Using iron alum in surface water treatment

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Abstract. Surface water contains clay, bacteria, dissolved metals, organic matter, color, other suspended solids. The purpose of coagulation and flocculation is to remove these suspended particles which ensure proper operation in treatment plant. Improper use of coagulant dosage affects water quality after treatment, cause operation problems and production costs. A study is being conducted at a surface water treatment plant at Dong Nai River with the capacity of 300,000 m³/day. The treatment process uses iron alum for coagulation and flocculation. Due to the high corrosion property of iron alum and the residue effects of the quality of treated water, it requires strict control in the treatment process as well as the chemical dosage. The main aim of this study is to determine appropriate amount of alum used for the coagulation-flocculation process. Research method is data collection including: turbidity, pH, flow rate of raw water, dosage of iron alum, lime, polymer used in current treatment process. Then, find the model using iron alum by linear regression analysis and BMA methods on R tool platform. Next, verify the appropriate linear regression model of iron alum by Jar test experiment. Results revealed that the BMA model is not suitable for the application because one Jar test results has a mean turbidity value greater than 4 NTU, which does not meet the water quality requirements after sedimentation tank according to the water treatment regulation. The linear regression analysis showed that raw water turbidity and season are two independent factors related to the alum dosage, of which these two factors explain about 78% of the differences that affect the coagulation-flocculation process. This study was successful in determining the appropriate iron alum dosage for the water treatment plant, which can be applied similarly to build appropriate chemical model for water surface water plants and raw water resources.

1. Introduction

Raw water (untreated water found naturally in the environment) can come from many sources, including surface water like rivers, lakes, oceans, or groundwater. Among the various sources of water, surface water is one of the main sources of water treatment to produce drinking water [1]. However, the main issue in the surface water is the existence of turbidity [2]. Water turbidity is caused by the presence of suspended material including algae, clay, silt, metal oxides resulting from soil erosion, viruses, bacteria, minerals matters such as asbestos, silicate, fine particles of organic matter and soluble material [3]. In order to remove these impurities, some methods such as...
Coagulation and flocculation are applied [4,5]. Chemical coagulation process in treatments is one of the most significant factors in eliminating or reducing the turbidity, color and microorganisms due to its simplicity and cost-effectiveness [6, 7]. Coagulation is the removal of suspended particles in water with an average size of 5 to 200 nm colloidal particles [8]. Most common coagulant material to remove water turbidity from mineral and synthetic types includes iron salts and aluminum includes ferrous sulfate, ferric sulfate, ferric chloride, aluminum sulfate (alum), poly ferric sulfate (PFS) and poly aluminum chloride (PAC) [9]. The efficiency of coagulation and flocculation depends on factors such as temperature, ionic strength, pH, type and dose of coagulant material, the size and distribution kind, TDS, concentration and properties of organic materials and colloidal particles in suspension [10,11,12].

During raw water treatment, the determination of coagulant dosage is one of the most considerations among various works conducted in unit processes [13]. Antecedently, the coagulant quantities are generally determined by the empiric Jar test technique that induces problems of excess or insufficient reagent, particularly during the period of fast variation in water quality [14,15]. These process of determination lead to increasing iron content and residual iron content of drinking water, which creates an unpleasant taste, odor, color, and higher opaqueness [16]. The aluminum salts remaining in water produce large volumes of sludge and disposal type in the environment [17]. While many elements found in drinking water are essential for a healthy life, an increase in the concentration of these elements (e.g. Ni, Cd, Mn, Fe, C, Zn) might cause serious health problems [18]. Drinking water with high sulfate and chlorine or calcium carbonate causes indigestion and excessive mineral content causes severe diarrhea [19]. High TDS content of water creates a salty and unpleasant taste [20]. The solutions of ferric sulfate and chloride are aggressive, corrosive acidic liquids, hence, they must be isolated from all corrodible metals. Similar to ferric sulfate, ferric chloride exhibits a wide pH range for coagulation, and the ferric ion does not easily become soluble. From what is evidenced above, it can be inferred that water treatment using iron coagulants tends to require close process control [21,22].

