PATTERN RECOGNITION OF FRACTAL PROFILES IN COAGULATION-FLOCCULATION PROCESS OF WASTEWATER VIA NEURAL NETWORK

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ABSTRACT

The optimum chemical dosage is presumably the goal of every chemical water or wastewater treatment plant as in a coagulation-flocculation process. However, due to difficulties in on line measurement and complexity of chemical reaction, the optimum dosage is very hard to be determined by conventional methods. This paper presents a new low cost sensor to measure size changes of flocs that are being formed during a coagulation flocculation process by measuring fractal dimensions. It is based on real time images of flocs that are being captured during the coagulation-flocculation process. A neural network model using Matlab version 6 (The Mathworks Inc., U.S.) was developed in order to recognise the general pattern of fractal profiles in a coagulation-flocculation process of wastewater. Back propagation neural networks (BPN), which are a type of feed-forward networks, with 10 neuron on an input layer, 1 neuron on an output layer, 16 neurons on a hidden layer were used with log sigmoid activation functions. In this BPN model, the gradient descent momentum was used to minimize the errors. The training and testing of such networks were based on input output data from real-time experimental runs on the coagulation-flocculation process. The network converged with 7181 epoch. The developed neural gave good recognition performance with 95% success rate.

Keywords: *Coagulation-Flocculation, Fractal Dimension, Neural Networks, Pattern Recognition*

1. INTRODUCTION

Coagulation-flocculation is one of the important processes in water and wastewater treatment module. It involves the addition of a chemical coagulant or flocculant typically aluminium or iron salt, in order to remove turbidity or color prior to the next stage of floc settling in the treatment process. Determination of optimum and economical dosage of chemical coagulant-flocculant is an important criteria in the process operation since chemical cost represents a huge portion of operational cost in a chemical treatment plant. A conventional method to determine optimum coagulant dosage or pH for a coagulation-flocculation process is by a jar test. It is an off-line analysis and time consuming where results can only be obtained after several hours. Besides, the results obtained do not represent the actual or current status of wastewater, hence leading to underdosing or overdosing of coagulant. Low dosage or underdosing generally results in poor removal of the raw water turbidity. Additionally, high dosage or overdosing, leads to more sludge forming (which are difficult to dewater), chemical wastage and an increase in the operational cost of the treatment. It can also cause Alzheimer's disease in the case of alum as the coagulant, and also restabilise the larger formed flocs to break into smaller ones, thereby finally leading to improper treatment as well.

Hence, a proper control of dosage is predominantly required if the coagulation-flocculation process is to be optimised. As condition changes, the treatment system must respond with appropriate adjustments of the chemical feed rate. Such control is obviously impossible if an "appropriate adjustment" does not exist with the chosen coagulant. Hence, a good control algorithm is required to determine how a dosage is to be adjusted as the condition changes [1].

On Line Vision Based Detection

On line determination of optimum coagulant dosage has long been studied by many researchers. New alternative method managed to be applied in water treatment such as streaming current detector, turbidity probe, zeta meter and optical sensor which appear to be satisfactory techniques in determination of optimum dosage [2]. However these existing techniques are limited to a certain process condition, very expensive and sometimes require tedious handling procedure. In addition, many small and medium industries are not willing to put heavy investment for environmental protection. Hence, a low cost solution should be the main criteria.

Digital imaging method coupled with image analysis system has shown a good potential in surveillance and monitoring of chemical process [3]. Traditionally, study of coagulation-flocculation process focuses on particle surface charge and solid-liquid separation efficiency in order to determine the performance of the process. Fewer studies have provided insight particle characteristics including fractal dimension. Removal of colloidal particles under typical water treatment condition results in flocs that have been shown to be fractal [4]. The purpose of this study was to track down the current status of coagulation-flocculation process based on fractal image of flocs. The fractal profiles obtained from the coagulation-flocculation process would be fed into a neural network for the purpose of pattern recognition.

