

Optimization of drinking water treatment process by modeling the aluminum sulfate dose

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ABSTRACT: In the water treatment processes, the determination of the optimal dose of the coagulant is an issue of particular concern. Coagulant dosing is correlated to raw water quality determined by some parameters (Turbidity, pH, Temperature and Conductivity). The objective of this study is to provide water treatment operators with a tool that enables to predict and replace, sometimes, the manual method (jar testing) used in this plant to predict the optimum coagulant dose. The model is constructed using actual process data for a water treatment plant located in the middle of Morocco (Meknes). This non linear model is related to turbidity, pH and temperature parameters. The comparison between the aluminum dose measured and the alum doses calculated by the model constructed shows a very interesting results compared to the data obtained from the jar test. In fact, modeling can reduce the aluminum sulfate consumption by more than 10%. The model can be applied in the determination of the aluminum doses in the water treatment plant and be extended to others.

Key words: Coagulation, Turbidity, aluminum sulphate, water treatment.

1. INTRODUCTION

The demand on water supply is increasing over the last century due to improved lifestyle, industrial development and population growth. This increased demand is facing a paradox to produce treated water with high quality at lower cost. In order to reduce the water cost, it is very important to optimize the operating expenses in the water treatment plant (power, chemicals and operator's expenses) and many measures should be performed in this vision.

The optimization of water treatment plant is not a disciplinary to maximize the treatment objective and minimize the cost of the water produced. But it consists on the understanding of the functioning of the treatment plant and treasure the experience of the operators in dealing with all treatment process related to different aspects.

The treatment of drinking water comprises the coagulation, flocculation, sedimentation, filtration and disinfection of raw water produced by the springs. During the rainfall period, the water's turbidity increases, colloidal particles are removed in the treatment plant by means of a chemical coagulation process: consisting in the charge destabilization of the suspended particles by adding coagulant. The coagulant used is aluminum sulfate; it is the most widely used coagulant in Morocco as well as many other countries in the drinking water industry. It is mainly used because of its effectiveness, accessibility and low price. As a common practice, aluminum sulfate is applied according to the jar test results. The main difficulty is to determine the optimal dose of aluminum sulfate related to raw water characteristics. Both manual and automatic methods are used to predict optimum coagulant dose [1], [2], [3]. Automatic method is ensured by streaming current detectors [4], [5], [6], [7]. However, manual method is consisting to determine the quantity of the coagulant to apply experimentally and based on the jar test results. Jar test involves taking a raw water samples and applying different quantities of coagulant to each sample [2]. After a short period of time, each sample is assessed for water quality and the dosage that produces the optimal result used a set point. This operation should be repeated by the operators each time when the quality of raw water changes. The aluminum sulfate is the compound likely to be mathematically modeled and therefore its value can be

estimated according to the data available in the treatment plant [8], [9], [10]. The optimization of using the coagulant is very interesting approach because under dosing of coagulant can lead to poor quality drinking water while too much coagulant leads to many operating problems (less efficient filtration and sedimentation, pH), health problems can increase the cost of treated water [11], [12].

Some attempts have been made to model the relationships between raw water quality characteristics and the optima coagulant dosage rate [13], [14], [15], [16].

This paper addresses the problem of building model to predict the optimal coagulant dose from raw water characteristics (Turbidity level, pH, Temperature, total dissolved solids).

This study was developed in a water treatment plant located in Meknes in the middle of Moroccan Kingdom, whose source is two big springs Bittit (630 l/s) and Ribaa (400 l/s). The quality of water produced by the springs changes according to the rainfall in the region. Sometimes, it can be affected by the snow in the Atlas Mountains. The water treatment plant, as part of other water resources, water to more than 700.000 inhabitants of Meknes city, and it has a nominal capacity of 600 l/s of treated water. Figure 1 presents a schematic overview of the various operations necessary to treat the water.

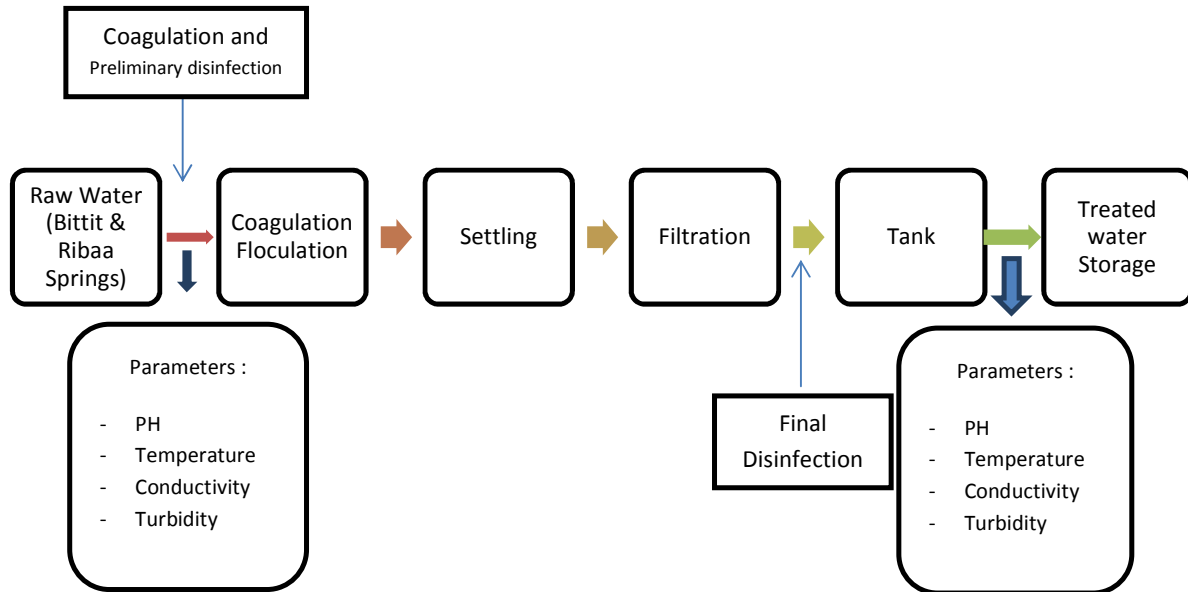


Figure 1: simplified synopsis of the water treatment plant.

