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Research Article

Optimal Alum Dosage Prediction Required to Treat Effluent Water Turbidity using Artificial Neural Network

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Abstract

The present study was conducted for the purpose of simulation of some units that was used intensively in a conventional water treatment plant. A pilot plant used to test the simulated raw water by mixing kaolinite clay with tap water and treated with difference alum dosage. The simulation tool that was used recently based on artificial intelligence and experimental tests, which is the neural network (ANN). The ANN was used to simulate and predict the required alum dosage for treated the turbidity in raw water. The experimental work was studied in a pilot plant scale, where a rig was designed and manufactured to simulated these treatment units. The synthetic turbidity was used to create the turbidity water that was used in this work. The experimental study was consisted of four runs with different inlet flow rate; each run contained five different influent turbidity sets (25, 50, 75, 100, 150) NTU and ten series of alum dosage varies form (5 – 50) mg/l for each turbidity set. The collected data for the neural network was about 200 set of data. The inverse model had a nine input parameters and one-output parameters, which is the alum dosage. The correlation coefficient of this model was 0.96, while the error indices were 4.1 mg/l, 2.84 mg/l, and 13.3% for RMSE, MAE, and MAPE respectively.

***Keywords**: Artificial Intelligence; Artificial Neural Network (ANN); Inverse Model; Correlation Coefficient (R); Root Mean Square Error; Mean Absolute Error; and Mean Absolute Percentage Error.*

1. Introduction

In the last century engineers that involved in water treatments, faced principles, challenges to produce efficient and better water quality treatment plants and at the same time trying to minimize construction and operation cost. Treatment plant operation and design need many technical and nontechnical workers capable of manage and operate plants effectively. Design and operation of treatment plants needs range of knowledge and experience so that today's water treatment engineers need knowledge about fundamental of processes and practical experience. Pilot plants could link water quality factors and treatment plant variables. Likewise, operators and technicians can use the pilot plant study to optimize chemical feed and important information necessary for managing plants. Pilot plant and experimental studies are time consuming and sometimes costly for large treatment plants, so that examining of product water quality processes depends on the operator's experience (Syed, 2000).

Simulation and modeling is a term used for getting information about the unit or process before actually manufacturing and operating of that unit. Modeling process depends on the actual size of the unit and then scaled down to a small size but with full properties and characteristics of the actual size, which called prototype. After modeling, a full study will develop of the prototype for getting information useful in the future design and study any fatal error may occur. In water treatment simulation, it is not possible to scale down treatment unit and make a prototype so that there is another type of scaling which called pilot plant. In the last few years, the huge steps in artificial intelligence (AI) development, open new opportunity for modeling water treatment plant units. One of the most important AI tools used in the prediction of treated water quality is an artificial neural network (ANN). ANN used many times for online predication of alum dose, and residual turbidity after treatment (Serena and Norton 2008).

Zhang and Stanley, (1999) investigated modeling of coagulation, flocculation, and sedimentation processes in water treatment plant with an artificial neural network feed forward model. The model capable to predict the power activated carbon and optimum alum doses over different influent conditions. The model tried to find a recognizable repeated pattern between the influent and effluent parameters, the model will try to fit a past operation data record and found a pattern

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for modeling the actual microscopic reactions between parameters.

Guan and Shang (2008) studied of developing a neural network model to predict optimal coagulant dosage required for water treatment in water facility in north Taiwan. The poly aluminum chloride (PAC) used as a coagulant. Two models developed based on combination of neural network (ANN) with adaptive based fuzzy-network inference system (ANFIS) to assist in the prediction process of (PAC) dose. The treatment plant studied in this research was a conventional facility have a filtration, sedimentation, flocculation, and coagulation units.

Robenson, Shukor, and Aziz (2009) established of an inverse model capable to predict the optimal alum dosage required in the coagulation process of Sabah WTP in Malaysia. The proposed model tested for use in replace of the conventional Jar test to determine the optimal dosage. The multilayer perceptron neural network used to develop such a model, the optimum architecture of the network found by trial of many networks but the best network was [11-27-9-1] provided r-value of 0.95 and mean absolute error (MAE) of 0.024 mg/l. The artificial intelligence models used to overcome the limitations of the jar test in obtaining alum dosage.

