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Identification of water treatment plant based on feedforward neural network*

by

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Abstract: Coagulation process is the main process in conventional water treatment process sequence. It influences the following treatment process aspects: maintaining plant efficiency and increasing the quality of the produced water. This is accomplished by adding chemicals to raw water, such as alum sulphate. To secure the appropriate plant performance, a mathematical model is proposed in this paper for the coagulation unit, followed by the development of the control strategy. Classic PID and neural network based controller regulating the process are used. Tests were performed, based on the real data for water treatment, using MATLAB/SIMULINK. Simulation results showed better values for both settling time and overshoot in the case of using neural network based controller than PID.

Keywords: water treatment plant, coagulation process, PID, neural network control

1. Introduction

Conventional treatment is the most common method used in water treatment plants (WTPs). It comprises typically coagulation, flocculation, filtration, and then chlorination, just as does our plant under test. Two successive coagulation /flocculation processes remove more than 60% of total raw water turbidity and microbial load. So, the fundamental role of these two steps appears very clearly in the subsequent filtration step, and then in product water.

Turbid raw water is contaminated with colloidal, dissolved, suspended particles, amoebic cysts, algae, organic and inorganic compounds, characterized by their light weight, instability, and static negative charges. So, repulsive zeta

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potential force (electrokinetic potential in colloidal dispersion, see., e.g., Wills and Finch, 2015) is created, which keeps these particles apart, resulting in high turbidity, undesirable odor, color and taste. Thus, neutralizing these negatively charged particles is done by using positive ions, such as sodium, calcium or aluminum compounds, known as coagulation process, followed by floc formation, which uses as facilitating means rapid/gentle stirring. The colloids are attracted to these flocs, and ultimately they are able to settle in a clarification basin for sufficient retention time (Apostol et al., 2011; Engelhardt, 2010; Rangeti, 2014).

The net ionic charge of water after coagulation provides an evaluation for plant performance, indicating the level of floc formation, turbidity removal, chemicals cost, and then minimum residual aluminum in produced water.

The measuring methods and devices for ionic charge are either streaming current detector or zeta potential test (Engelhardt, 2010; Ghernaout, 2015), or the charge can be calculated from a system of equations (Bello et al., 2014) representing the coagulation process.

The constructive results from system modeling and control are needed for the site engineer to describe the process behavior with respect to different input parameters or different operating conditions, the respective effort involving trying many control techniques and simulating the plant within the expected ranges of values, which helps to predict plant performance.

Most of industrial processes are characterized by nonlinear behavior and time delays. For such systems, control community proposed different feedback/feed forward techniques to achieve the desired performance, compensating for noise and varying conditions. There are numerous studies (see, e.g., Anuradha et al., 2009; Ghutke, 2015; Heddam et al., 2012; Jiang, 2008; Kumar et al., 2013; Vasičkaninová et al., 2011), which discuss this issue.

The present work contains: definition of the coagulation system, overview on Shbin El-Kom WTP in Egypt, treatment operation and the data needed, and system implementation using linear PID controller and neural network.

2. Water treatment plant

The water treatment plant that is considered here is located in the Delta region on Nile River. The region has high population and high intensity of pollution coming from human activities, industrial unwanted products, or sudden events related to environmental conditions. Nile River supplies the treatment plant with raw water. Treatment is of a conventional type, accomplished by alum and chlorine addition.

The plant produces around 40,000 cubic meters of water daily, serving more than one million people.

Optimal operation and preventive maintenance for machinery and piping in any water treatment plant is an important issue regarding ensuring the proper system running. The hydraulic system of the coagulation unit is composed of dosing pumps, solution pipes and calibration. The concrete coagulation tank of rapid stirring works typically at 99 rpm for possibly perfect mixing of chemicals with raw water.

This is followed by slow mixing, with 33 rpm for floc formation, and then sedimentation in the clarification basin. Next, there is filtration with rapid sand filters, and finally disinfection. All these stages are automated by programmable logic controller (PLC) with SCADA used for monitoring. The available instruments are installed at all the appropriate locations for calibration regarding the desired quantities. The Egyptian code for water and waste water management constitutes a guide for maintenance and operation of WTPs in Egypt. Fig. 1 shows the coagulation tank unit considered.

