Artificial Intelligence Based Alum Dosage Control in Water Treatment Plant

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***Abstract*—Supplying good quality of drinking water is a challenging task during the rainy season and floods. During this period water becomes highly polluted with suspended solids which increase the water turbidity. Alum is used to reduce the turbidity of the water. Typically in water treatment plants alum dosage is decided by the Jar test and the desired alum dosage is added manually. This research proposes an automatic alum dosage mixing process. The alum dosage is controlled by an intelligent controller which consists of a dosage predictor, an inverse model of the dosage pump and a Pulse Width Modulation (PWM) controller. The optimal alum dosage is predicted by the dosage predictor. The PWM controller controls the flow rate of the alum dosing pump. This proposed method has been implemented in a laboratory based water treatment plant and it ensures the automation in water treatment plant to supply good quality drinking water.**

Keyword-Chemical dosing, Dosage predictor, Feedforward controller, Pulse width modulation, Water treatment plant

I. INTRODUCTION

The treatment of water aims at providing quality drinking water to the public by removing suspended solids. The removal of turbidity is an important component of the water treatment. The water treatment plant includes three main stages namely, coagulation, flocculation, and sedimentation [1, 2]. Coagulation is a fast mixing process where alum is mixed with raw water. Here alum acts as a coagulant. Rapid mixing leads to the formation of a sticky substance called floc. Flocculation is the process of slowly mixing the coagulated water and thereby increasing the probability of particle collision. The unstable particles collide and stick together to form larger flocs. After raw water and chemicals have been mixed and the flocs are formed, the water containing the flocs flows to the sedimentation or settling basin. Because the floc has a higher specific gravity than water it settles in the bottom of the sedimentation tank [2]. The flocs settled at the bottom of the sedimentation tank are called sludge which will be removed frequently.

The purpose of dosage control is to reduce the turbidity of the drinking water to the accepted standard. Feed forward controller is preferred to control the coagulant dosage in the water treatment process [3].The quality of the water is measured at the input side of the water treatment plant and the desired amount of alum must be added to take corrective action. In the previous literature studies, prediction model of coagulant dosage was developed using neural network [4]. The prediction model of Artificial Neural Network (ANN) is compared with regression model and time series models; the ANN model shows precise prediction [5]. Prediction model of optimal alum dosage and treated water quality parameter were developed using ANN [6]. The prediction models of coagulant dosage were developed using ANN and Adaptive Neuro Fuzzy Inference System (ANFIS). In presence of input water quality parameters, ANN model is better than ANFIS and in the absence of input water quality parameters ANFIS performs better because one of the input parameter is previous day coagulant dosage [1].

In all the above studies, ANN and ANFIS networks are assisting the plant operator for selecting the optimal alum dosage. This paper focuses on the development of an intelligent control of the alum dosing pump using a steady state feedforward controller, which uses artificial intelligence and a PWM controller. The steady state feedforward controller is sufficient when only load change occurs in the process [7]. The load change considered here is the changes in the raw water quality parameters. The feedforward controller detects the disturbances which enters the process and adjusts the manipulated variable due to which the controlled variable is held constant [8]. The proposed control strategy is tested in a laboratory based water treatment plant and the same approach can be implemented in any real time water treatment plant.

II. METHODOLOGY

The artificial intelligent networks ANN and ANFIS require lot of data for training and testing the network. The data collection is done by performing Jar Test for 95 water samples. From the Jar test optimal alum dosage is determined for each sample. These data are used in the development of intelligent networks. The inputs for the networks are water quality parameters like turbidity, pH and conductivity and the output is optimal alum dosage.

