as follows; in Section 2, the issues of dense and sparse fuzzy rules will be discussed; in Section 3, the proposed hybrid fuzzy modelling system for use in hydrocyclone control will be discussed; in section 4, case studies and results will be shown; and finally conclusion is presented.

2. Spare Fuzzy Rules

Fuzzy logic (FL) is becoming popular in dealing with data analysis problems that are normally handled by statistical approaches or ANNs. In general, fuzzy control systems are the most important applications of fuzzy theory. This is a generalized form of expert control using fuzzy sets with fuzzy rules for modeling a system. In classical fuzzy approaches from Zadeh [11] and Mamdani [12], the basic idea is to calculate the conclusion by evaluating the degree of matches from the observation that triggered one or several rules in the model. However, conventional FL data analysis systems do not have any learning algorithms to build the analysis model. Rather, they make use of human knowledge, past experience or detailed analysis of the available data by other means in order to build the fuzzy rules for the data analysis. The advantages of using FL are the ability to handle imprecise data and to interpret the analysis model built. The data analysis model can also incorporate human knowledge by modifying the fuzzy rule base. The data analysis model can also be changed easily by modifying the fuzzy rule base. The major limitation is the difficulty in building the fuzzy rules. However, if fuzzy rules could be extracted from measured input-output data, it would be very useful. This area has attracted much attention the past few years [13, 14, 15]. However, the crucial issue here is the number of fuzzy rules that are extracted by the fuzzy rule extraction technique.

Sugeno and Yasukawa's qualitative modeling (SY) method [16] has gained much attention in the fuzzy research field mainly due to its advantage of building fuzzy rule bases automatically from sample input-out data. The usual fuzzy controller identification methods generate dense fuzzy rule bases, so that the rule premises form a fuzzy partition of the input space (see Figure 3). In a dense fuzzy rule base, the number of rules is very high, as it depends on the number of inputs k and the number of partitions per variable T in an exponential way. Assuming all the partitions are consistent in all premises and consequents, the total number of rules is $|R| = O(T^k)$. In order to avoid this exponential number of rules, the SY method puts emphasis on the rule consequents, i.e., the output space, and first finds a partition in Y. The determination of premises in the input space X is done by splitting appropriately the inverse images of the output clusters. Using this approach, the partitioning of the input space is done in a secondary manner, thus the number of fuzzy rules does not increase exponentially with the number of inputs. All these can be shown in Figure 4. However, in the original SY modeling, there are a few issues left still unaddressed. This has lead to an improvement to the original SY method known as the Improved SY modeling [15]. The prediction or control accuracy of such fuzzy model depends largely on how well the parameters are identified i.e. parameters identification.

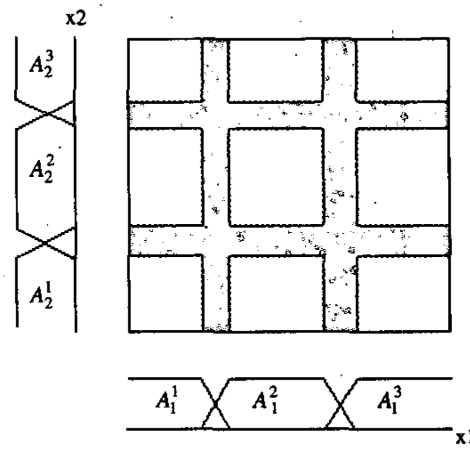

Figure 3. Ordinary partition of input space.

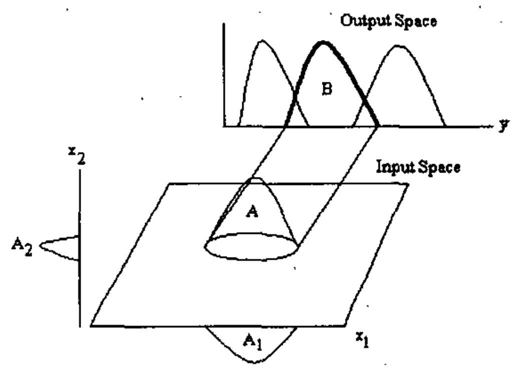

Figure 4. Fuzzy cluster A for two input dimensions.

3. Hybrid Fuzzy system using Memetic algorithms

In this paper, we extend the Improved SY modeling [15] by using memetic algorithms (MAs) to optimize further the fuzzy parameters. The initial results, which have been published in reference [17] has shown promising simulated results. Here we will extend this initial finding to construct a hybrid fuzzy system that is suitable for use as a hydrocyclone parameter identification control system.