Maier (2004) showed that modeling of alum dosage used in the coagulation process. Normally the optimum coagulant dose obtained by jar test, but this test is time-consuming, costly, and not effective for real time change in water quality. Many samples of water collected from a different number of sources in southern Australia and analyzed for water quality of raw and treated water, such as turbidity, color, and dissolved organic carbon (DOC), pH, residual alum, and alkalinity. About twenty-nine samples of water collected from 14 different sites in the Victoria states and South Australia. Two models developed for the coagulation process in this paper used.

2. Objectives of Study

The main aim of conducting this study is to develop a mathematical model using artificial neural network that capable to predict the optimal alum dosage required to treat effluent water turbidity from the simulation of pilot plant for (coagulation – flocculation – sedimentation) process in a conventional water treatment plant.

3. Materials and Methods

3.1 Introduction

Securing and conservation an appropriate water supply was one of the important steps in the human settlement development. The earliest study and enhancements primarily focused on the available water quantity. However, the increasing of population, and increasing water contaminant puts much more pressure on the quality of water sources. However, regulations became more sensitive, delicate, and more distinguished about water quality level.

3.2 Artificial Neural Network (ANN)

The ANN (artificial neural networks), which is commonly called neural networks (NN), has asserted right from beginning of the definition, that the brain of humans is processing data in a different way from the standard digital computer. The brain of humans is considered as a highly *complex, parallel, and high nonlinear processing computer* (system of information processing). It has the ability to self-discovery of its thematic constituents, which was referred to as *neuron* cell so it can do a certain computations too much quicker than any super-computer available today. To be more specific, the human brain normally performs perceptual recognition occupation in approximately 100–200 milliseconds, where a trivial take a great deal and longer time on a fast, and powerful computer (Baxter, 2002).

3.3 Multilayer Feedforward Neural Network

The details of a basic feedforward neural network are very easy to identify. On the left portion of the network there are the inputs to the first layer of neurons (input layer), followed by a network of interconnected neuron layers, and finally the outputs from the last layer of neurons. This network architecture, earning the feedforward network name from feeding the inputs forward through the each layer of neuron to the next layer in the network. The activation functions used in the neurons process do not affect the behavior of the network by feedforward the input signal.

3.4 Feedforward Backpropagation Multilayer Neural Network Training Algorithm

The choose of suitable activation functions as in figure (1) that listed previously for neural network training with the backpropagation algorithm will depend on the type and pattern of the output data.

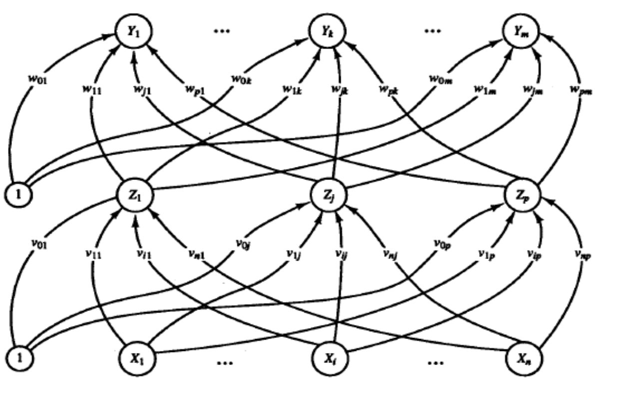

Figure 1 Backpropagation Neural Network with One Hidden Layer

The relationship between the value of the activation function and it is derivative, the log-sigmoid and tan-sigmoid have no additional math of the exponential required because the backpropagation need to compute the derivatives of the activation function (Fausett, 2000).

3.5 Data Division and Preprocessing

Once the neural network model parameters of input and output variables identified the datasets of modelling constructs and evaluated. Each data pattern initially may be examined for errors, outliers, and blank entries. Scatter plots of each variable can used to detect outlier values that must be excluded from the data sets. The remaining data sets will divided into three data groups:

1) The training group: the training set of data is the largest group and used to train the model and adjust the network weights.
2) The test group: this group used as a semi-independent check for evaluating the learning progress of the network. Without this group, the model simply memorizes the interactions found in each set of the training data and would not provide an accurate prediction on any data outside the training set.
3) The validation group: this group of data used as independent validation for the trained model after training. This group of data, which not exposed to the model and used to evaluate the prediction accuracy of the model.