A. Performance Index.

The network created using ANN and ANFIS were validated by correlation coefficient and root mean square error. Correlation coefficient's value nearer to one shows close relation between actual and predicted values. For root mean square error the value nearer to zero shows the accuracy of predicted values. The Eq. 1 and Eq. 2 shows the correlation coefficient (R) and Root Mean Square Error (RMSE).

$$R = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}}, \tag{1}$$

where n is the number of samples, x, y are the actual and predicted values of this study

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(x-y)^2}. \tag{2}$$

B. Artificial Neural Network.

Neural network is suitable for predictive control [9, 10]. Neural network was used to predict the optimal alum dosage. In the development of ANN, 95 samples were used and among the 95 samples 80 samples were used for training the network and 15 samples were used for testing. The trained data were not involved in testing. The input and output mapping is performed by the neural network. The inputs to the network are turbidity, pH and conductivity. The output is alum dosage. The MATLAB nftool was used for the network development. The network was trained with levenberg-marquardt backpropagation algorithm [11]. Since this research concentrates on the static steady state behaviour of dosage control feed forward neural network [12, 13] was chosen.

C. Adaptive Neuro Fuzzy Inference System.

In the case of nonlinear mapping between the inputs and output, ANFIS shows better performance [14]. ANFIS was used to map the turbidity, pH and conductivity with the alum dosage. The inputs are turbidity, pH and conductivity. The output is alum dosage. It used 80 samples for training and 15 samples for testing. The MATLAB software was used for creating the network. Each input has 2 member functions as shown in Fig. 1. The member function chosen was gbellmf. The genfis1 function generates fuzzy inference system structure using the training data. The input and output mapping was performed by the anfis function. The network was trained using 1000 epochs.

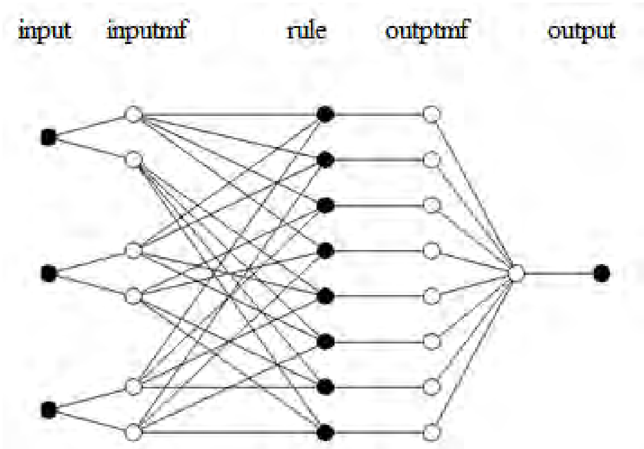

Fig.1 ANFIS Structure

III. REAL TIME IMPLEMENTATION OF DOSING CONTROL

The ANN and ANFIS networks developed were tested in the laboratory based water treatment plant. This plant included the three major water treatment processes namely coagulation, flocculation, sedimentation and a dosing tank with pump as shown in Fig. 2. The dosage was fed to the coagulation tank. The option for removing sludge is given in the sedimentation process. If the load disturbance frequently affects the process, feedforward control is suitable [15]. In the water treatment process, feed forward controller was opted since the controller has to take the corrective action immediately after changes occur in the raw water quality. Input raw water quality parameters were measured and the required alum dosage was added at the input raw water immediately in the coagulation tank.

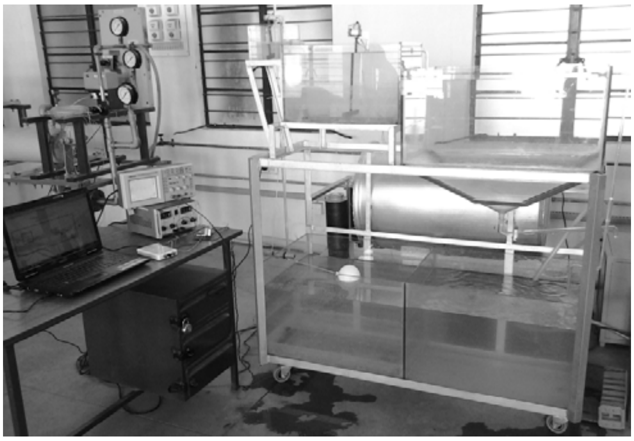

Fig.2 Laboratory Based Water Treatment Plant

The coagulant used is alum which is available in the form of solid. Controlling the flow rate of solid alum is difficult. Hence a saturated solution of alum was prepared by mixing known quantity of alum with known quantity of distilled water. 10 liters of water is required to fully dissolve one kg of alum. This saturated solution was fed to the water treatment plant by a pump. As per the laboratory based water treatment plant requirement the pump must be operated between 0.72464×10-6 to 5.0×10-6 cubic meter per second. The pump speed is controlled by PWM [16].