2. ARTIFICIAL NEURAL NETWORK SYSTEM

In this research, recognition of fractal profiles was achieved through a neural network system. Artificial Neural Network (ANN) is a branch of artificial intelligence that is capable of learning from history or past example. ANN is chosen in most of pattern recognition tasks due to its ability to match large input information simultaneously and then generating generalised output. Neural computing system posses these capabilities as well as the ability to learn and build unique structures specific to a particular problem [5-6]. A simple neural network architecture has at least an input layer, a hidden layer and an output layer. A typical architecture of an artificial neural network is shown in Figure 1.

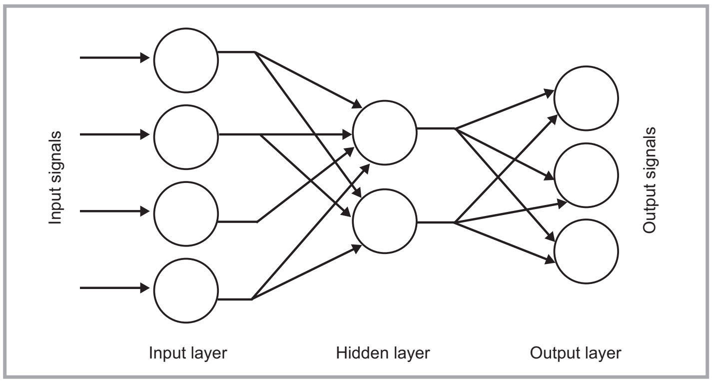

Figure 1 Architecture of a typical artificial neural network

Feed Forward Back Propagation Neural Network

Feed forward back propagation neural network (FBPN) technique was used to recognise the fractal profile in this research. The back propagation model was introduced by Rumelhart *et al* [7]. This network has served a useful method to train multilayer neural network for a wide variety of applications.

In BPN, the learning algorithm has two phases. First, a training input pattern is introduced to the network input layer. The network consequently propagates the input pattern from a layer to another layer until the output pattern is generated by the output layer. If the pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated. As with any other neural network, back propagation is determined by the network architecture, the activation function used by the neurons and the learning algorithm that specifies the procedure for adjusting weights [8]. The activation function plays a major role in the convergence process of the back propagation learning [9]. The choice of an appropriate activation function leads to the learning with lesser time and more stabilised network [10]. In this research, the activation function used for the output and hidden layers was log sigmoid transfer function. This transfer function is commonly used in back propagation network, partly because it is differentiable [11]. This type of activation function was chosen because its output value is in the range of 0 to 1 where network input moves from negative to positive infinity. In this FBPN model, adaptive learning rate with momentum function (traingdx) is used to minimize the mean squared error (MSE). Adaptive learning rate was chosen because it can give faster convergence. MSE is a useful indicator of the network's performance. The back propagation training algorithm attemps to minimise the criterion. When the value of the MSE in an entirity passes through all training sets, or epoch is sufficiently small, the network is considered to have converged [8].

3. MATERIALS AND METHOD

In order to obtain the input/output data required to develop and validate the ANN models, wastewater samples were collected from a number of sources in order to get various quality of wastewater. Sample dilution was performed in order to minimise the coagulant consumption since the original wastewater samples were very high in turbidity and the treatment process required a lot of chemical coagulant in order to reach the optimum values. Alum [$Al2(SO4)3.7H_2O$] was prepared in a different concentration before the experiment was performed. The experimental apparatus (Figure 2) consisted of a 7 L Perspex wastewater reactor with a variable mixing speed stirrer (IKA, Germany), a submersible lamp with a variable light intensity and a peristaltic pump to transfer coagulant into the wastewater reactor. The image analysis system comprised of Microsoft Windows-based PC, a Universal Serial Bus (USB) web camera (640x480) (Logitech, Switzerland) an in-house image acquisition library and an image-processing library. The libraries were implemented as C++ classes. The profiles data were later used to develop a neural network system to recognise the pattern of fractal dimension during a coagulation-flocculation process.