Many measurements of variables such as: turbidity level, PH, conductivity, temperature is needed to carry out the jar test in order to determine the optimal dose of the aluminum sulfate. The raw water variables used in this study are presented with the following variation levels as shown in Table 1.

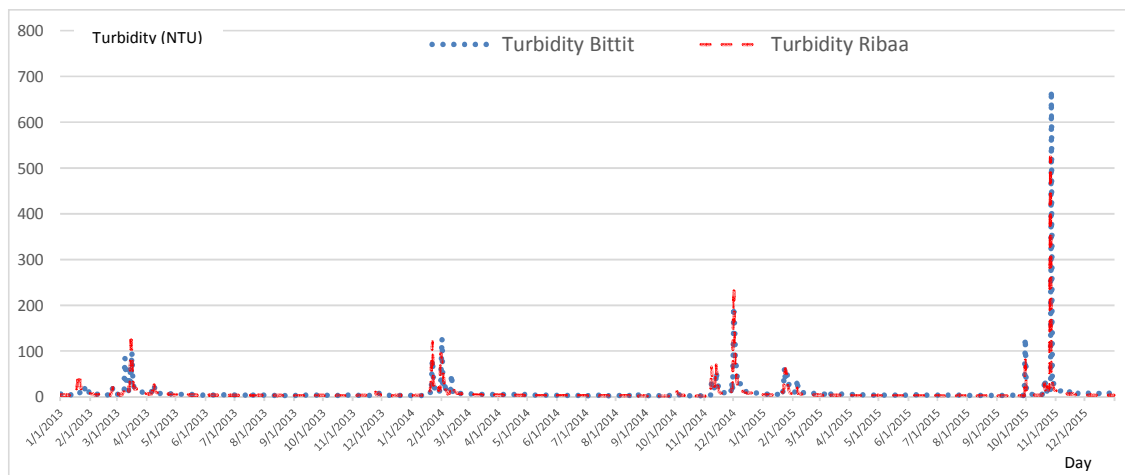
Table 1: statistical summary of raw water conditions from 01/01/2013 to 31/12/2015 (National Office of Electricity and Drinking Water ONEE, 2015)

Variables	Min	Max
Turbidity: Bittit (NTU)	1.7	669.71
Turbidity: Ribaa (NTU)	1.62	524.03
pH	6.80	7.74

Temperature: (°C)	14	24.70
Conductivity micro s/cm	509	624

72

73 In the rainfall period, the turbidity of raw water changes from time to time as shown in Figure 2, the
74 turbidity of the raw water can increase to reach levels more than 500 NTU:



75

76 **Figure 2: statistical data of turbidity level of the spring's water from 01/01/2013 to 31/12/2015**
77 **(National Office of Electricity and Drinking Water ONEE, 2015).**

78

79 However, the turbidity level is less than 10 NTU this three last years (2013, 2014 and 2015) for more
80 than 88% of the year. However, in 64% of the year the turbidity is less than 10 NTU for the seven last
81 years as shown in Table 2.

82

83 **Table 2: Turbidity levels distribution from 2009 to 2015 (Number of days per turbidity level).**

84

Year	Number of days					Total
	Turbidity less or equal than 5 NTU	Turbidity more than 5 and less or equal than 10 NTU	Turbidity more than 10 and less or equal than 20 NTU	Turbidity more than 20 and less or equal than 40 NTU	Turbidity more than 40 NTU	
2009	147	60	101	34	23	365
2010	0	0	113	148	104	365
2011	0	132	144	59	30	365
2012	301	38	17	5	5	366
2013	260	74	23	8	0	365
2014	247	62	32	20	4	365
2015	184	132	34	10	5	365
For the three last years (2013, 2014 and 2015):						
Total	691	268	89	38	9	1095
<u>Aggregated</u>	691	959	1048	1086	1095	

data						
Percentage	63%	24%	8%	3%	1%	
Percentage of Aggregated data	63%	88%	96%	99%	100%	
For the seven last years (from 2009 to 2015)						
Total	1139	498	464	284	171	2556
Aggregated data	1139	1637	2101	2385	2556	
Percentage	45%	19%	18%	11%	7%	
Percentage of Aggregated data	45%	64%	82%	93%	100%	

85

86 **Table 3** gives the **max and min value** of raw water turbidity by month from 2013 to 2015:

87 **Table 3: statistical data of turbidity min and max (NTU) measured in 2013, 2014 and 2015 per**
88 **month (National Office of Electricity and Drinking Water ONEE, 2015)**