A. Pulse Width Modulation.

Open loop control was implemented for the alum dosing system. PWM is used by most of the open loop control systems. In such control systems, duty cycle is the manipulated variable which controls the controlled variable [17]. PWM is a commonly used technique for controlling the electrical devices. The control action was derived by controlling the average value of the voltage fed to the pump. The power supplied to the pump was varied by the duty cycle. Power supplied to the load was increased by keeping the switch in on position for a long period compared to the off period and the power supplied to the load was decreased by keeping the switch in off position for a long period compared to the on period. Duty cycle is expressed in percentage, 100% being fully on and 0% being fully off. The alum flow rate through the pump was decided by the duty cycle. IC L298 acted as the switch between supply and the load. The pump was driven by 9 V DC.

B. Dosing Pump Calibration.

The raw water flow rate was fixed at 3.33×10-5m3/sec. The amount of alum required for the water treatment process was calculated using ANFIS, because of high predicting capability. The manipulated variable in the dosage control system was the duty cycle of the PWM controller.

In the proposed dosing system it is necessary to find the duty cycle for various flow rate of the pump. To determine the relation between duty cycle and the flow rate an experiment was conducted to find the flow rate of the pump for various duty cycles. Flow rate was measured using a standard jar. The pump was switched on with any one duty cycle and the process fluid was allowed to fill the standard jar. The time taken to fill one liter of process fluid in the standard jar was found using a timer. The same procedure was continued to find the flow rate of each duty cycle. A polynomial equation model for the pump was developed using the MATLAB curve fitting tool. The input to the model is flow rate and the output is duty cycle hence it is termed as inverse model of the dosing pump. Thus the inverse model of the dosing pump decides the duty cycle. This duty cycle was given as an input for the PWM controller.

The desired flow rate of the dosing pump was calculated using the LabVIEW. ANFIS network developed by the MATLAB was invoked by LabVIEW MATLAB script. The input to the ANFIS controller was raw water turbidity, pH and conductivity. The output is alum dosage. From the alum dosage, the dosing pump flow rate was calculated and the inverse model of the dosing pump determines the required duty cycle for the PWM controller. Thus the PWM controller controls the dosing pump with the desired flow rate. The overview of intelligent dosing system is shown in Fig. 3.

The real time implementation is shown in the Fig. 4. The evalfis function in the MATLAB script determines optimal alum dosage using the inputs and the ANFIS network. The inputs are turbidity, pH, and conductivity.

The dosing pump was interfaced with the LabVIEW through NI myDAQ which is an USB based data acquisition card.