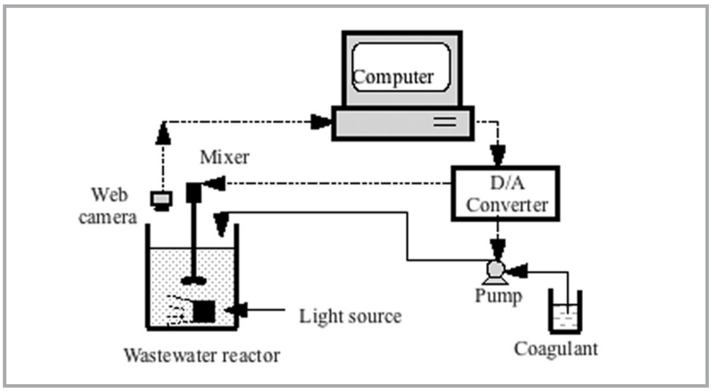

Figure 2 Experimental set-up for data acquisition system in a coagulation-flocculation process

4. RESULTS AND DISCUSSIONS

Typical Profiles of Fractal Dimension

A typical profile of fractal value changes with alum dosage is shown in Figure 3. With the increasing of coagulant dosage, the fractal value increases from its initial value to a maximum level, and then gradually declines to a slightly stable value. These results were validated with jar test results. The residual turbidity of these suspensions, measured after mixing and settling is included in this figure. The maximum level of fractal values corresponded to the lowest value of the residual turbidity (Figure 3), thereby validating the effectiveness of the fractal value to determine the optimal dosage of coagulant. The initial and maximum value of fractal dimensions will vary for different experimental runs even though

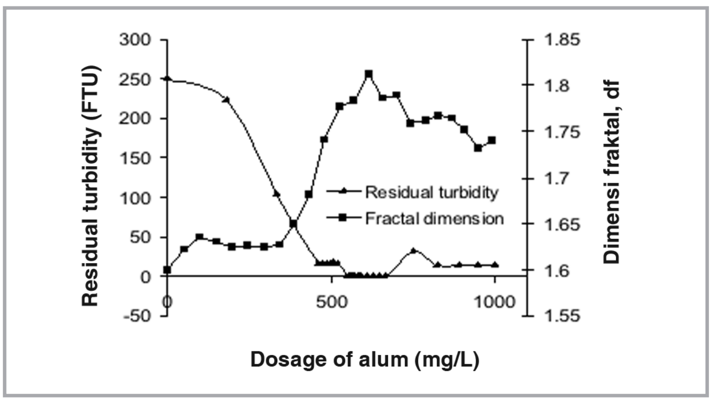

Figure 3 Typical fractal value curve corresponding to the residual turbidity with varying alum dosage

the same condition and quality of wastewater being used (Figure 4). However, the maximum fractal value still falls at the same range. This phenomenon was expected as the research was conducted by using a real wastewater. Moreover, it is impossible to omit all the noise in image quality due to other light sources. Besides, conducting the experiment in a dark room was not practical.

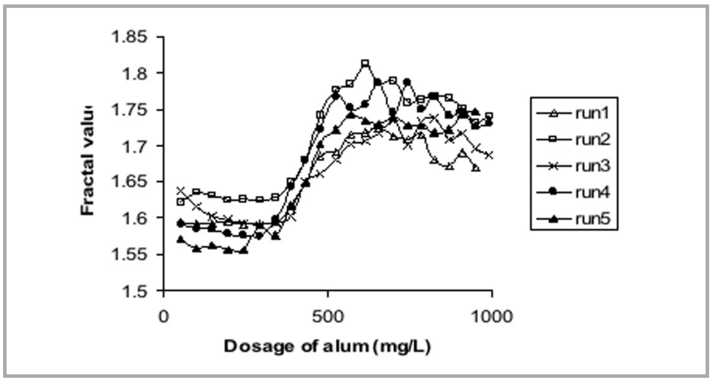

Figure 4 Fractal profile curves with varying alum dosage from different experimental runs

