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An Intelligent Modeling of Coagulant Dosing System for Water Treatment Plants based on Artificial Neural Network

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Abstract: Coagulation –flocculation process remains a very essential part in the water treatment chain. It involves both physical and chemical phenomena and hence susceptible to high percentage of errors due to human factor. In order to reduce this percentage error and obtain optimal treatment efficiency, an intelligent coagulant dosing based on Artificial Neural Network (ANN) was proposed. Design of the Coagulant dosing using processed Moringa oleifera seed as coagulant was achieved through ANN that helps in water quality forecast and soft measure. Effort was made to suggest the optimization tips in the form of Artificial Intelligent tools that can be used for optimization of coagulation process. Such coagulant dosing based ANN will be a useful method to address most errors common in water treatment cause by human factors. Experimental results with simulated and real data show that the newly developed system is able to accurately predict coagulant dosage needed in water treatment for a small size rural community. The correlation between actual and ANN estimation of coagulant dosing model is 0.97 of 1.00. This high Correlation of coefficient indicates that the ANN model is a perfect match.

Key words: Artificial Neural Network, Back propagation algorithm, Coagulation, turbidity, water treatment.

INTRODUCTION

Water is indispensable to life. Water supply and sanitation are basic needs required to solve survival problems. However, waterborne diseases still kill on the average 25,000 people every day in developing countries while millions suffer the debilitating effects of these diseases (Kalbamatten and Burns, 1983). The basic human physiological requirement for water is about 2.5litres per day (Gleick, 1996) Drinking water is obtained from different sources like well, river etc. This drinking water should be free from chemical as well as other contaminants, since the potential of contaminated water to transmit diseases is very high. For instance, a person with cholera excretes about 1013 bacteria each day (Gleick, 1996; Microbiology, 2010) Various impurities, from branches of trees, human and animal waste to invisible microorganisms, may be present in these waters, to render the water safe for drinking, it has to be treated property. Conventional water treatment plant for portable water is shown in Figure 1.

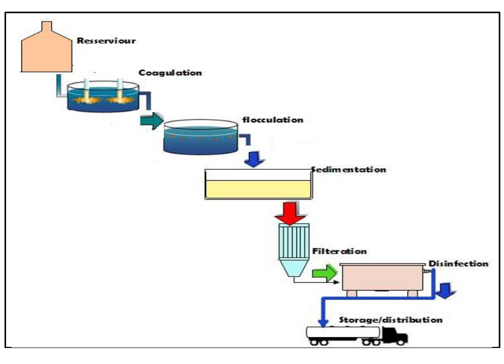

Fig. 1: Conventional Water treatment process.

Conventional coagulation–flocculation-sedimentation practices are essential pretreatment for many water purification systems. The processes agglomerate suspended solids together into larger particles so that physical filtration processes can remove them easily. Particulate removal by these methods makes later filtering processes more effective. A coagulant is added to source water to facilitate bonding among particulates.

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Coagulants work by creating a chemical reaction and eliminating the negative charges that cause particles to repel each other. The coagulant-source water mixture is then slowly stirred in a process known as flocculation. This water churning induces particles to collide and clump together into larger and more easily removable clots, or “flocs.”

The process requires chemical knowledge of source water characteristics to ensure that an effective coagulant mix is employed. Inappropriate coagulants make these treatment methods ineffective (Cheng, *et al.*, 2010). The most widely used coagulant is aluminium sulphate which is commonly called as alum. Certain health hazards have been related to the presence of aluminium residuals following its use in water treatment (Rondeau, *et al.*, 2001). Recently, researchers are turning toward chemical free coagulants such as using seed of M*oringa oleifera* (Muyibi, *et al.*, 2001; García-Fayos, *et al.*, 2010; Ali, *et al.*, 2009). Natural coagulants such as *Moringa oleifera* are usually presumed safe for human health (Ndabigengesere and Narasiah, 1998; Sutherland, *et al.*, 1994). Studies have found the *Moringa oleifera* seeds are non-toxic, and recommended its use as coagulant in water treatment in developing countries (Folkard, *et al.,* 1994; Bina, *et al*., 2010; García-Fayos, et al, 2010). For this paper, *Moringa oleifera* is use as the coagulant.

The chemistry of coagulation/flocculation consists of three processes - flash mix, coagulation,and flocculation. Each of these processes is shown in Figure 2 below. The main purpose of the coagulation/flocculation process is the removal of turbidity from the water. Turbidity is a cloudy appearance of water caused by small particles suspended therein. Water with little or no turbidity will be clear.