3.6 Water Turbidity Preparation

The experimental work was conducted with synthetic turbid water.

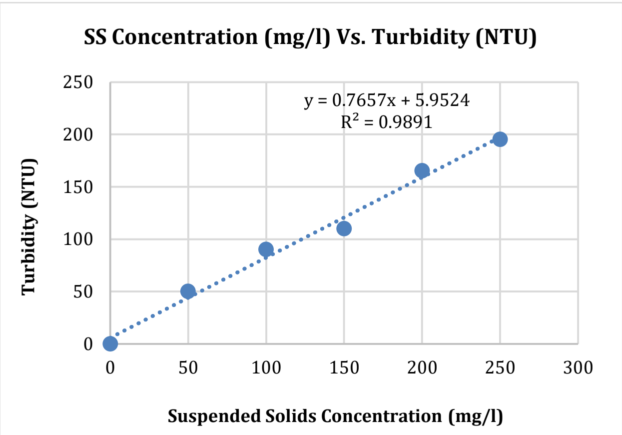

Figure 2 The Relationship between the Suspended Solids Concentration and Turbidity

Two tanks of 500-litter volume of each tank where used to store the turbid water, which pumped to the first tank (rapid mixing tank) by a centrifugal pump with 30 l/min flow rate. The kaolinite Clay $Al_2Si_2O_5(OH)_4$ was used to produce the synthetic turbid water required for each test set. The drawing of a experiment tests series conducted to relate the suspended solids (SS) with the turbidity (NTU) shown in figure (2), plotted line where used to get the fitted formula, which was used in the calculation of the initial level of required turbidity.

3.7 Chemical Preparation (Alum Preparation)

The alum $(Al_2(SO_4)_3.18H_2O)$ was used as a coagulant agent in the rapid mixing tank. The preparation of this coagulant has made by dissolving 15g of dry alum in a one liter of distilled water to preparing concentrated solution of the alum, six hour before any test. The concentrated solution added to the chemical tank (plastic tank with a volume of 20 litters) then diluted with 15 litters of tap water and mixed very well to get a solution of (1 g/l) of alum that was injected to the rapid mixing tank by a regulated dose pump to insure the required dose pumped to the tank.

3.8 Measured Parameters

Some indicators of water quality and parameters of WTP measured, recorded, and analyzed for both raw and treated water. The water parameters measured were turbidity, temperature, pH, and conductivities, while the measured WTP parameters were coagulation time, flocculation time, and surface overflow rate (SOR). These parameters were measured for both raw and treated water immediately after water sample collected for better and accurate results. The measurement of these parameters was taken every one hour. The next section will describe the devices used in the measuring process. All parameters were measured through following the details and procedures that described in the standard methods for water and wastewater tests and procedures.

3.9 Description of Experimental Apparatus

The experimental tests conducted in a pilot plant (lab scale device) consist of a rapid mixing tank (coagulation process), slow mixing tank (flocculation process), and sedimentation tank (settling process). The schematic diagram of the experimental