Year : 2013 / Turbidity (NTU)				
	Bittit Spring		Ribaa Spring	
Month	min	max	min	max
January	3,70	18,95	10,00	50,00
February	4,50	19,00	3,95	20,65
March	4,95	98,40	4,50	136,66
April	6,40	21,95	4,90	32,77
May	3,93	6,30	3,80	5,30
June	3,72	4,40	3,34	4,89
July	3,30	4,33	2,92	3,62
August	3,00	3,80	2,70	3,46
September	3,10	4,64	2,68	4,15
October	2,90	3,99	2,46	3,62
November	2,70	7,44	2,90	10,00
December	3,07	4,23	2,60	3,95
Year : 2014				
	Bittit Spring		Ribaa Spring	
Month	min	max	min	max
January	3,06	81,69	3,00	120,66
February	6,48	128,00	5,93	78,90
March	4,86	6,91	3,90	5,65
April	4,30	4,90	3,30	4,19
May	3,17	4,77	2,48	3,37
June	3,00	3,86	2,60	2,87
July	2,36	4,50	2,16	2,49
August	1,74	4,20	1,88	2,28
September	1,80	3,50	1,64	1,90
October	1,89	4,20	1,67	11,64
November	1,80	55,50	1,68	69,29

December	6,57	197,50	5,06	235,89
Year : 2015				
	Bittit Spring		Ribaa Spring	
Month	min	max	min	max
January	5,09	63,10	3,96	61,59
February	6,33	38,52	3,98	19,45
March	4,97	6,27	3,26	4,64
April	3,65	5,60	2,80	3,76
May	3,50	5,23	2,68	3,06
June	3,40	4,52	2,61	3,19
July	2,80	4,75	2,40	3,60
August	2,60	3,26	2,45	2,74
September	2,70	128,45	2,35	86,63
October	4,35	669,71	3,22	524,03
November	6,76	17,18	3,99	13,19
December	7,18	9,54	3,42	4,02

The chemicals used in the water treatment process consume about 50% the total operating expenses of the water treatment. The energy cost is between 10 to 15% related to the total cost in 2013, 2014 and 2015 as shown in the Figure 3.

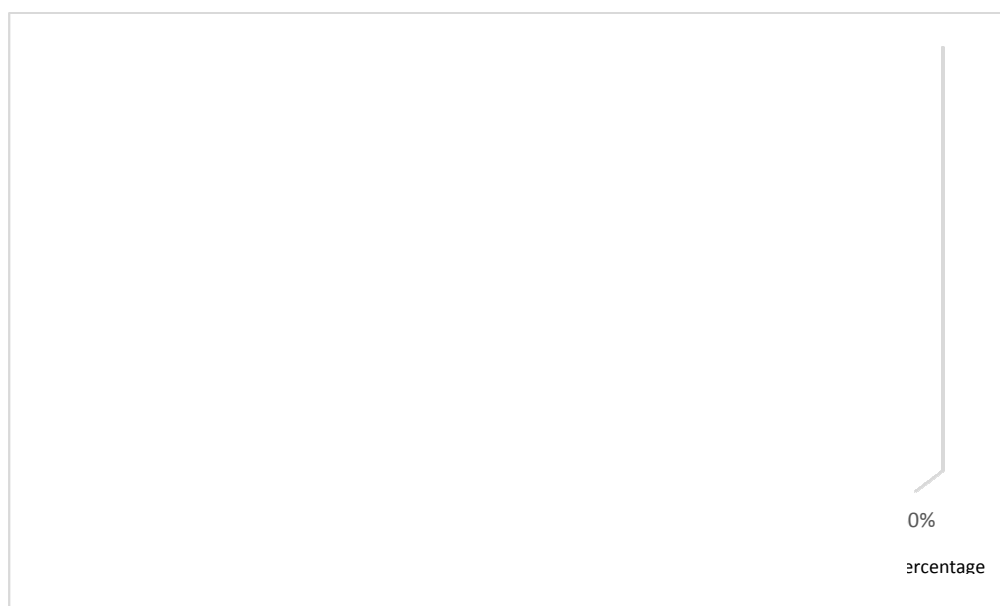


Figure 3: operations expenses of the water treatment plant in 2013, 2014 and 2015 (National Office of Electricity and Drinking Water ONEE, 2015).

In addition, used as coagulant, the aluminum sulfate (**Alum**) consumption is more than **70%** of the total chemicals consumption in the water treatment plant. Le polyelectrolyte (Poly) consumption is less than 10% and the chlorine is between 16 and 26% of the total chemicals used in the water treatment plant according to the water quality as shown **by Figure 4:**

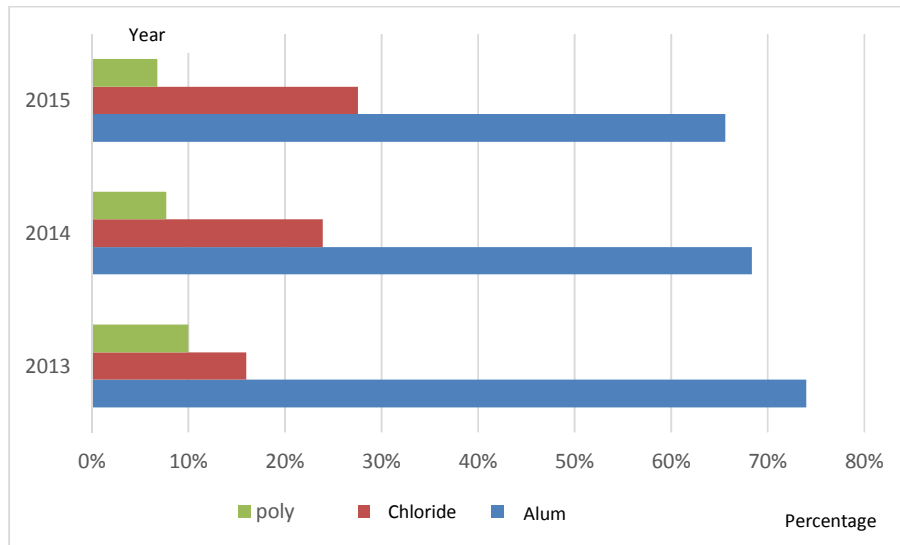


Figure 4: Percentage of chemicals expenses consumed by the water treatment plant in 2013, 2014 and 2015 (National Office of Electricity and Drinking Water ONEE, 2015).