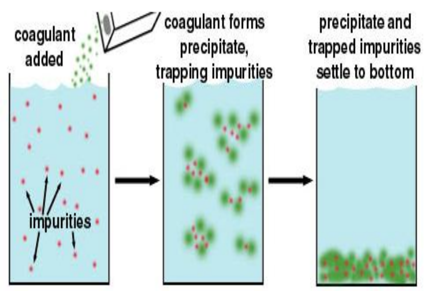

Fig. 2: Coagulation process(Source: Water, 2009)

Current Conventional water treatment plant use jar test to determine the coagulant dosage. Jar test is a laboratory technique where sample of water to be treated are poured into series of glass beaker and various dosage of coagulant are added to the beaker (Ali, Muyibi, Salleh, Alam and Salleh, 2010). It is empirical process which involves manual calculation of the relationship between the parameter given and selection. With the use of ANN, it introduces criteria given for selection and optimization is done very fast, efficient and removal of uncertainty before the water is supplied to the public.
In this paper, only coagulation dosing model will be design for a small- sized rural community water supply.

Artificial nueral network in water treatment:

A. Related works:

Water industry is now facing increased pressure to produce higher quality treated water at a lower cost. The efficiency of a treatment process closely relates to the design and operation of the plant. Most of the design and operation are still based on human experts. However decision making becomes a very hard because the human experts, who have to make decisions, can hardly process the huge amounts of data. To improve the operating performance and decision making process, an artificial Intelligence tool is needed. Recent works have taken advantage of artificial intelligence in Neural Network to design water treatment process. Owing to the inherent characteristic of ANN like learning and adaptive capabilities, pattern mapping and classification and ability to generalize, not only to reproduce previously seen data, but also provide correct predictions in similar situations gives the trained networks ability to infer. This offers a convenient way to reduce the amount of data as well as to form an implicit model without having to form a traditional, physical model of the underlying phenomenon (Pillai, 2009).

(Mirsepassi, Cathers and Dharmappa, 1995) have used ANN in real time operation of water treatment plants in which was use to learn the non-linear performance relationships of historical data of a plant. Therein a backpropagation network is used to determine the alum and polymer dosages so as to provide operational guidance for plant operators. Researchers like (Dogan, *et al*., 2007) have used ANN to develop a model for predicting and forecasting daily Biochemical oxygen demand (BOD) needed in inlet of wastewater biochemical treatment plant. Similarly, a neural network was adaptively use to model the control of a continuous wastewater treatment process by (Syu and Chen, 1998). A Back-propagation algorithm was applied to determine pH which was found to be a one of the factors affecting the coagulation condition of the suspended particles during the treatment process. Likewise (Raduly, Gernaey, Capodaglio and Mikkelsen, 2007) used Neural networks to evaluate the performance of wastewater treatment plant, due the fact that the plant behavior is affected by a wide range of influent disturbances, NN was used to combine an influent disturbance generator with a mechanistic waste-water treatment process to model the influent time series. Recently (Wang, 2010) used Auto-Associative Neural Network (AANN) is use in fault detection and sensor data validation in water treatment plant. Similarly, (Xiaojie, *et al.*, 2011) have reported the application of Feed-forward artificial neural network to establish network model in order to predict coagulant dosage of water plant.

METHOD AND MATERIALS

Artificial Neural Network (ANN) as emerged as a powerful tool for computational model based on biological neural networks (Haykin, 2008).

In most cases ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Figure 3 shows architecture of Feedforward NN model used in predicting coagulant dosage.

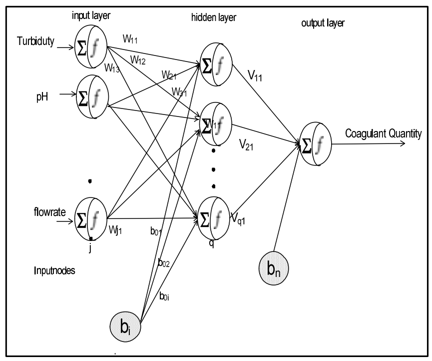

Fig. 3: Multilayer feedforward NN for prediction of coagulant dosage.

The input layer has 3 input neuron variables (pH, turbidity and flow rate) which have the most influence on the coagulant dosage. It has one output at the output layer which is the quantity of *moringa oleifera* required for treatment of water, given parameters.

