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ANN-Based Modeling for Coagulant Dosage in Drinking Water Treatment Plant

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Abstract - *The rapid growth of population has exerted the portable water demand, which requires exploration of raw water sources, developing treatment systems. The main function of water treatment plants is to protect human health and the environment from excessive overloading of various pollutants. Coagulation is an essential part of drinking water treatment process allowing the removal of suspended colloidal particles in water. The chemical coagulation is the process of destabilizing the colloidal particles suspended in raw water by the addition of coagulants. The coagulant dosage rate is nonlinearly related to raw water characteristics such as turbidity, pH, and alkalinity. The most common coagulants used are Aluminum Sulfate (Alum). Optimizing coagulation for selecting the best coagulation condition and coagulation dosage is important. The main test used to determine the optimum coagulation conditions is the jar test, which requires a long experimental time. Modeling can be used to overcome this limitation. In this study, a model for approximation of coagulant dosage rate in water treatment plant in Punalur, Kollam has been developed using the Artificial Neural Network (ANN). The ANN is known as an excellent estimator of nonlinear relationships between accumulated input and output numerical data. Using this nature of the ANN, the optimal coagulant dosing rate can be predicted from the operating data with accuracy and in time. Optimization of the Coagulation process using ANN can reduce the amount of chemicals being used, testing time and consequently reduced the operational cost. Document*

Key Words: Artificial neural network, coagulation process, drinking water treatment, optimization, modelling

1.INTRODUCTION

This Water plays a major contributing role in the ecological sustainability of socio-economic systems at all scales. Water is essential for the maintenance of healthy ecosystems and biodiversity. Also human activities of all sorts rely on water appropriation from different sources and on engineered deliveries in qualities and quantities. Water is by own merit a human right, a competitive factor of production, and a necessity for viable ecosystems. The basic human physiological requirement for water is about 2.5 litres per day. The water for drinking is obtained from different source like well, river, lake etc. But now the contamination in water is increasing due to human activities, the chances for transmitting diseases from this contaminated water are very high. Ever increasing pollution levels are primarily responsible for impairing natural environment and water crisis is increasing day by day. The impurities like branches of trees, human and animal waste to invisible microorganisms, will make the water unsafe for drinking. Treating the available water is only solution to this crisis.

Water treatment may be defined as the action of making use of a water source to obtain good quality water. Water treatment includes physical, chemical and biological process. The main function of water treatment plants is to protect human health and the environment from excessive overloading of various pollutants. To improve water treatment process control, introduction of new technologies is needed which will help to increase the operational efficiency of chemical process in the treatment plant. Chemical coagulation is one of the most important treatment processes in drinking water treatment plant (WTP). It is one of the primary water treatment processes, which is a widely used simple and cost effective method. Coagulant can make various kinds of suspension in water to gather together and reduce the turbidity of water. It is key to reduce the burden of the follow-up craft such as filter and disinfector, to ensure the water quality. Coagulants worked by creating a chemical reaction and eliminating the negative charges that cause particles to repel Coagulants work by creating a chemical reaction and eliminating the negative charges that cause particles to repel each other. The coagulant and water is slowly stirred by flocculation. This induces particles to collide and clump together into larger and more easily removable flocs. Optimized coagulation control is essential for maintenance of satisfactory treated water quality and economic plant operation. Poor control of coagulation will leads to wastage of chemicals, so failure to meet the water quality standards, and less efficient operation of sedimentation and filtration units..

The most commonly used coagulant in India is aluminium sulphate which is commonly called as alum because of its lower cost and its widespread availability. The conventional method used for controlling coagulant dosage relies heavily upon manual intervention. These include manual method such as jar tests and automatic control. The jar test was developed almost 100 years ago is still applied to determine optimal coagulation conditions and the tests are relatively expensive and it requires a long experimental time. Jar test generally carried out in periodical basis. However, this test is not suited for real-time control of a continuous process, especially when the raw water quality rapidly varies in time and amplitude. Therefore, proposing new models for predicting the optimum alum dosage seems an appropriate way to alleviate costs and improve the health of drinking water. It is very difficult to set up its mathematical model accurately basing on its reactive mechanism at present, because the coagulation is a complicated physical and chemical course.