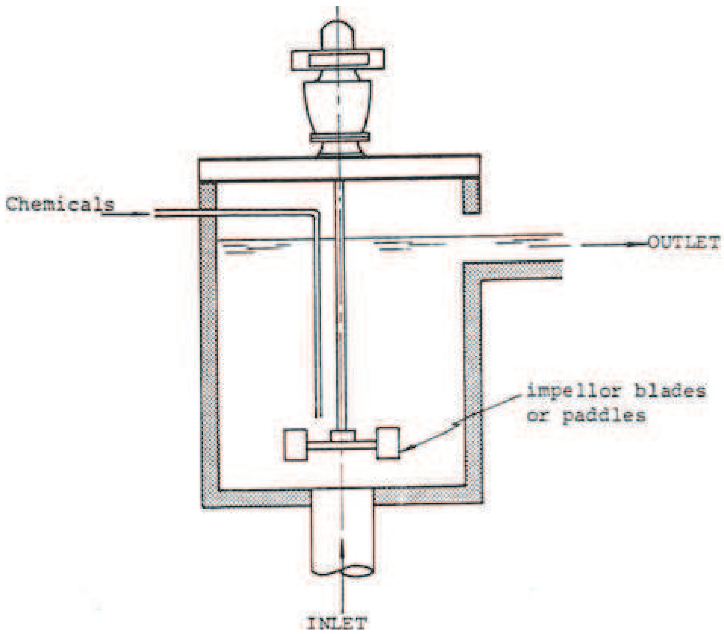

Figure 1. Coagulation unit

The chemical reaction that is involved in the coagulation process is as follows:

$$Al_2(SO_4)_2(alum\ sulphate) + 3Ca(HCO_2)_2(Alkalinity) \rightarrow$$
$$2Al(OH)_2 + 3CaSO_4 + 6CO_2$$
$$Al_2(SO_4)_2 + 3Ca(OH)_2(caustic\ soda) \rightarrow 2AL(OH)_3 + 3CaSO_4$$

The most common coagulant is alum sulphate, which is used here as the primary coagulant. When alkalinity is not sufficient, caustic soda is used as co-coagulant, and both cases will be considered in the analysis.

The coagulation reaction depends on many factors, such as raw water turbidity, temperature and pH. The pH values ranging between 5.5 and 7.5 are the best to ensure coagulation (Engelhardt, 2010), this value being reduced slightly after the addition of the chemicals. It is important to check all the intervening factors after coagulation has taken place to ensure that their values are maintained within the acceptable ranges, thus leading to the correct course of the process.

3. System identification

The way the coagulation dosing unit is modeled depends on the concept of representation of the continuous stirred tank reactor system, CSTR (see Bello et al., 2013; 2014), and can be written down as follows:

$$V * \frac{dX}{dt} = [HCO_{3in}^{-}]q_{in} - [Al_{in}^{3+}]q_a - [Ca_{in}^{2+}]qb - Xq_{out}. \tag{1}$$

If $X < 0$, then

$$[H^{+}] = -\frac{X}{2} * \left(\sqrt{1 + 4 * \frac{Kw}{x^2}} + 1\right). \tag{2}$$

If $X > 0$, then

$$[H^{+}] = -\frac{X}{2} * \left(\sqrt{1 + 4 * \frac{Kw}{x^2}} - 1\right) \tag{3}$$

$$pH = -log(H^{+})$$

$$\sigma = (\frac{2}{\pi}n\epsilon\kappa)^{\frac{1}{2}} * sinh1.15(pH_0 - pH). \tag{4}$$

Table 1 shows the variables accounted for in the identified system. Here, q_{in}, q_a, q_b, q_{out} refer, respectively, to the inlet, coagulant, co-coagulant, and outlet flow rates of the dosing unit. The surface charge is considered the controlled output variable, while the coagulant flow rate q_a is the control input variable of the model. The control strategy is aimed at forcing the output variable to a predefined set point. The process was successfully implemented in MATLAB/SIMULINK as shown in Fig. 2.