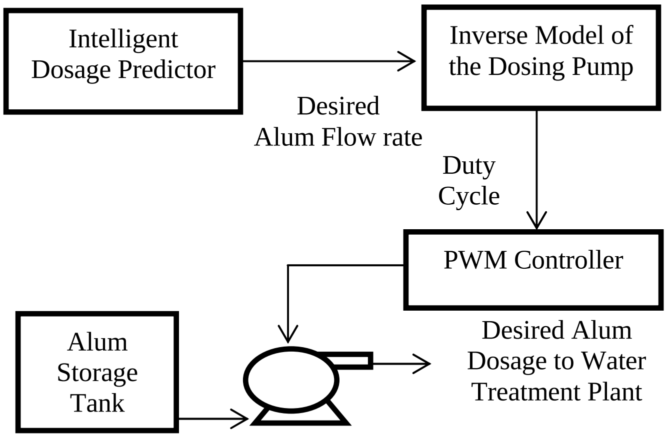

Fig. 3 Intelligent dosing control system

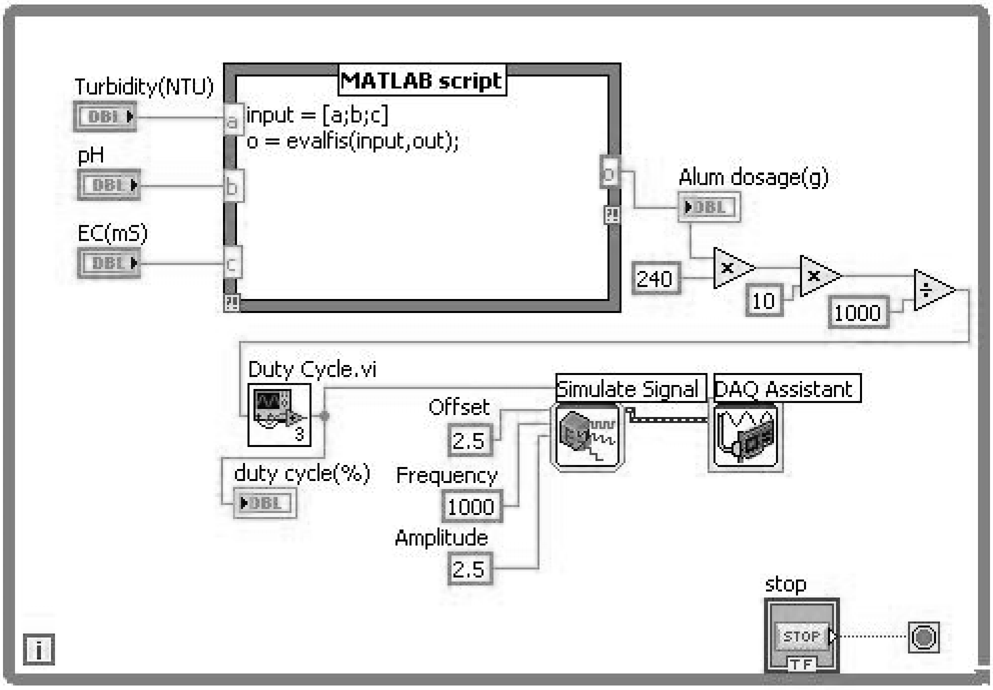

Fig.4 Implementation of intelligent dosing control system using LabVIEW

IV. Results and Discussion

This section includes the results of predictor model and the inverse model of dosage pump. ANN and ANFIS predictors have been compared and the efficacy of the inverse model of dosage pump is also described. The predictor networks are compared based on the correlation coefficient and root mean square error and the inverse model of the dosing pump is validated based on correlation coefficient of actual and the predicted duty cycle.

A. Predictor Model

The ANN network created by MATLAB was tested and validated using 15 samples. The actual and the predicted alum dosages of tested and trained data are shown in Fig. 5 and Fig. 6. The correlation coefficient of testing data is 0.6188 and the root mean square error is 0.3215. The training data has the correlation coefficient of 0.5832 and the root mean square error is 0.1706. Based on the correlation coefficient, the testing data has the close relation between the actual and the predicted alum dosages. The root mean square error is less for the training data. The testing and training data in ANN has few deviated predicted dosages.