II. METHODOLOGY

The prediction of optimal coagulant dose from raw water characteristics is a nonlinear regression problem. The identification aims at modeling and parameter estimation. It consists of constructing a mathematical model that can describe the behavior "-Input-output" of the system [17]. The problem is to determine the model parameters from input and output data. The analysis of experimental data for different periods of the year in the water treatment plant allow obtain mathematical models describing the changes in dose of Alum based on the input parameters of the raw water using Statgraphics software.

The model to develop will be based on the data available in the plant from 01/06/2014 to 31/12/2015 (495 data). The data validation, processing and modeling of the coagulant dosage rate are the main steps to construct the model as presented by Figure 5.

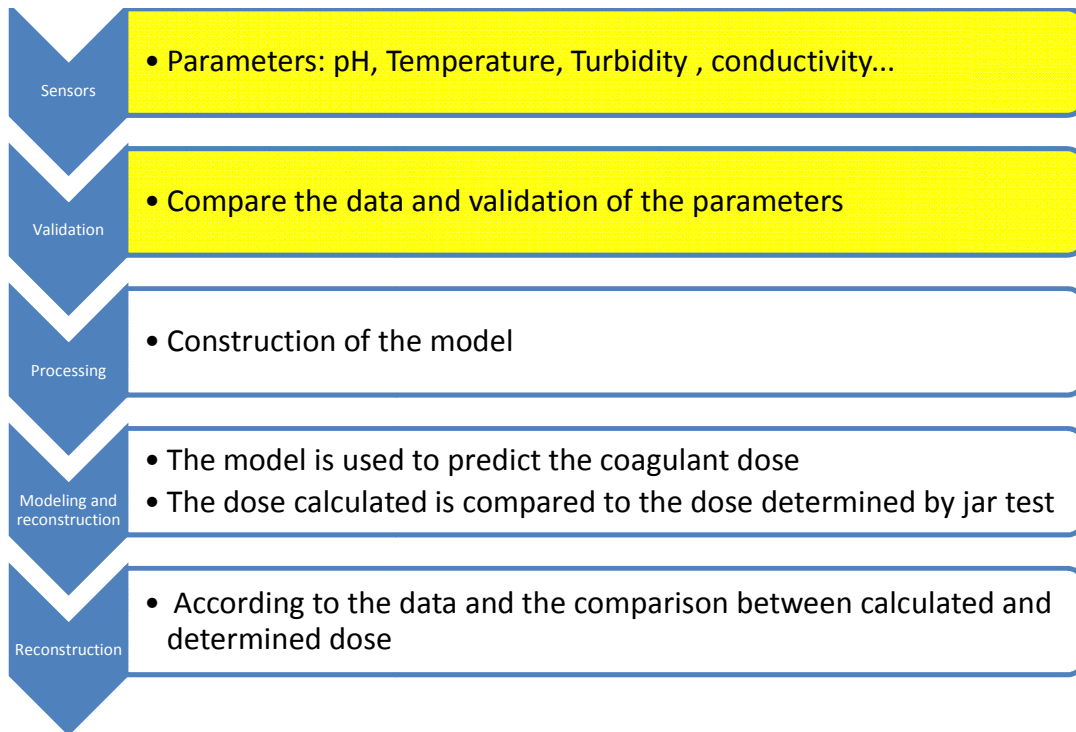


Figure 5: structure of the model for the prediction of the coagulant dosage rate.

According to the data recorded in the water treatment plant, many models are identified and analyzed using Statgraphics software which indicates the relationship between the Aluminum doses measured and calculated by different models. Only eleven models from the simplest to a complex one are examined regarding to the output (aluminum sulfate dose calculated).

After the construction of the models, they are compared each one to the other. Two statistical tests are performed on models in order to choose the model fitted with the observed data. First, an ANOVA test is performed on models to determine if there is a significant difference between models and observed data. Finally, the Euclidian distance method is applied to models in order to choose the more representative of the observed data.

III. RESULTS AND DISCUSSIONS:

For this study, two groups of turbidity are identified:

- Group1: less turbid raw water (turbidity ≤ 10 NTU).
- Group2: turbid raw water (turbidity > 10 NTU and ≤ 20 NTU).

We considered turbidity (Turb), PH (PH), temperature (Temp) as explanatory variables of the dose of Aluminum sulfate (ASD) variable behavior (dependent variable). After the validation and processing the available data, eleven models are built as presented in Table 4.

2.1. Turbidity ≤ 10 NTU:

- ANOVA test:
The table 4 gives the results of the ANOVA test, there is no significant difference between the observed data and the calculated data of different models except the model 2.

Table 4: Models used to predict the aluminum sulfate dose for turbidity less than 10 NTU.