Artificial neural networks (ANNs) are one of the machine learning methods used in many scientific fields today. (Sadaf Haghiri et.al,2018) An ANN is able to anticipate nonlinear and complex relationships between inputs and outputs, and is often used to replace linear multiple-variable regressions. A neural network is able to learn patterns from data, which allows it to map complex input-output relationships (Rodriguez & Sérodes, 1999). ANN has been applied to an increasing number of real-world problems of considerable complexity. Considered good pattern recognition engines, they offer ideal solutions to a variety of problems such as prediction and modelling where the industrial processes are highly complex. ANN has been increasingly applied on the optimizing coagulation. ANN can be used instant of jar test so the limitations can overcome with a various advantages such as dosage prediction, human mistake elimination, time saving, and chemical expenses reduction. The main focus of this study is to optimize the coagulant dosage of water treatment plant, Panamkuttymala, Punalur, Kollam, commenced in 2006.

1.1 OBJECTIVES

- To evaluate the current coagulation practices at Water Treatment Plant (WTP)
- To formulate a ANN model for predicting coagulation dosage.
- To find out the optimized coagulation dosage through ANN model.

2. Methodology

2.1 Study Area

The Panamkuttymala, drinking water treatment plant, Punalur, Kollam, commenced in 2006 was used as an application site for this study. The plant has a nominal capacity to process 73 MLD. The raw water from Kallada dam is treated for distributing drinking water in Kollam district. The Plant has an ability to treat water with turbidity up to 420 NTU. If the turbidity exceeds 420 NTU the pumping will stopped. So turbidity has a vital role on the working of WTP.

Fig-1 Aerial view of water treatment plant Panamkuttymala, Punalur, Kollam

2.2 Alum Dosage

Alum dosage is the input for the ANN modeling, which is expressed in ppm. The alum dosage varies from 6 to 20ppm.

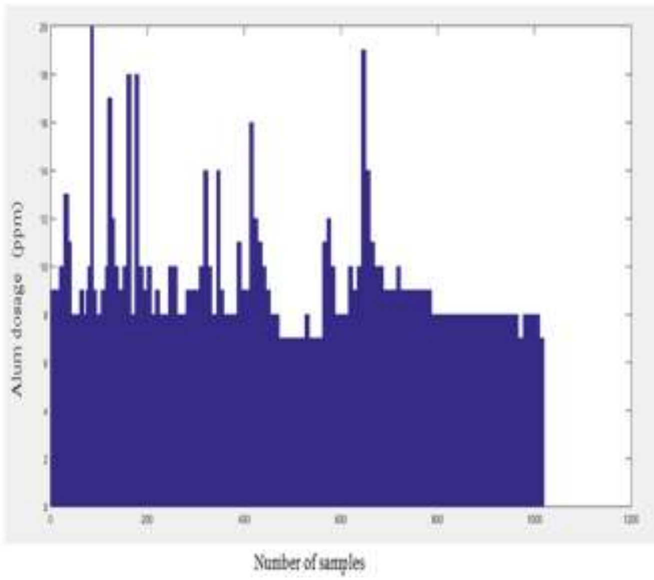

Fig 2 Alum dosage value variation.

2.3 The parameters selected for modeling

Proper selection of neural network input parameters is important, Since some parameters may be correlated to each other (redundant), have too much measurement noise, or not be related to the output at all, it is important to evaluate which inputs are appropriate. Input parameters are initially selected based on probability of relationship to the output and availability of data or feasibility of data collection.