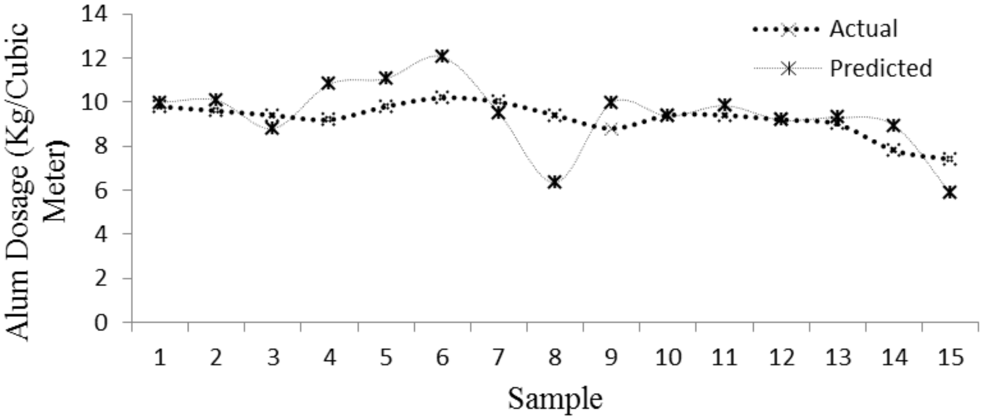

Fig. 5 Actual and predicted values of tested data in NN

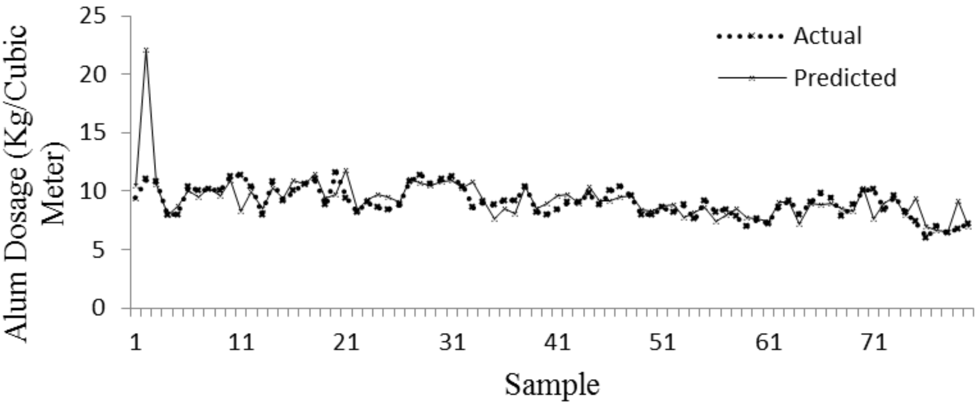

Fig.6 Actual and predicted values of trained data in NN

ANFIS network was also validated using the same 15 samples. Fig. 7 and Fig. 8 shows the actual and the predicted values of tested and trained data for ANFIS. The correlation coefficient of testing data is 0.831 and for training data is 0.834. So the ANFIS predictor has the close relation between actual and the predicted alum dosages. The root mean square error for the predicted dosages of testing data is 0.1161 and training data is 0.0781. So the root mean square error also very less when compared with the ANN predicted alum dosages.