4. Water treatment data

Water quality parameters are measured daily with the help of the on-site laboratory. These parameters include temperature, pH, turbidity, residual chlorine, residual aluminum, total alkalinity, total hardness, ammonia, total dissolved solids TDS, and conductivity, and, besides this, the bacteriological parameters, such as total coli form, fecal coli form, and finally the chemical parameters.

Samples are taken from raw, clarified, filtered and treated water at different plant stages, with measurements and tests being based on standard methods for water treatment (Clesceri et al., 1998). The limits of each variable are set according to the stipulations from the Egyptian Ministry of Health, and the data set used for neural network training are taken for the entire range over a year, so as to consider all the varying conditions and weather changes (Tomperi et al., 2013).

Table 1. The used variables for the plant

Variable	**Value**
Case 1	
Aluminum concentration $[Al^{+3}]$	0.0000370625mol/L
Bicarbonate concentration,	0.0000012293 mol/L
Case 2	
Aluminum concentration $[Al^{+3}]$	0.000016308 mol/L
Bicarbonate concentration, $[HCO_3^-]$	0.00000029 mol/L
$[^{+2}]$ calcium concentration	0.0006986 mol/L
Q_b	5.1203e + 03 L/min
Q_a	32638.39861 L/min
Tank volume	145 000 litres
Disassociation constant of water, K_w	10^{-14}
Temperature	298 K
Disassociation constant of water, K_w	10^{-14}
Ionic strength,	50^{*10^6} mol/L
Faraday constant,	96490 $C^{eq^{-1}}$
Universal gas constant,	8.314 J mol−1K
Electron charge,	$1.6^{*10^{-19}}$
Relative dielectric permittivity,	80
Boltzman constant	$1.38 * \frac{10^{-22} j}{K}$

5. Water treatment control strategy

Intelligent control makes use of many techniques, including such ones as artificial neural networks, fuzzy logic controllers, neuro-fuzzy or ANFIS methods, which are widely used in modeling and control of industrial applications, due to their prediction and generalization ability, capacity of representing nonlinear relationships between cause and effect parameters, and lack of necessity of specifying accurate mathematical relations to express the respective processes (Ghutke, 2015).

The artificial neural networks or ANNs are based on the structure and properties of the biological nervous system, which contain a vast amount of connected neurons, and can deal with large amounts of data as well as adapt to changes (Cordoba et al., 2014; Wu and Lo, 2008).

The here used network controller is based on the ANNs of feed forward type, see Fig. 3. It consist of inputs (four in the figure, but, actually, four or five, depending upon the case, 1 or 2) having the following meaning: error between process output and set point, and, besides, the raw water quality variables, which influence optimal coagulant quantity, such as turbidity, PH, inlet flow rate and temperature (see Heddam et al., 2012; Olanrewaju et al., 2012), the sole output being the coagulant flow rate. The hidden neurons are determined by the trial and error process, carried out until the best results have been achieved. The network was trained offline with the back propagation algorithm using the *trainlm* function.

The thus determined ANN controller can predict chemical flow rate, allowing for the manipulation of the coagulation process helping to obtain the desired output. Table 2 shows the network data used for both cases, while Fig. 4 shows the network structure for Case 1.

Table 2. The ANNs used for both cases

	Case 1	Case 2
Input neurons	4	4
Output neurons	1	1
Hidden neurons	5	6
Backpropagation algorithm	Levenberg-Marquardt	
Hidden layer function	Log sigmoid	
Inputs	Temperature, pH, Flow rate, Error	Temperature, Flow rate, Turbidity, Error

6. Simulation results

For coagulation control, the predefined process was firstly implemented using the data of the underlying WTP, and neural controller was successfully employed to regulate the output to the desired set point in MATLAB/SIMULINK environment, shown in Fig. 5.

A comparison of simulation results with those for the PID controller is provided in Fig. 6 (a and b). Table 3 shows that better responses are obtained with ANN than with PID concerning settling time and overshoot.

7. Conclusion

This short paper gives a quick overview of a water treatment plant with focus on coagulation process, which is considered as the first and essential step in the whole treatment. Identification of coagulation dosing unit is proposed in order to help in system description and control. Two control fashions are used,

Table 3. Response characteristics

	Case 1		Case 2	
	PID	ANN	PID	ANN
Settling time (minutes)	42	21	35	20
Overshoot %	20.29 %	1.23 %	36.25 %	19.88 %

intelligent and conventional, the plant response is characterized by the fast settling time and less overshoot with neural network controller, when compared to classic PID.