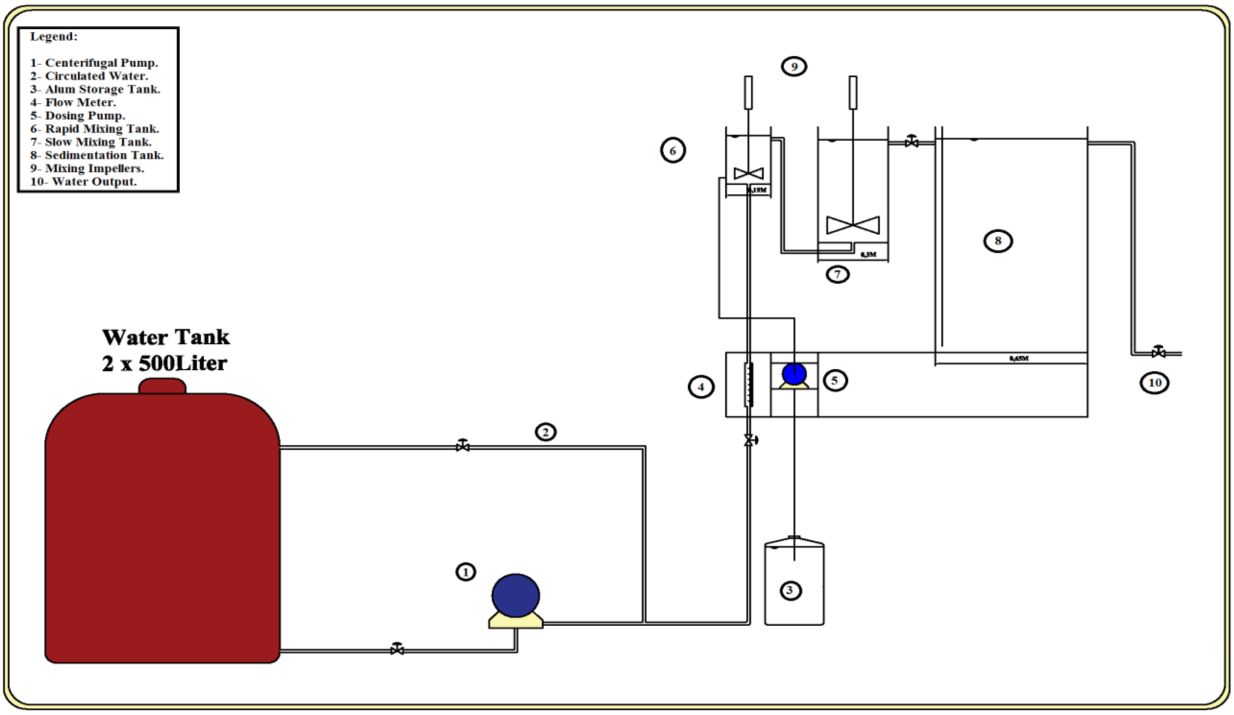

Figure 3 Schematic diagram of Experimental Apparatus

3.9.1 Rapid Mixing Tank

Rapid mixing tank was manufactured from glass 10mm thickness and glued with silicon. The purpose of using the glass tank was to do visual observation of the physical phenomena due to it is importance. This tank designed according to the specification and requirement of rapid mixing tank. The tank dimensions were 19cm, 19cm, and 21cm in length, width, and height respectively. The agitation process of this tank was obtained by mechanical impeller, where the speed of the impeller was kept constant at (110 RPM) for all experimental series held in the tank.

3.9.2 Slow Mixing Tank

Slow mixing tank was manufactured from glass 10mm thickness and glued with silicon, the reason of using glass tank because the visual observation is so important to watch the stages of floc formation that occurred in the tank. This tank designed with the specification and requirement of slow mixing tank. The tank dimensions were 30cm, 30cm, and 46cm in length, width, and height respectively. The agitation in this tank was obtained by a mechanical impeller, where the speed of the impeller was kept constant at (25 rpm) for all experimental series held in this tank.

3.9.3 Sedimentation Tank

Sedimentation tank was manufactured from glass 10mm thickness and glued with silicon. This tank designed by using the specification and requirement of the settling basin. The surface area of settling tank is important because it is controlled the surface overflow rate (SOR), which has effect on the settling efficiency. The surface area of sedimentation tank was multiplied by a factor ranged (1.5 to 2) to get high performance for the pilot plant sedimentation tank. The dimensions of this tank were 65cm, 30cm, and 100cm in length, width, and height respectively. The inlet was designed of a glass baffle 3cm away from the inlet and extended to the bottom of tank.