Model ID	Model	Variance	Mean squares between groups	Mean squares within group	F	F critic
M1	$ASD = a + b \cdot Turb^2$	0,411683761	2,8836E-05	1,135265673	2,54002E-05	3,850888022
M2	$ASD = a \cdot Turb$	11,18087015	370,0752732	6,519858869	56,76123988	3,850888022
M3	$ASD = a + B \cdot PH + c \cdot PH^2 + d \cdot Turb^2$	0,459349673	0,000346606	1,159098629	0,000299031	3,850888022
M4	$ASD = a \cdot PH + b \cdot PH^2 + c \cdot Turb^2$	0,41235782	0,000271781	1,135602703	0,000239327	3,850888022
M5	$ASD = a + b \cdot PH + c \cdot Temp + d \cdot Turb + e \cdot Temp^2 + f \cdot Temp \cdot PH + g \cdot Temp \cdot Turb + h \cdot PH^2 + i \cdot PH \cdot Turb + j \cdot Turb^2 + k \cdot Temp \cdot PH \cdot Turb$	0,598009211	0,003622458	1,228428398	0,002948856	3,850888022
M6	$ASD = a + b \cdot Turb + c \cdot PH$	0,398624611	0,000260786	1,128736098	0,000231042	3,850888022
M7	$ASD = a \cdot Turb + b \cdot PH$	0,404036521	0,001562999	1,131442053	0,001381422	3,850888022
M8	$ASD = a + b \cdot Turb$	0,398033322	3,48569E-05	1,128440454	3,08895E-05	3,850888022
M9	$ASD = a \cdot Temp + b \cdot Turb + c \cdot PH$	0,451748045	0,0017627	1,155297815	0,001525754	3,850888022
M10	$ASD = a + b \cdot PH + c \cdot Temp + d \cdot Turb$	0,443782468	0,00010845	1,151315027	9,41964E-05	3,850888022
M11	$ASD = b \cdot PH + c \cdot Temp + d \cdot Turb + e \cdot Temp^2 + f \cdot Temp \cdot PH + g \cdot Temp \cdot Turb + h \cdot PH^2 + i \cdot PH \cdot Turb + j \cdot Turb^2 + k \cdot Temp \cdot PH \cdot Turb$	0,511660954	0,001235877	1,18525427	0,00104271	3,850888022

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- 151 • The Euclidian distance test:
 152 The Euclidian distance is calculated between the model i and the data observed (Vobs). The
 153 results are exposed in **Table 5**:
 154

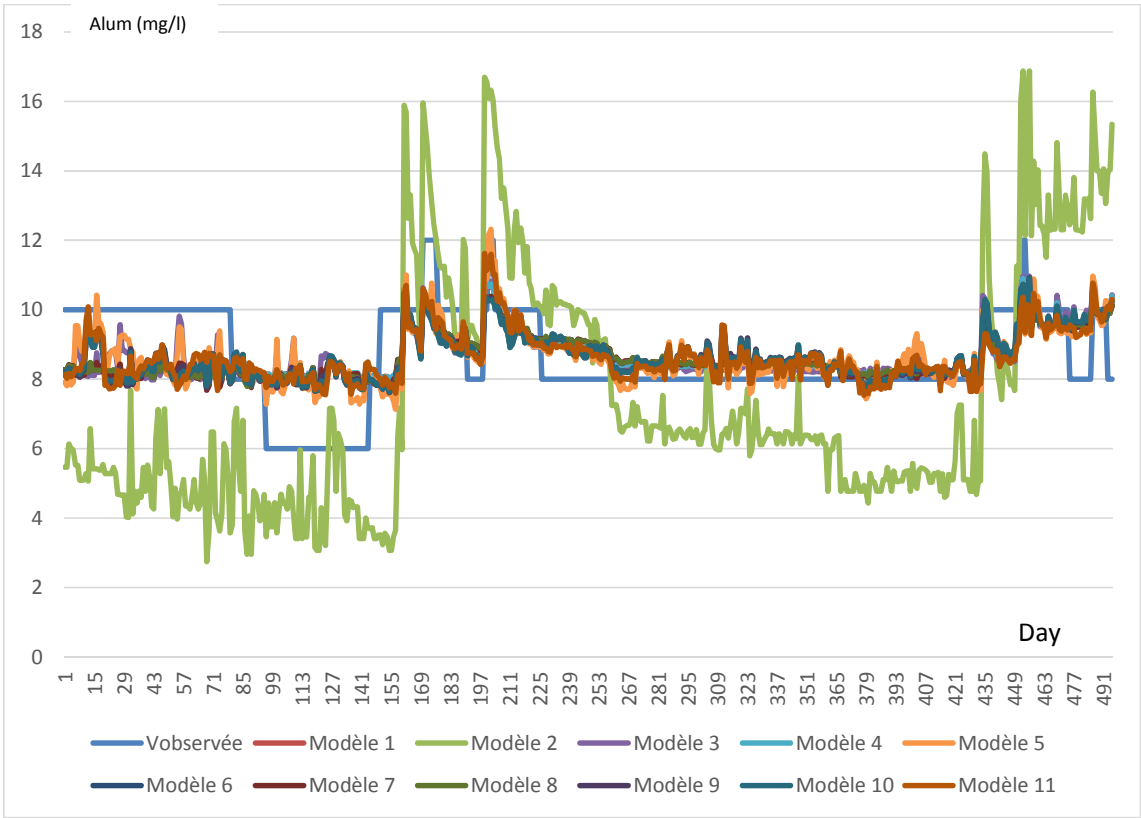
Table 5: The Euclidian distance calculated per models, turbidity less than 10 NTU.