B. Prediction of Moringa Oleifera Dosage:

The correlation between coagulant and raw water characteristics is non-linear relationship. Therefore the intelligent coagulation dosing is in two stages. First stage involves determination of the parameters affecting the prediction of optimal dosage of *Moringa* seed as coagulant. These parameters are then considered as input variables to the neural network for training to determine the quantity of Coagulant need for treating water. The parameters used are the turbidity level, that is low, medium and high. Determination of the category of turbidity is crucial in the dosing system because this serve as input to the next stage of the NN. The final parameters are the turbidity levels, flow rate, pH value and coagulant rate (passive parameter). 200 samples were used for each turbidity level. Jar test were conducted to obtain the coagulant rate. The river water for the jar test was collected from Sungai Pusu at the International Islamic University Malaysia campus, results of coagulant dosage for different turbidity levels (Low 20-70 NTU, Medium 71-160 NTU and High >160 NTU) is as shown in table 1.

Table1: Jar test result for river water of low, medium and high turbidity

Turbidity Level	Input Turbidity (NTU)	Coagulant Dosage *moringa oleifera* (mg/L)
Low	20-70	0.05
Medium	71-160	0.10
High	>160	0.20

C. ANN Training and activation function:

The network is composed of a set of nodes/neurons and connections arranged in layers. Each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and passed through an activation function which scales the output to a fixed range of values. The backpropagation (BP) algorithm (P. McCollum, 2009 ; Chun-Yang 2010) was used for the training .

BP algorithm is used in either sequential or batch training, which consist of four main steps as follows:

1. Initialization: set all weights and threshold level to random number, uniformly distributed in small range (Simon, 1999)
2. Activation: activate the forward phase of the BP algorithm by applying input and desired output
3. Weight training: update weights in the backward phase by propagating the error backwards
4. Iteration: increments iteration number *p* by one and repeat the cycle from step 2 until the overall error value drops below some predetermined threshold.

From Figure 3, for the training data input (turbidity, flow rate and pH value) is represented by *X* and weights by *W*, Hidden layer H. For vector $X_m = (x_1, x_2, \ldots x_m)^T$ is applied to input of the network, the network input/output relationship is given by;

$$y(n) = f\left(\sum_{q=0} H_q V_{qi} + b_n\right) \text{ and}$$

$$H_q = f_h\left(\sum_{m=0} X_m W_{hm} + b_i\right) \tag{1}$$

Where W_{hm} is the weight between input and hidden neuron, V_{qi} weight between hidden neuron and output neuron , b_i is for the bias term of hidden neuron *i* while b_n is the bias of output neuron *n*.

In order to obtain best training iteration, training was terminate at interval of hundred iteration and the network error developed as follow::

$$E = y_n - d_n \tag{2}$$

where d_n is the desired output and y_n is the output of network. The objective is to find the set of parameters that minimize the sum of the squared of the error function, where the average sum square error of the network is defined as;

$$E = \frac{1}{N}\sum_{n=1}^{N}(y_n - d_n)^2 \tag{3}$$

where *N* is the total number of neuron in the output layer. The network weight update is given by;

$$W_{hm}^{new} = W_{hm}^{old} + \Delta W_{hm} \tag{4}$$

Where

$$\Delta W_{hm} = -\eta \, \nabla E|_{W_{hm}} \tag{5}$$

η is the learning rate, $\nabla E|_{W_{hm}}$ is the gradient of the cost function.. For the activation function, the sigmoid transfer function is used. Given by:

$$f(z) = \frac{1}{1 + exp^{-\lambda z}} \tag{6}$$

where the derivatives of $f(z)$ is

$$f'(z) = z(1 - z) \tag{7}$$

RESULT AND DISCUSION

It is assumed that for a small rural community of about 2000 population, water consumption per day per person is about 150liters. Therefore for the total community population will need flow-rate of 30000liter per day. Six hundred turbidity parameters for low high and medium were generated randomly (200 for each level). 40% of the data sets were used for training subsequent 40% for test and 20% for validation. The ANN was trained using 500 iterations. This process took about 2munites to complete the iterations. Figure 4 show the network training for 500 iteration with error of 0.0001.

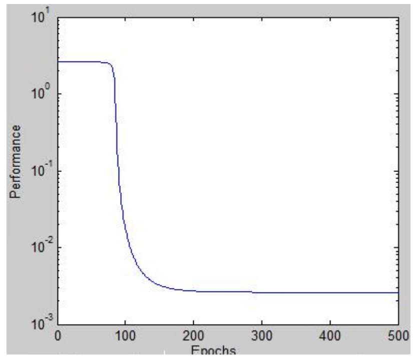

Fig. 4: NN training for 5000 epoch with MSE of 0.0001.