Optimum coagulant dosage in water treatment is generally evaluated by Jar test method which is used experimentally to determine the optimal conditions for the coagulation. On the other hand, the Jar test still has limitations in that they are time-consuming, intermittent, and are subject to variations in operator’s observations. As a result, the Jar test is often overlooked. Furthermore, if conducting too often, Jar testing will consume a lot of chemicals for testing, and it also requires experience to obtain good results in determining the required coagulant dosage [23].

Some previous studies have optimized and controlled of coagulant dosing in a drinking water treatment plant by modelling method. In 2010, study of Salim Heddam et al explored that an Adaptive Neuro-Fuzzy Inference System (ANFIS) was used for modelling of coagulant dosage in drinking water treatment plant of Boudouaou, Algeria. Six on-line variables of raw water quality including turbidity, conductivity, temperature, dissolved oxygen, ultraviolet absorbance, and the pH of water, and alum dosage were used to build the coagulant dosage model [25].

In [26], a multilayer perceptron (MLP) neural network model was used to predict the coagulant dosage in a Water treatment plant at the city of Saint Foy, Canada, and raw water quality parameters (collected from the process sensors), pH, turbidity, temperature, and conductivity were used as input to the MLP model.

In [27], the ideal of input of a regression model to predict/determine the optimal coagulant dosage to be added to the water, as an alternative to jar tests. The research of Leonaldo Silva Gomes et al established a regression model which uses a small number of input variables to correctly predict the dosages of PAC and AS in areal WTP in the State of Ceará, Brazil.

In this study, the operational data are collected from Saigon Clean Water Business & Investment Joint Stock Company WTP (SWIC water treatment plant) in Ho Chi Minh City, Vietnam. The collected
data were used for predicting the appropriate ferric chloride dose based on linear regression analysis. The Bayesian hierarchical modeling approach used in this research provides a robust method for appropriate ferric chloride dose that is used to estimate linear relationships between turbidity in raw water inputs and ferric chloride dose in coagulant process. The study of Holger R Maier in 2014 also demonstrated that modelling can be used to overcome these limitations of using Jar tests to determine the optimum coagulant dose and artificial neural network models that are used to model alum dosing of southern Australian surface waters. The performance of the models is found to be particularly exceptional, with correlation (R2) values ranging from 0.90 to 0.98 for the process models predicting treated water turbidity and color. An R2 value of 0.94 is obtained for the process inverse model used to predict optimum alum doses, the simulation tools enable operators to obtain optimum alum doses easily and enable alum dosing rates to be controlled automatically in real time [24].

Thanks to this predictor, the Jar test limitation is eliminated, and also the coagulant optimization is carried very fast and efficiently, and the quality of treated water is greatly improved before being supplied to the public.

2. Materials and Methods
To find out the factors that directly affect the increase and decrease of alum iron (FeCl3) dose, the research team carried out the Jar test data collection and operated actual data in 2018 at the SWIC water treatment plant. Raw data is aggregated and edited to fit the R. data analysis software format. Data fields (study variables) collected include: dry/rainy season, raw water turbidity, post-treatment pH, dose of alum, dose of lime, dose of polymer, raw water flow, post-treatment water flow. The variables are then conducted for correlation analysis, in order to remove unimportant variables. Variables with low correlation coefficients that did not affect the linear model were removed. After identifying the important variables that affect the linear model, they simulated a linear regression model for alum optimization.

The assumption in the multivariate regression model is that the dependent variable is the alum iron variable and the independent variables are the remaining variables. Based on the results of the multivariate linear regression model, the variables that are not significant (P> 0.05) were removed. The multivariate linear regression model is assumed to be shortened to statistically significant variables (p value <0.05), using post-inspection methods to ensure an optimized model of iron alum is assumed to be a multivariate linear regression model. The post-inspection steps include: Condition 1: the residual value must follow the normal distribution law and have an average of 0; Condition 2: the correlation between variables must be a linear correlation; Condition 3: remainder must have constant variance; Condition 4: the dependent variables must be independent of each other; Condition 5: testing the model is likely to be affected by peripheral values. The post-test conditions are satisfactory, the hypothesized that the appropriate model of iron alum is confirmed as a linear regression model. In fact, there are many other methods that can build an "optimal” multivariate linear regression model such as stepwise regression, AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), BMA (Bayesian Model Average). The research team selected the BMA method to build a multivariate linear regression model, which is the basis for comparing the most optimal model selection. The ultimate model of iron alum is finally tested by Jar test and practical operation test.