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<i>Vobs/ Mi</i>	<i>Somme (Y obs - Y Mi)^2</i>
Vobs - M1	714,718
Vobs - M2	5096,723
Vobs - M3	691,737
Vobs - M4	714,571
Vobs - M5	617,589
Vobs - M6	721,019
Vobs - M7	721,807

Vobs - M8	721,496
Vobs - M9	699,537
Vobs - M10	698,825
Vobs - M11	663,757

157



158

159 **Figure 6: Simulation of aluminum sulfate dose (mg/l) by different models and dose measured**
160 **for turbidity less than 10 NTU.**

161 **Figure 6** shows that, except the model 2, the others are much fitted to the measured values trend
162 and can explain the evolution of the consumption of the aluminum sulfate in the water treatment
163 plant. Moreover, the model 5 is much fitted to the measured values of the Alum doses as shown
164 by **Figure 7**.

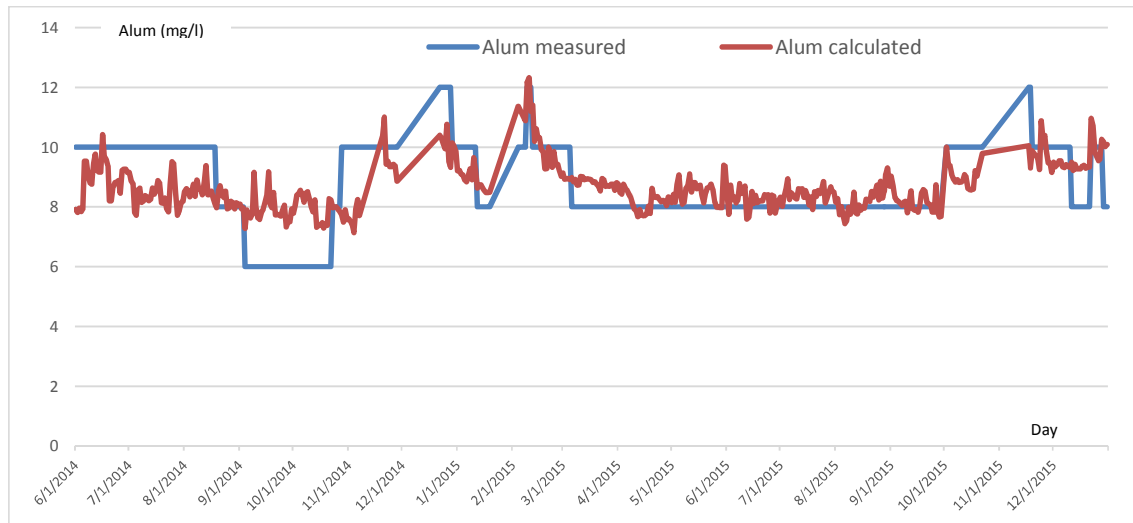


Figure 7: Simulation of aluminum sulfate dose (mg/l) by different model 5 and dose measured for turbidity less than 10 NTU.

2.2. Turbidity > 10 NTU and ≤ 20 NTU:

- ANOVA test:

Table 6 gives the results of the ANOVA test, there is no significant difference between the observed data and the calculated data of different models except the models 2 and 7.

Table 6: Models used to predict the aluminum sulfate dose for turbidity between 10 and 20 NTU.

Model ID	Model	Variance	Mean squares between groups	Mean squares within group	F	F critic
M1	$ASD = a + b \cdot Turb^2$	0,234749871	2,122644009	3,264689885	0,650182432	3,932437831
M2	$ASD = a \cdot Turb$	29,96359016	180,9770354	18,12911003	9,98267621	3,932437831
M3	$ASD = a + b \cdot PH + c \cdot PH^2 + d \cdot Turb^2$	0,651787305	1,911098825	3,473208602	0,550240151	3,932437831
M4	$ASD = a \cdot PH + b \cdot PH^2 + c \cdot Turb^2$	0,243033647	2,065336707	3,268831773	0,631827164	3,932437831
M5	$ASD = a + b \cdot PH + c \cdot Temp + d \cdot Turb + e \cdot Temp^2 + f \cdot Temp \cdot PH + g \cdot Temp \cdot Turb + h \cdot PH^2 + i \cdot PH \cdot Turb + j \cdot Turb^2 + k \cdot Temp \cdot PH \cdot Turb$	2,328561881	2,430658689	4,31159589	0,56374919	3,932437831
M6	$ASD = a + b \cdot Turb + c \cdot PH$	0,244220963	2,061881321	3,269425431	0,630655559	3,932437831
M7	$ASD = a \cdot Turb + b \cdot PH$	0,005194236	142,5703974	3,149912067	45,26170712	3,932437831
M8	$ASD = a + b \cdot Turb$	0,235017994	2,122833224	3,264823946	0,650213689	3,932437831
M9	$ASD = a \cdot Temp + b \cdot Turb + c \cdot PH$	0,503452321	2,171104533	3,39904111	0,638740299	3,932437831
M10	$ASD = a + b \cdot PH + c \cdot Temp + d \cdot Turb$	0,507533169	2,02223202	3,401081534	0,594584987	3,932437831
M11	$ASD = b \cdot PH + c \cdot Temp + d \cdot Turb + e \cdot Temp^2 + f \cdot Temp \cdot PH + g \cdot Temp \cdot Turb + h \cdot PH^2 + i \cdot PH \cdot$	2,139660069	2,006669248	4,217144984	0,475835964	3,932437831

	Turb + j* Turb^2 + k* Temp *PH* Turb					
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- 175 • The Euclidian distance test:
 176 The Euclidian distance is calculated between the model i and the data observed (Vobs). The
 177 results are exposed in [Table 7](#).