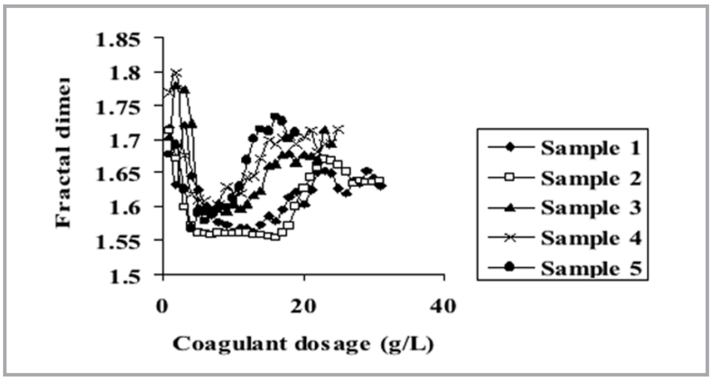

Figure 5 Fractal profile curves with varying alum dosage from different quality of wastewater sample

The results for different quality of wastewater (influent) also exhibited similar pattern of fractal profiles as shown in Figure 5. Notably the increment of residual turbidity of the wastewater was insignificant when the alum was over dosed beyond the optimal condition. Dental [1] had pointed out that the dominant mechanism of alum coagulation in the range of neutral pH (6.5-7) was the charge neutralisation and enmeshment or enmeshment in major. Although overdosing of coagulant might result in the re-stabilisation of particles, the floc formed from those particles was still large and sufficiently dense to settle at the end of the process.

Neural Network Architecture

In this study, training and testing were performed by using Matlab Version 6 (The Mathworks Inc., US) neural network programming. The architecture of the developed FBPN consisted of three layers with 10 input neurons on the input layer, 16 neurons on the hidden layer and 1 neuron on the output layer (Figure 6). Each input neuron on the input layer represented current changes of fractal value [ΔDf(t)] and the last nine consecutive fractal value changed of ΔDf(t-1), ΔDf(t-2), ΔDf(t-3), ΔDf(t-4), ΔDf(t-5), ΔDf(t-6) ΔDf(t-7), ΔDf(t-8), ΔDf(t-9). The output layer neuron represented the speed of pump whether at full speed (1) or fully stopped (0). The number of neurons

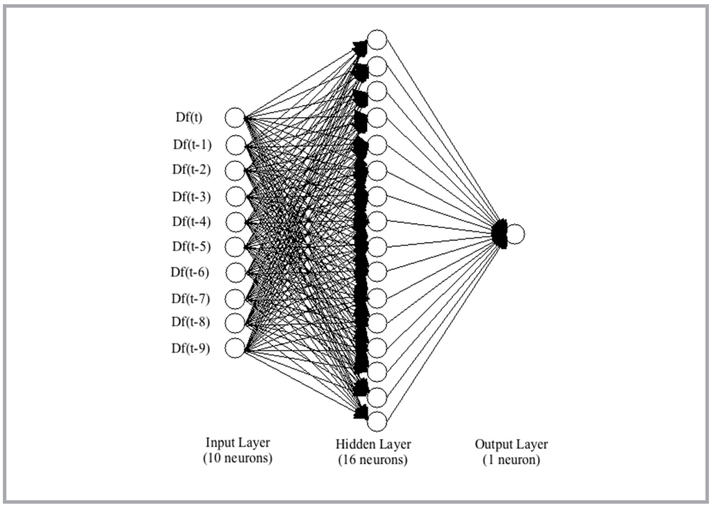

Figure 6 The architecture of the developed neural networks in recognising the pattern of fractal dimension during a coagulation-flocculation process

on the hidden layer was determined based on performance of the network during the training and testing stages. The treshold limit of 0.1 was set for the actual output, meaning that any actual output value larger than the treshold limit was defined as '1', i.e. the pump would dose the coagulant-flocculant agent at full speed or else the pump would be swithced off ('0') if the actual output was less than 0.1.