Flow diagram of steps in implementation process:
Collect and analyze data of turbidity, chemical dosage, etc. at SWIC water treatment plant

R are used to find out the correlation between variables compared to turning iron alum (FeCl3)

Simulate a model containing the highest correlation variables

Check the model if this is a linear model through hypothetical conditions

Build 2 linear models

Basic linear model

Not Satisfied

Satisfied

BMA linear model

Compare the above two models with the current chemical model of SWIC plant

Optimizing Linear Regression models

Check the models through the Jar-test test at SWIC plant to find the most appropriate model
The simulation of the Jar test at SWIC plant was to obtain the turbidity after result sedimentation by Jar test experiment. 800 ml of raw water sample was taken into a jar. Samples are then placed in the agitator the mixing speed should be adjusted to 120 cycles/minute to stir the sediment particles at the bottom of the jar at the same time adjust the time to 11 minutes for the entire cycle. Starting at the 11th minute, add the 2 solutions of alum and milk lime at the same time as calculated. Continue the process until the system has 10 minutes left. Proceed to add mud in and make contact with the mixture, then wait until the system has 6 minutes to go and proceed to add the polymer in. When the system notifies that there are 5 minutes left, reduce the mixing speed to 20 rpm. When the system reports that the mixing time is over, the final step is to take the sample out and fix it and keep it stable for 5 minutes. After 5 minutes, take 100-200 ml to measure the turbidity values directly through turbidity measuring devices in the laboratory. Note that the time for each batch of chemical feed does not last more than 30 seconds.

3. Results

Correlation chart and correlation coefficients of factors affecting iron alum are shown in Figure 1. Factors associated with influences on alum iron dosage include lime, raw water turbidity and affected by the season (dry/rainy) with correlation coefficients of 0.94, 0.88 and 0.7 respectively.

![Figure 1. The correlated factors that are likely to affect iron alum dose](image)
The nature of Lime in the Coagulant and flocculation process is that lime chemical is applied simultaneously with iron alum at primary mixing tank. 1. The purpose of lime is to create a stable pH environment - the ideal pH for iron alum environment is in the range of 7.5 - 8.5. In this environment, the flocculation is in the most perfect state and the flocculation time is the fastest. Therefore, lime is a factor that is dependent on iron alum. However, in the model we are considering, iron alum (FeCl₃) is the dependent variable and “Lime” is now the explanatory variable, so it is possible to eliminate the effect of lime on the amount of iron alum used. With the removal of lime from the linear model, the hypothetical model now considers only the effect of turbidity and the effect of season on iron alum.

Figure 2. Chart comparing average turbidity between seasons of 2016, 2017, 2018

Raw water turbidity is greatly influenced by the dry season and the rainy season (Figure 2). In the rainy season, the river water flow regime is changed, typically the flow rate and flow velocity. Besides, the rain will entangle the dirt wherever they go through and bring all the debris to rivers, streams, ponds, and lakes. Moreover, the flow rate of the river changes when the rain accidentally mixes the sediments in the river bed. These are also the main reasons leading to the increase in river turbidity in the rainy season. Therefore, we can explain the relationship between seasons, turbidity (rw.ntu) and iron alum (FeCl₃).

Table 1. The results of multivariate linear function analysis between iron alum, turbidity and season