Table 2 shows the statistical parameters, indicating that the ANN produced a reliable estimation of M*oringa oleifera* dosages based on the input turbidity, pH and flow rate. The Coefficient of efficiency exceeded 0.97 indicated that the model estimation is very close to the observed value. Correlation coefficient shows the relationship between the NN prediction and actual value. Correlation coefficient of 1 indicated a perfect match of the model. Meanwhile the mean absolute error of 0.0071 implies that the error is highly insignificant which signifies that a very high accuracy is achieved by the model.

Table 2: The best result obtained from ANN

Coagulant	Statistical Parameters				
	Coeff. of efficiency	Corr Coeff.	RMSE	Mean Absolute error	MSE
Moringa Oleifera	0.9778	1.000	0.0081	0.0071	0.0001

Figure 5, shows the validation plot of predicted and actual dosing. NN model accurately determine closely the dosage required for the varying turbidity. It can be seen that for low turbidity input (20-80NTU), the predicted *moringa oleifera* dosage is observed at 0.0580 mg/L while the actual is 0.0500 mg/L. The medium turbidity for predicted ANN model was recorded at 0.1019mg/L while the counterpart actual dosage is 0.1000mg/L. NN coagulant dosage for high turbidity input scored 0.188 mg/L while actual is 0.2000 mg/L. This validates that NN model estimate for the coagulant dosage is accurate.

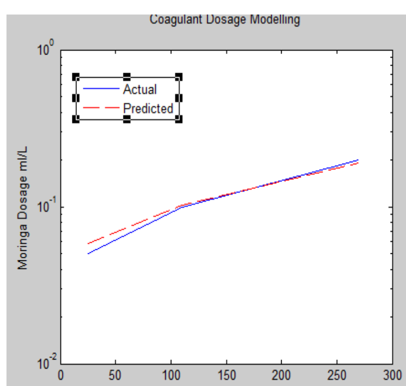

Fig. 5: Varying turbidity and required coagulant dosage (mg/L).

After determination of the correct dosage of each turbidity level, the model was used to estimate the quantity of coagulant needed when flowrate and turbidity rate is applied. Figure 6 shows the correlation between actual and the estimate coagulant (in kg) needed for daily treatment of water in treatment plant with a flowrate of 30000 litres of varying turbidity. The bar chart shows that for low input turbidity, the actual and estimated are very close values. 1.5kg of *Moringa oleifera* is needed. While ANN is estimated as 1.7kg to treat 300000 litres of water. For medium turbidity input of 300000 litres, ANN estimate 3.1kg of coagulant while the actual is 3.0kg. This is very interesting result because the difference is just about 3% which is insignificant value. It important to note that for the high turbidity input, ANN estimated 5.7kg of coagulant while the actual is 6.0kg. This indicated that the ANN model is performing better to reduce overdosing, it is better by 5%.

It can be deduced from Figure 6 that the estimated coagulant and actual coagulant needed for treatment of water are closely related. This means that without carrying out daily jar test, the ANN model can be used to predict the quantity of coagulant needed for water treatment. This can also be used as an automated dosing system without human intervention for real online system operation.

For high turbidity estimate, the value significantly reduced, this shows that in treatment process, it reduces overdosing which implies reduced cost.

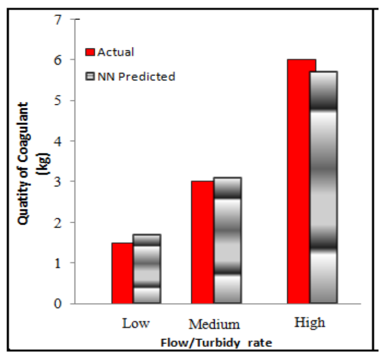

Fig. 6: Predicted and actual quantity of coagulant.

Conclusion:

The ANN predictive model for coagulant dosing can make the operation of water treatment plant more effective and accurate. The less error produced by ANN model indicated effective utilization of resources. The correlation between actual and predicted model is 0.97 of 1.00. The High Correlation of coefficient indicates that the NN model is a perfect match.

It is also pertinent to note that for high turbidity, the quantity of coagulant required is reduced which implied reduced in cost and over dosing.

One of the advantage of the ANN dosing model is that there will be no need for jar testing again, it also help in operational cost reduction, reduced error in dosing and ensuring quality of treatment process..

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