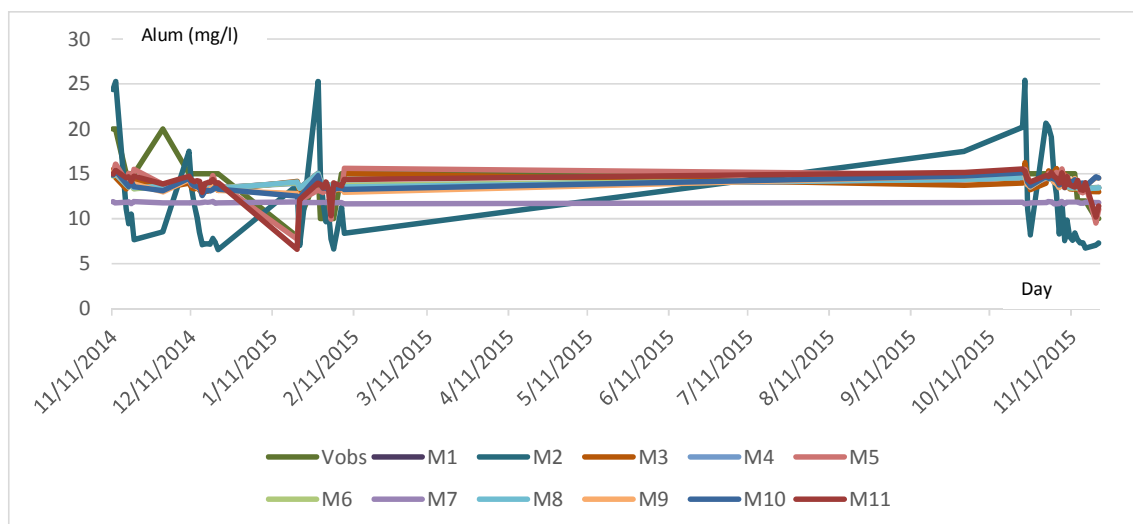
178 **Table 7: The Euclidian distance calculated per models, turbidity between 10 and 20 NTU.**

<i>Vobs/ Mi</i>	<i>Somme (Y obs - Y Mi)^2</i>
Vobs - M1	298,372
Vobs - M2	1734,448
Vobs - M3	279,321
Vobs - M4	298,020
Vobs - M5	177,806
Vobs - M6	299,416
Vobs - M7	613,245
Vobs - M8	299,856
Vobs - M9	288,519
Vobs - M10	286,634
Vobs - M11	194,085

179

180 Figure 8 shows that the models are much fitted to the measured values of the aluminum sulfate
 181 consumption except the model 2.

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184 **Figure 8: Simulation of aluminum sulfate dose (mg/l) by different models and dose measured**
 185 **for turbidity between 10 and 20 NTU.**

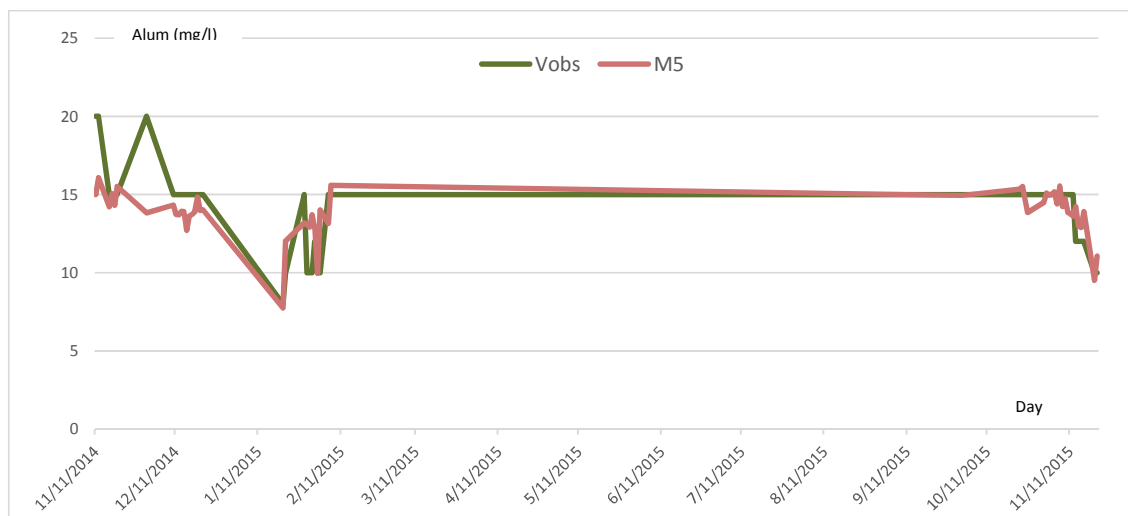


Figure 9: Simulation of aluminum sulfate dose (mg/l) by the model 5 and dose measured for turbidity between 10 and 20 NTU.

Figure 9 shows the results of the calculated dose of the aluminum sulfate using the model 5. It is clear that the calculated dose is fitted to the measured dose.

According to the Euclidian distance test, for both levels of turbidity (less than 10 NTU and between 10 and 20 NTU), the model 5 is the most representative of observed data and it can be selected to predict the dose of the aluminum sulfate in the water treatment plant.

The constructed model is used to predict the aluminum sulfate dose each hour in the water treatment plant. The parameters used in the model are continually changing. Thus, the Alum dose is changing from hour to other as shown in Figures 10 and 11.