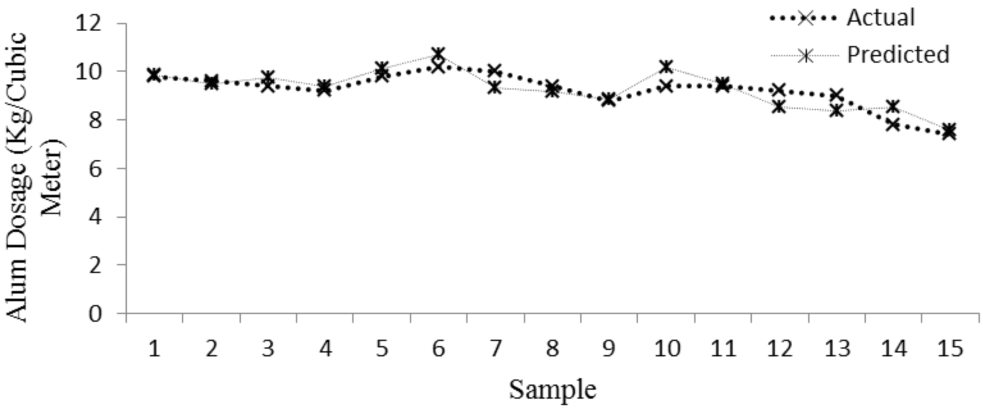

Fig.7 Actual and predicted values of tested data in ANFIS

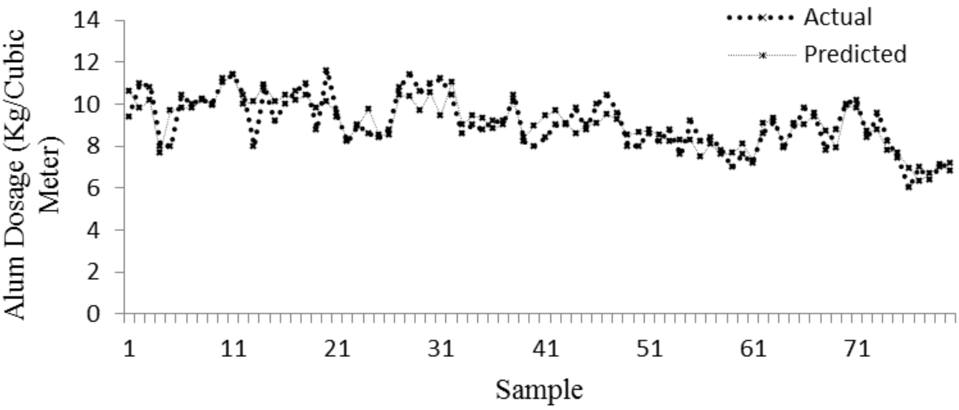

Fig. 8 Actual and predicted values of trained data in ANFIS

To compare the efficacy of both networks, correlation coefficient and root mean square error were used. The comparative analysis is shown in Table 1 which justifies the ANFIS efficacy.

Table 1 Comparative analysis of ANN and ANFIS

Network Type	**Data Type**	**Correlation Coefficient (R)**	**Root Mean Square Error (RMSE)**
NN	Testing data	0.6188	0.3215
NN	Training data	0.5832	0.1706
ANFIS	Testing data	0.8310	0.1161
ANFIS	Training data	0.8374	0.0781

From the above figures and the table it is clear that the predicted alum dosage from the ANFIS closely follows the actual dosage.

B. Inverse Model of the Dosing Pump.

The inverse model developed using MATLAB cftool decides the duty cycle for the PWM controller. The fitted and the actual duty cycles are shown in Fig. 9. The R- square value is 0.9974 hence the fitted and the actual data are very closely related. This inverse model was used in the real time control.

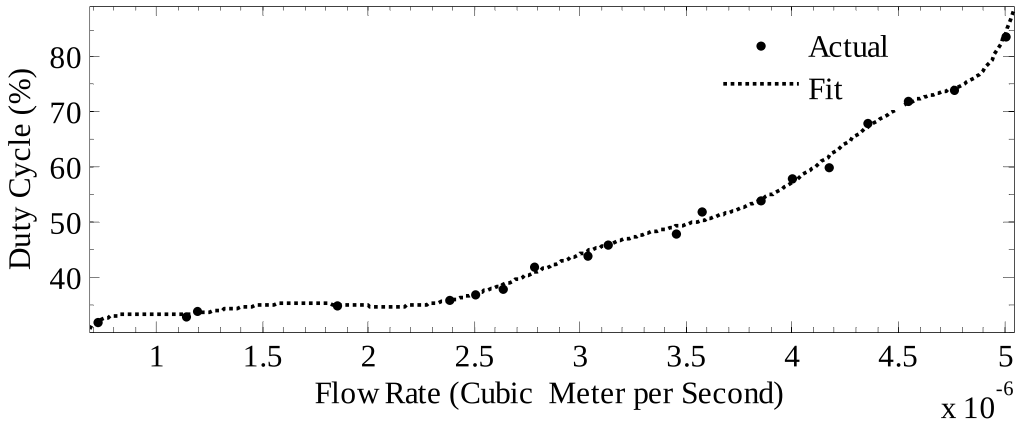

Fig. 9 Actual and predicted duty cycle for the PWM controller

V. Conclusion

An alum dosage predictor was developed using ANN and ANFIS. Both the predictors were compared. Because of the better predicting capability ANFIS was used in the real time implementation. The desired flow rate of the alum was found using predicted alum dosage. A PWM controlled pump was used to control the alum dosage. This intelligent steady state feedforward controller was tested with the existing laboratory based water treatment plant. The plant was interfaced with LabVIEW for automation. The proposed scheme can be adopted for the actual water treatment plants. This facility enables the automatic control of alum dosage and thereby serves human community with good quality drinking water.

ACKNOWLEDGEMENT

The Authors sincerely thank Karunya University for providing all necessary resources to carryout the above research work.

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