In the area of optimization, there are two kinds of search methods: global search and local search. Global optimizers are useful when the search space is likely to have many minima, making it hard to locate the true global minimum [18]. Examples of global search methods are genetic algorithms. Genetic algorithms are search algorithms that use operators found in natural genetics to guide the trek through a search space. On the other hand, local improvement procedures can quickly find the exact local optimum of a small region of the search space, but are typically poor global searchers. Because local procedures do not guarantee optimality, in practice, several random starting points may be generated and used as input into the local search technique and the best solution is recorded. This optimization technique, commonly known as multi-start algorithm has been used extensively. Nevertheless it is a blind search technique since it does not take into account past information.

Genetic algorithms, unlike multi-start, utilize past information in the search process. Therefore, local improvement procedures have been incorporated into GAs to improve their performance through what could be termed "learning". Such hybrid GAs, which utilizes local learning heavily, are known as memetic algorithms. These techniques have been used successfully to solve a wide variety of realistic problems and will be used here in this paper [19]. Memetic Algorithms are population-based approaches for heuristic search in optimization problems [20]. Basically, they are genetic algorithms that apply a separate local search process to refine individuals. One big difference between memes and genes is that memes are processed and possibly improved by the people that hold them - something that cannot happen to genes.

To construct a hybrid fuzzy system using memetic algorithms to optimize the fuzzy parameters, the Improved SY modeling algorithm [15] is used to extract the sparse fuzzy rules from the input-output data. After which, the MAs are used to optimize the fuzzy parameters generated from the Improved SY fuzzy modeling. The Improved SY modelling is used as the starting points to provide some prior knowledge of the fuzzy parameters. MAs are then used to search the nearest region of each parameter as follow:

$$\begin{aligned} low-bound \le x1 &\le \left(\hat{p}1+\hat{p}2\right)/2 \\ \left(\hat{p}1+\hat{p}2\right)/2 \le x2 &\le \left(\hat{p}2+\hat{p}3\right)/2 \\ \left(\hat{p}2+\hat{p}3\right)/2 \le x3 &\le \left(\hat{p}3+\hat{p}4\right)/2 \\ \left(\hat{p}3+\hat{p}4\right)/2 \le x4 &\le up-bound \end{aligned} \tag{1}$$

where $\hat{p}1$, $\hat{p}2$, $\hat{p}3$, $\hat{p}4$ are the fuzzy parameters generated after the parameters identification process from the Improved SY fuzzy model.

The following describe the algorithm used to optimize the fuzzy parameters of the sparse fuzzy rules.

Procedure Parameter identification using memetic algorithms

BEGIN

Step 1: Initialize

- Generate an initial MA population according to each parameter's own range as in (1).

Step 2: **For** each individual in the population

- Perform local search on it according to corresponding range.
- Replace the genotype in the population with the locally improved solution.

End For

Step 3:

- Evaluate all individuals in the population.
- Apply standard MA operators to create a new population; i.e., Selection, Mutation and Crossover.

Step 4: **Stopping condition satisfied?**

- **Yes: stop and output results**
- **No: goto step 2.**

END

4. Results and Discussions

The data used in this paper was obtained from a closed circuit slurry test-rig. The slurry, mixed in a 500 liter reservoir, made from -212 mesh ground silica particles was circulated through the cyclone. There are a total of 139 data. Four parameters of hydrocyclone were selected for used in this experiment. These parameters were the conventional parameters (inlet flowrate, inlet density, spigot opening, and vortex height) on which the classical formulae approach was based on [2].

The automatic control strategy for the on-line hydrocyclones control has been reported in [2]. In their application the *d50c* was set to desired value. The signals from the instruments were processed to calculate the present value of *d50c* using the conventional models. To minimize 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 *d50c* was obtained. The operating parameters were physically altered by suitable servomechanism systems.

This research is continuing on the implementation of the on-line control of the hydrocyclones by using this hybrid fuzzy modeling system. Evidence indicates that the desired values of the *d50c* can still be obtained using this hybrid fuzzy modeling system instead of the conventional methods, and other prior intelligent methods. In this application, once fuzzy control system have extracted the fuzzy rules, the values of *d50c* 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. A possible control using this hybrid fuzzy modeling system is suggested in Figure 5.