Performance of Pattern Recognition via Neural Network

Training process was conducted with 536 real data from 24 different runs. The session was initiated with smaller number of neurons on the hidden layer, and then was gradually increased until the achieved MSE was less than 0.0001. During the training session, the learning rate is adjusted to accelerate the convergence of the network. The network converged with 7181 epochs, with the hidden neurons of 16. The training performance is shown in Figure 7. The reliability of the developed neural network system was tested with other 216 sample data obtained from the other experimental runs. The neural network system showed a good recognition performance with 95% success rate. Figure 8 compares the calculated and actual network output for the tested samples. And, the neural network training results are summarised in Table 1.

Table 1: Neural Network training results

Parameter	Results
Input neuron	10
Hidden neuron	16
Output neuron	1
Number of epoch	7181
Training goal	0.0001
Momentum factor	0.6
Learning rate	0.2
Learning performance	0.000999682
Testing sample	216
Testing percentage	95%

5. CONCLUSIONS

This paper has presented a reliable low cost floc sensor to measure changes in floc size using fractal analysis based system on a real-time image of flocs during coagulation-flocculation process. Feed forward

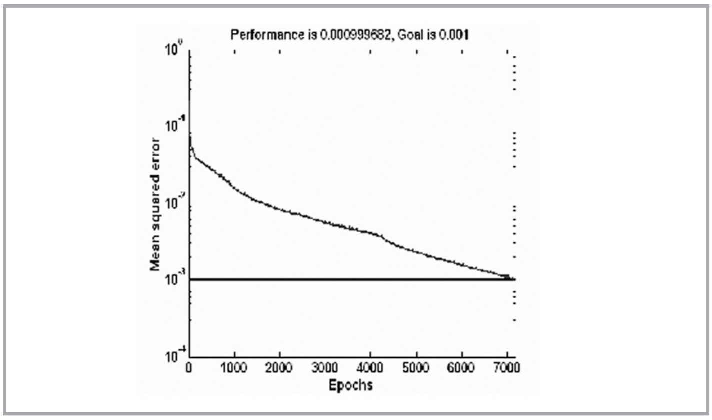

Figure 7 MSE vs. Eropah

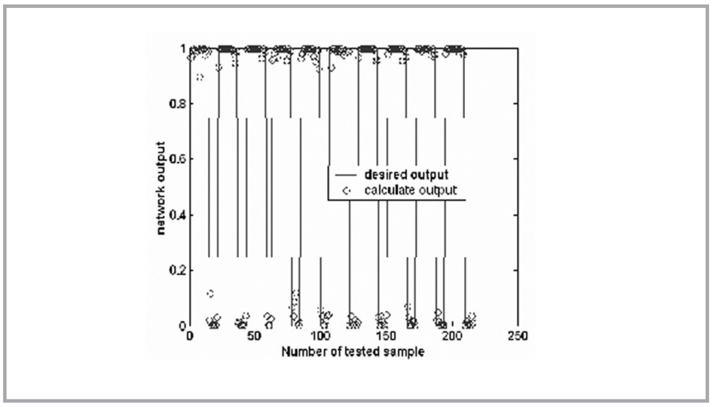

Figure 8 Actual and calculated network output for tested samples

back propagation neural network system was developed to recognize fractal profile obtained from experimental batch runs. Overall performance of training and testing of neural network system shows that the developed neural networks system was able to recognize the fractal profile during the coagulation-flocculation process. In future, the research will concentrate on developing a neural network based control system to control coagulation-flocculation process based on this neural network training and testing results.

ACKNOWLEDGEMENTS

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PROFILES

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