2.3.1 Initial turbidity and final turbidity

Water which is not clear but is, in the sense that inhibits transmission of light, is known as turbid water. Many substance can cause turbidity, including clays and other tiny inorganic particles, and organic matter. Turbidity is measured using a turbid meter. Turbid meters are photometers that measure the intensity of scattered light. Particles in water scatter light, so scattered light measured at right angles to a beam of incident light is proportional to the turbidity. For calibrating the turbidity meters formazin polymer is currently used as the primary standard, and the results are reported as nephelometric turbidity units (NTU). The turbidity reflects the concentration of suspended particulate matter in the water; it is one of the most important factors to determine the dosage. The turbidity value has an important role in the working of WTP. The WTP can treat the water with turbidity up to 420.If the water turbidity increase more than 420 then the water pumping will stop. The final turbidity of water should be less than 5NTU as per the Indian standards.

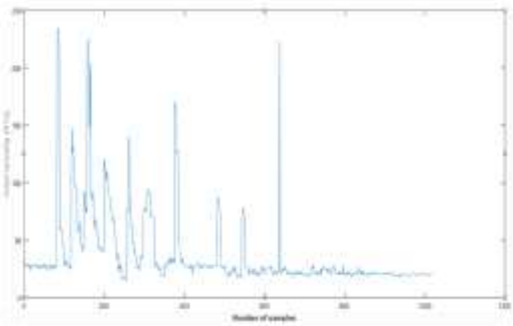

Fig 3: Initial turbidity in NTU

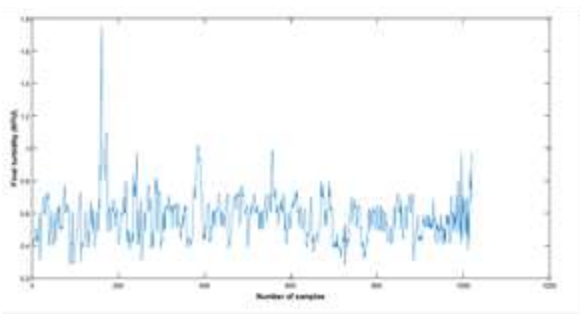

Fig 4: Final turbidity in NTU

2.3.2 pH

The pH of a solution is a measure of hydrogen (H+) ion, is a valuable parameter in the operation of biological units. The pH of the fresh sewage is slightly more than the water supplied to the community. The pH value of the raw water has impact on the hydrolysis products of the coagulant. Only in certain range of value, the coagulant plays the best role. The pH value varies from 7.5 to 8.5 which is important in the formation of floc.

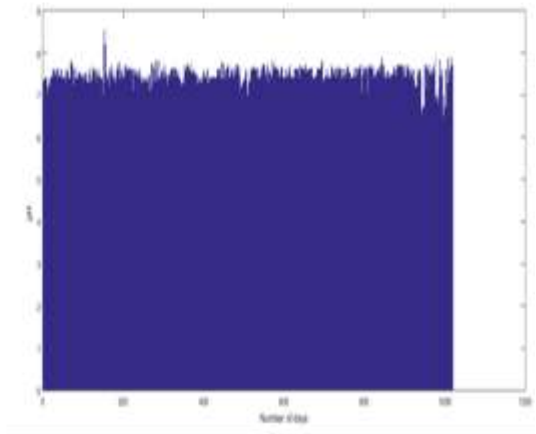

Fig 5: pH value variation

2.3.3 Alkalinity

The alkalinity of water is a measure of its capacity to neutralize acids. It also refers to the buffering capacity, or the capacity to resist a change in pH. Turbidity is frequently removed from drinking water by coagulation and flocculation. This process releases H+ into the water. Alkalinity must be present in excess of that destroyed by the H+ released for effective and complete coagulation to occur. Alkalinity influences how chemicals react with the raw water. Too little alkalinity will result in poor floc formation, so the system may want to consider adding a supplemental source of alkalinity. The alkalinity will range from 9 to 18.