3.6 Experimental Procedure

A series of chemical experimental tests has been conducted in the pilot plant consists of a preselected treatment train (coagulation-flocculation-sedimentation), where a different alum dose and water turbidity examined in the tests. The following procedure was followed and conducted, the next section will describe the way that how each experiment conducted:

1) Set the required flow rate for the inlet raw water by adjusting the flowmeter. Preparation of synthesis turbidity water like (25 NTU) in each raw water tank. This step was repeated for each set of turbidity of the tests.
2) The chemical tank filled with the concentrated alum and diluted with distilled water until a dose of (1 g/l) was achieved. The required alum dose (5 mg/l) obtained by regulating the dosing pump to inject the required flowrate dosage.
3) Set the required agitation speed of 110 rpm and 25 rpm for rapid and slow mixing tanks impellers respectively. The coagulation time, flocculation

time, and surface over flowrate of each run were calculated and recorded with the alum dosage represents the WTP characteristics.

4) A raw water sample was withdrawn just before the rapid mixing tank from the circulated water line and all water parameters were measured.
5) A water sample has been withdrawn from the outlet pipe of the sedimentation tank then all parameters measured immediately and recorded.
6) The steps from (3 – 7) repeated for each dose value, and the stopping condition was the dose reach a maximum value of (50 mg/l). These steps were conducted in the same procedure for all test runs.
7) The steps from (2 – 7) repeated for each turbidity series, until the stopping condition was reached, the stopping condition was all the selected turbidity (25, 50, 75, 100, 150) has been finished for each set.

The steps from (1 – 6) repeated until the maximum number of runs for the selected flowrate (which were four times flowrate changed in this experimental work) has been finished and all required data recorded for each run.

4. Results and Discussion

This model will be used in the inverse process for alum dosage prediction. The inputs of this model will be all system inputs, which are coagulation time, flocculation time, surface over flow rate, influent turbidity, temperature, pH, conductivity, effluent turbidity and pH. These parameters have direct or suspect to have a direct effect on the effluent water characteristics. The model output was the alum dosage that was required for better removal of influent turbidity. This model may be used to help treatment plant laboratory staff in the evaluation of required alum dosage for the current influent turbidity as a replacement of jar test.

The training subset consists of (70%) from the available data that is 140 data pattern will introduce to the network. *The validation subset* is used to monitor the error that happened during the process of training. The validation subset consists of (15%), which is 30 data pattern. *The test subset* is used to check the prediction capabilities of neural network, which is mean that neural network predict not just remember the input pattern.

The neural network was chose to have [9-10-10-1] neurons for input, hidden, and output layers respectively, for the process model for effluent turbidity and pH prediction, figure (4) show the optimal architecture of the chosen network.

The (RMSEs), (iMAE), and (MAPEs) were used to evaluate the prediction error of the model. The MAE is a good indicator for the measure of the absolute predictive power of the different models and may help to check the process model predictions are good or not? The model error will be checked normality and skewness, where the expected error from the network will have a normal distribution trend. Table (1) show the process model evaluation and validation values.

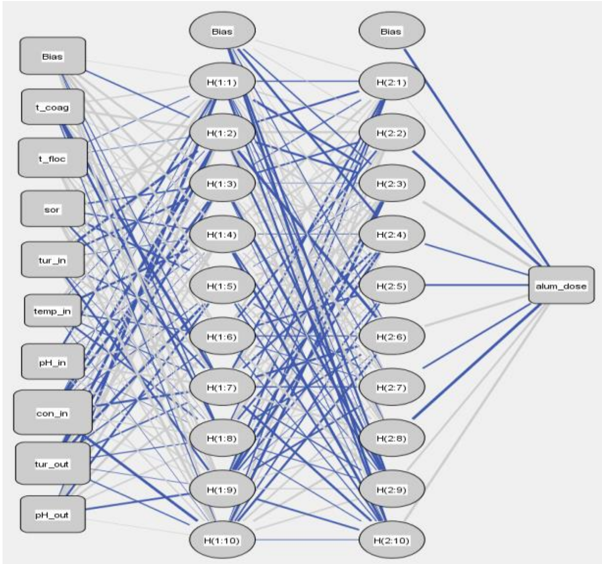

Figure 4 Optimal Inverse Model Network Architecture

Table 1 Summary of Error Measurements of Neural Network Inverse Model

Parameter	Predicted Turbidity	Predicted pH
Determination Coefficient (R^2).	0.92	0.749
Square Root of Mean Error (RMSE).	4.1 smg/l	0.19
Absolute Mean Error (MAE).	2.84 smg/l	0.14
Absolute Percentage of Mean Error (MAPE).	13.3%	2%
RMSE-Observed Standard Deviation ratio (RSR).	28.5%	50%