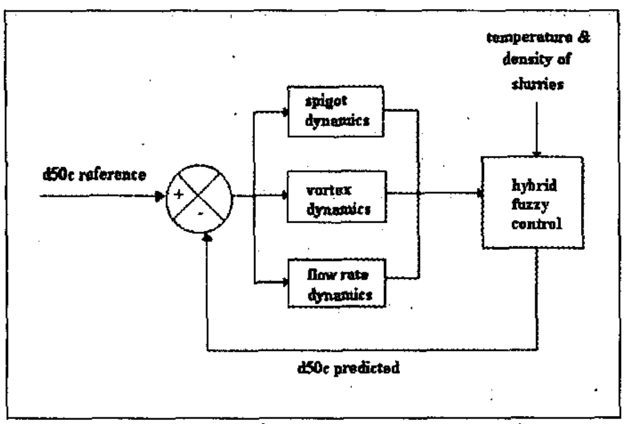

Figure 5. Online hybrid fuzzy hydrocyclone control system.

The Improved SY modeling algorithm is used to extract fuzzy rules from the experimental input-output data. After which, 3 fuzzy rules have been extracted for the hydrocyclone control. These fuzzy rules have been ported to Matlab fuzzy toolbox to generate a rule viewer as shown in Figure 6. The mean square error for this system is 0.0065. MAs are then used to further optimize the fuzzy parameters such that it can generate better results. The fuzzy rules and parameters after the optimization are shown in Figure 7. The mean square error after the MAs optimization is 0.0041. Using MAs optimization has increased the control accuracy. One important point to note from this hybrid fuzzy system is the low amount of fuzzy rules for human expert to be examined. With only three fuzzy rules and the MAs optimization technique, human expert can understand the control system more efficiently. The control model can be constructed in a short period of time using efficient computation intelligence techniques. As the fuzzy rules can be extracted using this proposed hybrid fuzzy modeling technique in a short period of time, it can be reconstructed easily under different operating condition. With the minimum fuzzy rules extracted from the experimental data, human analyst can understand, modify and update the control function easily.

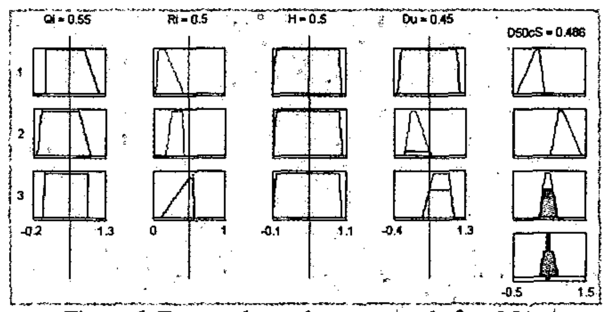

Figure 6. Fuzzy rules and parameters before MAs optimization

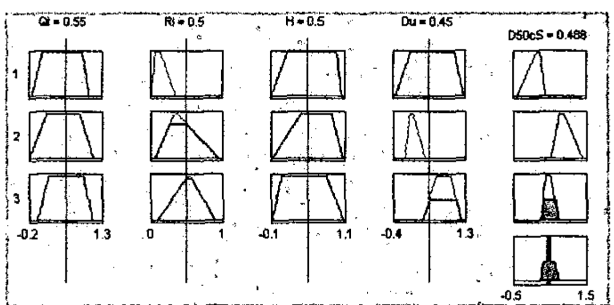

Figure 7. Fuzzy rules and parameters after MAs optimization

5. Conclusions

This paper has proposed a hybrid fuzzy control system that is suitable to be implemented as an alternative for automatic control strategy of the on-line hydrocyclones control. It uses the improved SY modeling that is computational efficient to extract the appropriate amount of fuzzy rules to model the control. After which, the memetic algorithms are used to further optimized the fuzzy parameters. Case studies using data collected from a real hydrocyclone model are used to illustrate the new hybrid fuzzy hydrocyclone control system. With just the use of 3 fuzzy rules, the hydrocyclone control can be carried out. With just a few fuzzy rules, the human analyst can understand the model easily. As the fuzzy rules can be extracted using this proposed hybrid fuzzy modeling technique in a short period of time, it can be reconstructed easily under different operating condition. Beside, results obtained from the test has shown that the proposed hybrid fuzzy modeling can produce better results than the Improved SY modeling, by making use of the prior knowledge generated from the Improved SY fuzzy modeling as a starting point for the local search.

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