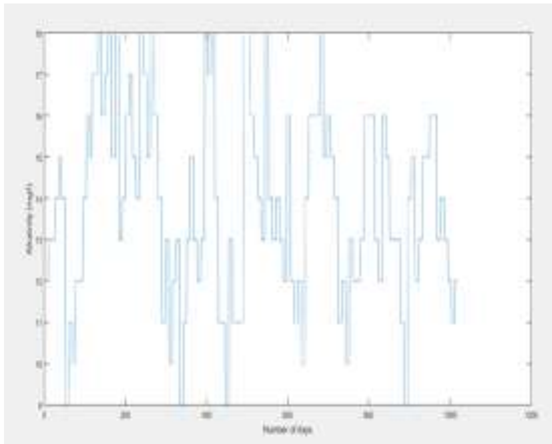

Fig 4.2 Alkalinity value variation

Table -1: Summary of data set

	Whole set	Train	Test
period	15/9/2018-14/4/2019	15/9/2018-21/1/2019	22/1/2019-14/4/2018
Number of days	211	125	86

Number of measurement for different alum dosage	13	13	13
Total number of samples	1769	1119	650

2.4 Modeling Software

The software used to develop neural networks was MAT LAB R2015a. The Microsoft Excel random number generator was used to randomize each data set so that neuro solutions could select data sets for training, validation, and testing. For each neural network, 60 percent of the data were used for training, with 20 percent dedicated to validation and the final 20 percent for testing. Validation data were used to test the network during training, to ensure that models were learning the trends in the training data, rather than memorizing the training data set itself. Testing data were used to evaluate model performance by predicting data not seen by the network during the training process.

2.5 Artificial neural network (ANN)

Artificial neural networks (ANNs), often referred to simply as neural networks, are a form of artificial intelligence roughly based on the structure of the human brain. As highly inter connected networks, they mimic the way in which the brain stores information by adjusting the relative weights of synapses that connect layers of nodes, or neurons. A neural network is able to learn patterns from data, which allows it to map complex input-output relationships (Rodriguez & Serodes, 1999).

ANN is generally modeled in three phases: model building, training and testing:

2.5.1 Model building phase:

The architecture of ANN, the number of the input and output nodes, the number of the hidden layers and hidden nodes and the connections between the nodes, is determined. The parameters such as learning function, activation function, learning ratio, and momentum are determined at this phase as well.

3.5.2 Training Phase:

The ANN has a learning process similar to that of the biological neural network. The learning of the ANN is achieved through the change of the weights of the nodes with the selected training algorithms. At this phase, data set is initially divided into two parts: Test and train. The training set is used to train the network. Minimizing the value of the error function such as MSE is the main objective at this phase. To this effect, the values of the weights between the neurons and the layers are changed. If the training set is learned well, it means that the model is constructed successfully. The error function calculates the error between the actual output and the predicted output. Learning rate is another parameter.

2.5.3 Testing Phase:

To evaluate the performance of the trained network, test set never seen by the network is given to the network and the ability of the network to generalize is measured. That is, the success of the network in training the model is evaluated by checking whether the difference between the actual and the predicted values of the outputs is minimized.

3 Results and discussions

3.1 ANN Development

ANN model is a parametric method; if the amount of recorded data is increased, the model accuracy will increase. The data set consist of 1769 sets of samples from 15/9/2018-14/4/2019. 60 percent of the data were used for training, with 20 percent dedicated to validation and the final 20 percent for testing.

3.2 Model building phase

MAT LAB R2015 a, is used in our analysis. This software does not require the manual determination of such parameters as transfer function, activation function, learning rate, and momentum. That's why; the manual designation of all parameters in question is not required at model building phase. ANN, the inputs were normalized and scaled into the same range before starting the learning phase. In this part, according to the real inputs taken from the water treatment plant, the final model was built, and the necessary pure input water and the output water characteristics are given to the model, with the amount of the necessary coagulant is given as the output. The number of inputs are 4 that is initial and final turbidity in NTU, alkalinity in mg/l, pH. Hidden layers are automatically added to the net during the training process by the software until the net is able to make good predictions. In our analysis, the optimal number of hidden neurons, the number of hidden neurons that should be added to the net to solve the prediction problem optimally. The number of hidden neurons is finding out by trial and error method.