Figures (5) to (12) show the results of Observed and Predicted Effluent Turbidity for influent raw water turbidities of (25, 50, 75, 100, 150) NTU with different alum dosages (5 – 50) mg/l. The process model has been implemented to find the predicted system (pilot plant) effluent turbidity. The plot of observed and predicted turbidity will be discussed in the next figures.

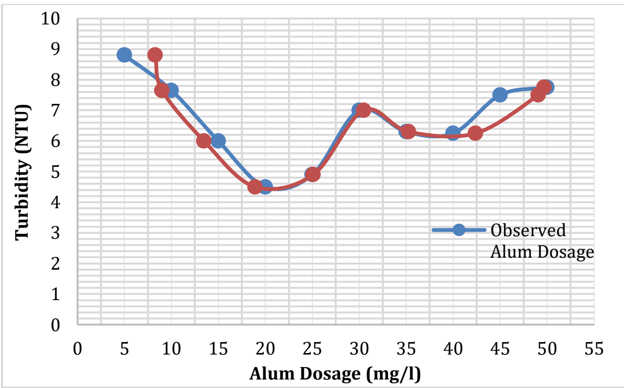

Figure 5 Plot of Observed and Predicted Alum Dosage with (25 NTU) Initial Turbidity for First Run

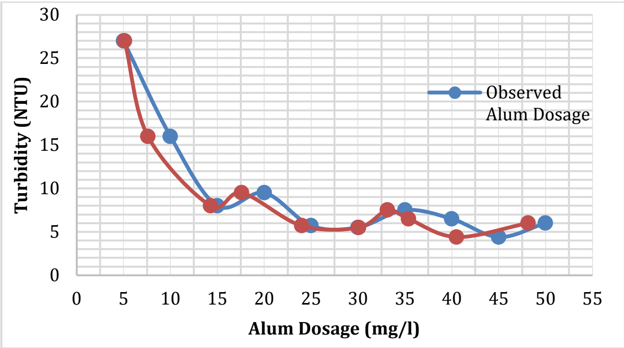

Figure 6 Plot of Observed and Predicted Alum Dosage with (75 NTU) Initial Turbidity for First Run

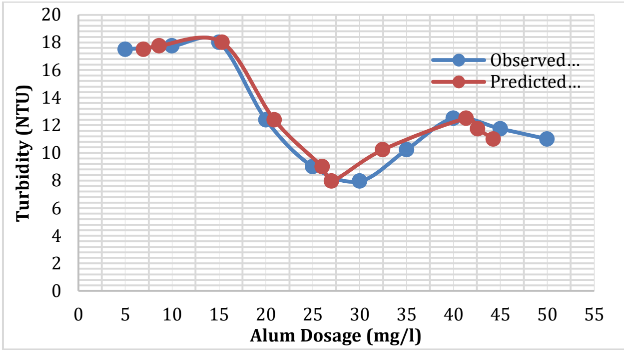

Figure 10 Plot of Observed and Predicted Alum Dosage with (100 NTU) Initial Turbidity for Third Run

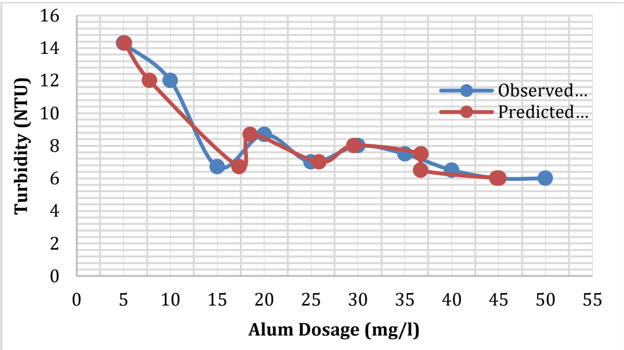

Figure 7 Plot of Observed and Predicted Alum Dosage with (25 NTU) Initial Turbidity for Second Run