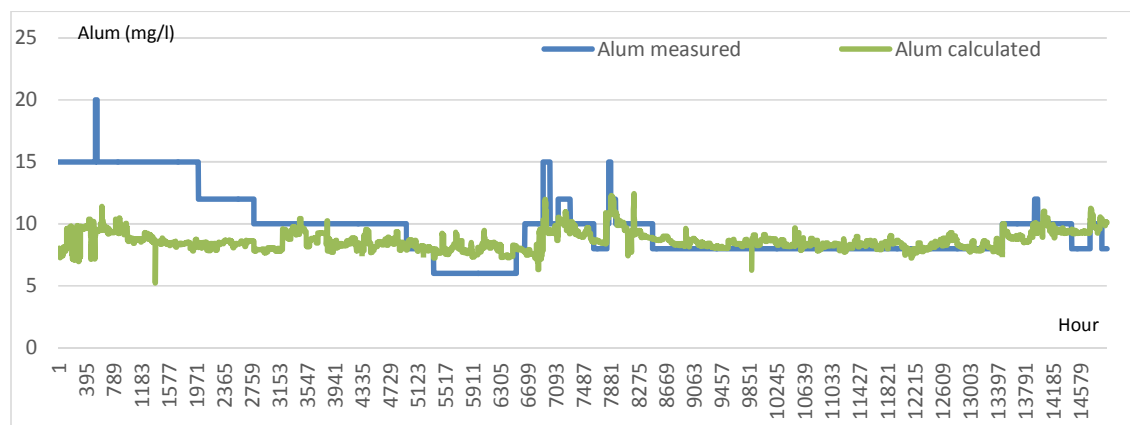


Figure 10: Comparison between the observed aluminum sulfate dose (Alum measured) and the calculated dose (Alum calculated M5) by using the model 5 per hour for turbidity less than 10 NTU.

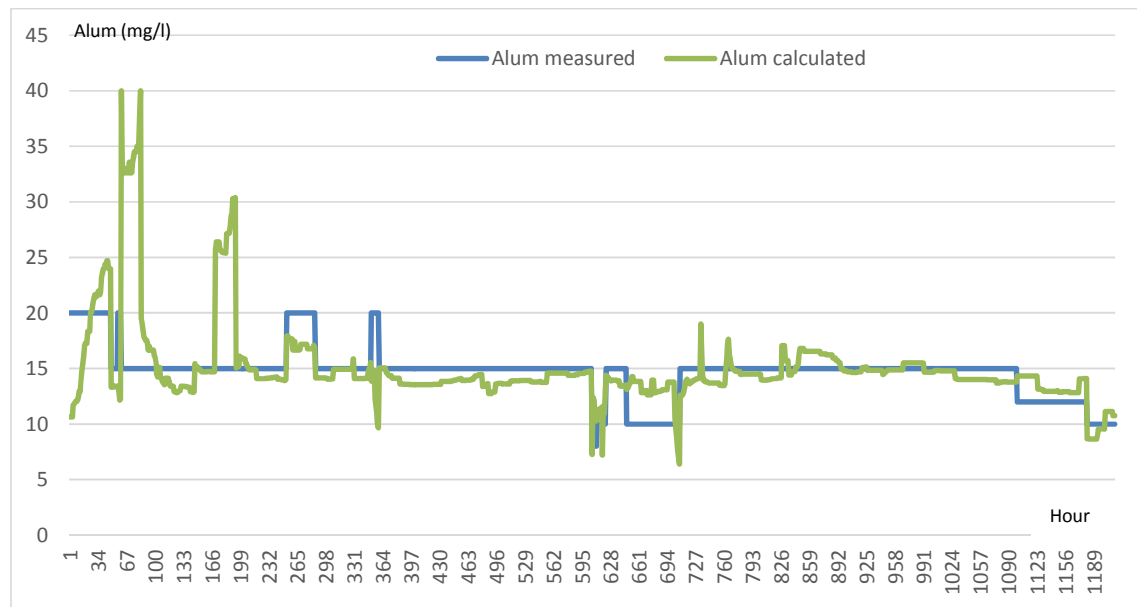


Figure 11: Comparison between the observed dose of the aluminum sulfate (Alum measured) and the calculated dose (Alum calculated M5) by using the model 5 per hour for turbidity between 10 and 20 NTU.

The aluminum sulfate dose can be estimated according to the data available in the treatment plant. Figures 10- 11 show that the calculated dose of the aluminum sulfate is near of the measured dose using the jar test. Then, the operator can use this model to control and monitor the aluminum sulfate dose in the water treatment plant. Also, the monitoring of the aluminum sulfate injection is possible by using this kind of model.

The optimization of the coagulant consumption is possible. The model can continually calculate the aluminum sulfate dose and this dose is predicted according to the change in the parameters of raw water. Instead to use a measured dose by jar test for twenty four hours minimum. In the other hand, this approach is very interesting in improving the water quality because under dosing of coagulant can lead to poor quality drinking water while too much coagulant leads to many operating problems (less efficient filtration and sedimentation, pH), healthy problems and can increase the cost of treated water.

IV. CONCLUSIONS

This paper has presented some preliminary results concerning the challenging task of controlling the coagulant dosing rate at water treatment plant using non linear model. The model is related to turbidity, pH and temperature parameters. The aim of the model is to provide water treatment operators with a tool that enables prediction of the aluminum sulfate dose using the parameters measured in the plant. Application of the models can reduce the aluminum sulfate consumption by more than 10% in the water treatment plant. The performance of the model can be improved according to the database in the water treatment plant and updating of the data base would certainly contribute to reach the representative model for predicting aluminum sulfate dose. This approach can improve the water quality and reduce many operating problems.

Disclaimer: - This manuscript was presented in the conference.

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232 Conference link is "<http://waset.org/pdf/books/?id=45249&pageNumber=1602>"

233 Date February 25-26, 2016 Dubai, UAE

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