3.3 Train and Test Phase

There are 1769 samples of raw water have been used to design ANN model used for the prediction of the optimal alum dosage. 1119 individual samples were used in training subsets, and 650 individual samples were used in testing subsets. To evaluate ANN performance generally R-squared (R^2), and Mean Squared Error (MSE) values are used. R^2

value ranges from 0 to 1. As its value gets closer to 1, the net is able to make better predictions. As the value gets closer to 0, the net is unable to make good predictions. The network with minimum MSE selected as the best model. The best model selected was neural network with 20 hidden neurons with MSE 0.023.

3.4 Prediction test

The prediction test was done with 13 sample data with 13 different actual alum dosages. The best model given the best prediction of alum. The result is shown in table 2. From the table the predicted value from ANN model and the actual alum dosage estimated are very close values. For lower turbidity the predicted values are very close to actual alum dosage. For high turbidity values the predicted dosage is less than the actual alum dosage.

Table -2: Actual alum and predicted alum in prediction test

Actual alum(ppm)	Predicted alum(ppm)	Error
9	9.01	-0.01
10	10.04	-0.04
20	19.11	0.89
6	6.349	-0.349
17	16.97	0.03
8	8.06	-0.06
7	7.03	-0.03
14	12.97	1.03
11	10.98	0.02
16	15.99	0.01
15	15.73	-0.73
18	18.01	-0.01
19	18.99	0.01

From the table 2, for low turbidity 7.72 NTU, the actual alum 6ppm Predicted alum 6.34ppm and medium turbidity 26.8 NTU, ANN estimate 10.04ppm of coagulant while the actual is 10ppm. The difference is just about 0.04% which is insignificant value and for high turbidity input 230.8 NTU, ANN estimated 19.72ppm of coagulant while the actual is 20ppm. The results using the model were very similar to the experimental values; therefore, the model was more effective and accurate in modeling nonlinear input-output relationships in the coagulation process.

3. CONCLUSIONS

Materials called coagulants are used to decrease water turbidity, with the required amount depending on the environmental conditions. It is key to reduce the burden of the follow-up craft such as filter and disinfector, to ensure the water quality (Zheying et.al,2009). Enhanced coagulation and sedimentation deter mine the over-all efiency of the water treatment process by reducing the load to the downstream processes including sand filtering. As a means of responding to the rapid change of raw water quality, the feed-forward control method is mostly used. (Dae-sung joo et al,2000). The coagulant dosage is determined by jar test in conventional method which consumes more time and may cause loss of chemical. There is no universally accepted model for the coagulant dosage of water treatment plant.so the process optimization is usually based on jar test results. It is very difficult to build a mathematical model for the alum dosage. From the literature review it has been clear that ANN based modeling of alum dosage is best among the other methods so the ANN based modeling was developed for the drinking water treatment plant, Pannamkuttymala, for optimizing the coagulation practices for the first time.

ANN is help full to estimate the non-linear relationships between inputs and outputs in a dataset. Multilayer ANN is contract to predict treated water quality parameters and the optimal coagulant dosage. Several architectures with one hidden layer and hidden neurons are built to obtain the right and proper ANN model (A. B. Sengulet.al,2013). The input parameters considered in this study were pH, initial and final turbidity, alkalinity, these are the most important effective parameters. The ANN model was developed and best model was selected for prediction. The selected ANN model is successful in predicting the alum dosage in the WTP, Panmkuttymala. The results shows the actual and estimated values are very close values. The ANN model is performing better to reduce overdosing for high turbidity, it is better by 4%. There for the over dosing of alum can be minimized.

The over dosing of coagulant will affect the proper working of filtration and disinfection tank. It also affects the final treated water quality. The over dosing of coagulant also cause Alzheimer's. so by using the ANN model the over dosing can prevent. The result also shows 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 to reduce cost.

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