| Affecting factors               | Divisor | Error   | p value       |
|---------------------------------|---------|---------|---------------|
| Affecting factors               | 22.9728 | 0.1762  | 2x10⁻⁶ < 0.05 |
| Starting value (intercept)      | 1.934   | 0.1622  | 2x10⁻⁶ < 0.05 |
| Turbidity                       | 0.31986 | 0.01329 | 2x10⁻⁶ < 0.05 |
| Season                          | 6.81129 | 0.71665 | 2x10⁻⁶ < 0.05 |
| R² - Coefficient of determination| 0.78    |         |               |
| Iron Alum Function in Dry season| (Iron alum dose) = 22.9728 + 0.1762 + 1.934 + 0.1622 + |
The influence of turbidity and season on iron alum equation is explained in Table 1. Estimates of initial values = 22.9728, turbidity = 0.31986 and season = 6.81129. The value of p <0.05 confirms the factors being considered to be statistically significant. The coefficient of multiple of $R^2 = 0.78$ explains 78% of the influence of turbidity and season on iron alum. Turbidity values are monitored and constantly changed. While the season value has categorical meaning, in the rainy season the season value is determined by 1, in the dry season the value of the season is determined by 0. The alum iron equation can now be classified as applied separately for dry season and rainy season. To evaluate and optimize the built iron alum model, BMA linear iron alum model (Table 2) is also considered.
Figure 3. Comparison chart of models using alum iron (FeCl3)

Note:

m1 (red line): Real value of iron alum (FeCl3) that SWIC plant uses over the days in 2018.
m2 (blue line): value of iron alum (FeCl3) used for the corresponding turbidity day by day in 2018; This value is exported from the linear model using conventional methods.
m3 (green line): value of iron alum (FeCl3) used for the corresponding turbidity day by day in 2018; This value is exported from the linear model using the BMA method.

After optimizing Linear Regression models, then result from Figure 3 shows that values of iron alum dose of Model m2 have actually reached value that we expected. Two linear lines of Model m2 and Model m1 (actual model) are almost asymptotic. Model m2 and m3 are moved to the next step of the research process. The next step is to put Model m2 and m3 into the Jar test process for the purpose of finding the best model.

Table 3. Jar test results

| Function                  | SAMPLE I (8h-26/02/2019) | SAMPLE II (8h-05/03/2019) | SAMPLE III (9h30 - 19/03/2019) |
|---------------------------|--------------------------|---------------------------|---------------------------------|
| Turbidity after sedimentation | 3.2          | 4.1           | 3.0                              | 2.6          | 3.1           | 2.7                              | 1.1          | 1.5           | 1.0                              |
The values of Table 3 are converted to the average after 3-4 times of Jar test for each sample. The results showing the NTU value in Table 3 must be less than 4; 4 NTU is the upper limit that SWIC plant specifies when water comes out of the settling tank to continue to the filtration tank. If one of the average results is obtained, at least one average result exceeds 4 NTU as the search model will not be selected. Specifically, in Table 3, BMA model will be rejected in the research process.

Jar test results and the actual operation test demonstrate that the "appropriate" model of iron alum (FeCl₃) chemical is completely feasible and applicable in practice. A suitable model will help to proactively build a plan to store chemicals in the most appropriate way, ensuring safety for water supply. The appropriate model will be deployed as an algorithm to integrate into the SCADA system to automate the operation of water treatment chemicals. The important thing in analyzing data is to find a suitable linear regression model is to build an accurate, reliable and precise database system.

4. Conclusions and Discussion

Based on results from the Jar test experiment, we select the model "m2" as the final result of the research process. However, in the near future, there will still be agents that are likely to cause surface water pollution on Dong Nai river water. Without measures to overcome these hazards, the turbidity of the source water will be very complicated. When the turbidity of water source spikes, that also means that these high turbidity data will directly become "jamming" objects that will reduce the predictability of the Model m2. The most important consideration is how to update as much as possible the data with high turbidity value to eliminate the case they become "jamming" agents.

Also, note that "R" software gives us the possibility of predicting an almost absolute precision of alum iron based on the data collected from practice. Therefore, during the editing process, data should be collected carefully and ensure accuracy, so that the model m2 can predict the most accurately.

The research method to build an "appropriate" model of iron alum (FeCl₃) with R data analysis software as shown can be applied similarly to build the appropriate model for other chemicals at water plants which have similar technological processes (such as lime, PAC, alum, etc.) or analyze data for other relevant scientific studies such as evaluation and forecast of raw water quality in the rivers through monitoring data. The research also shows that the collected data has a decisive influence on the accuracy and rationality of the model. There are no models that is "appropriate" permanently, but only the "most appropriate" model for each survey period or cycle.

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