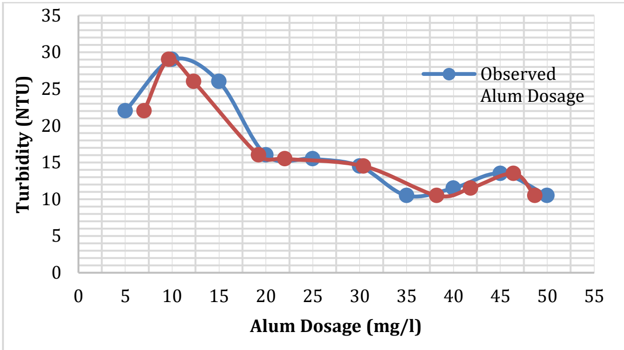

Figure 11 Plot of Observed and Predicted Alum Dosage with (50 NTU) Initial Turbidity for Fourth Run

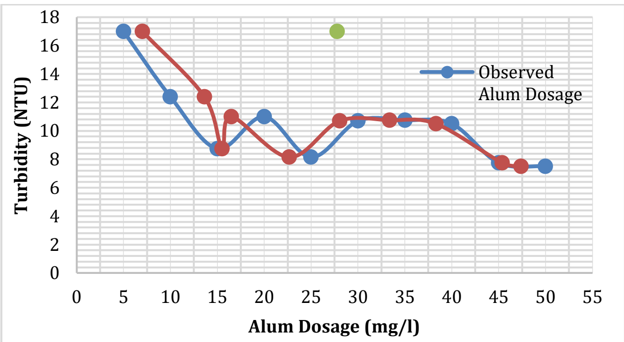

Figure 8 Plot of Observed and Predicted Alum Dosage with (75 NTU) Initial Turbidity for Second Run

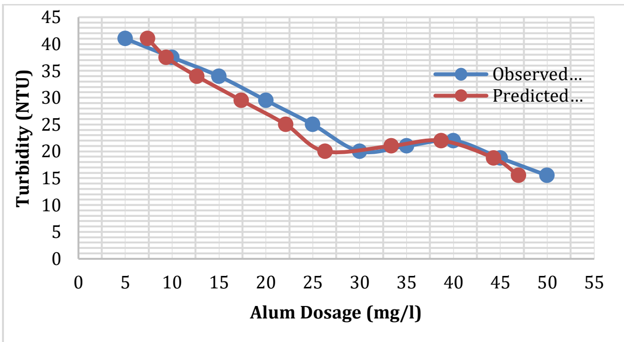

Figure 12 Plot of Observed and Predicted Alum Dosage with (100 NTU) Initial Turbidity for Fourth Run

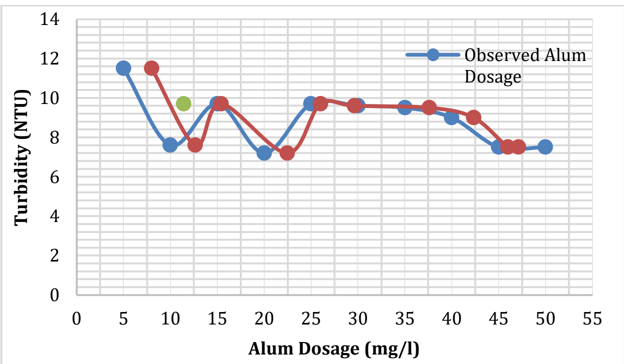

Figure 9 Plot of Observed and Predicted Alum Dosage with (50 NTU) Initial Turbidity for Third Run

Conclusions

1) The artificial neural network conducted and has been showed a good operation in the modeling process for alum dosage prediction and can operate very well even with little collected data from the experimental tests.
2) The error indices of the inverse model were 4.1, 2.84, 13.3% for RMSE, MAE, and MAPE respectively. These error values of the model showed a good and reliable model prediction performance.

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