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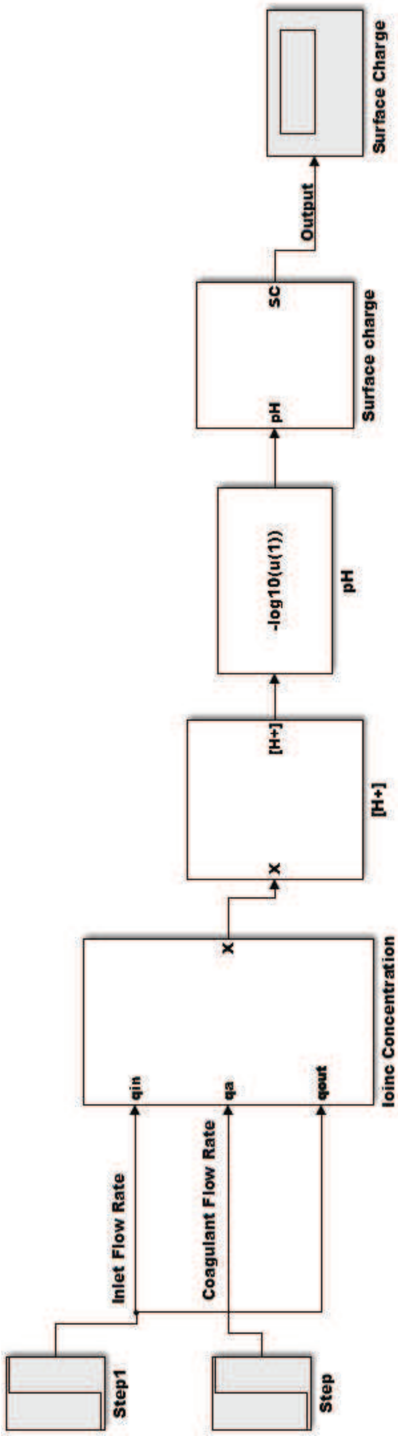

Figure 2. Coagulation system implemented in MATLAB environment

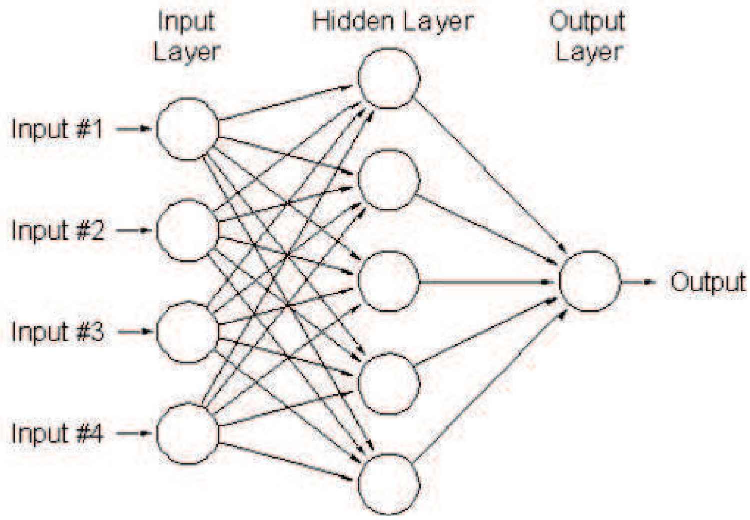

Figure 3. Feed forward neural network structure

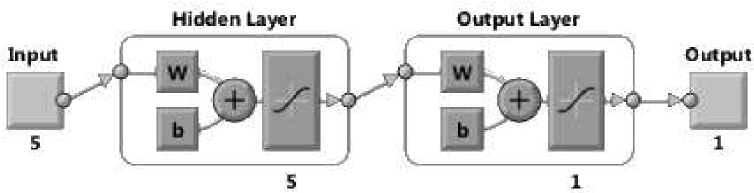

Figure 4. The ANN structure for case1

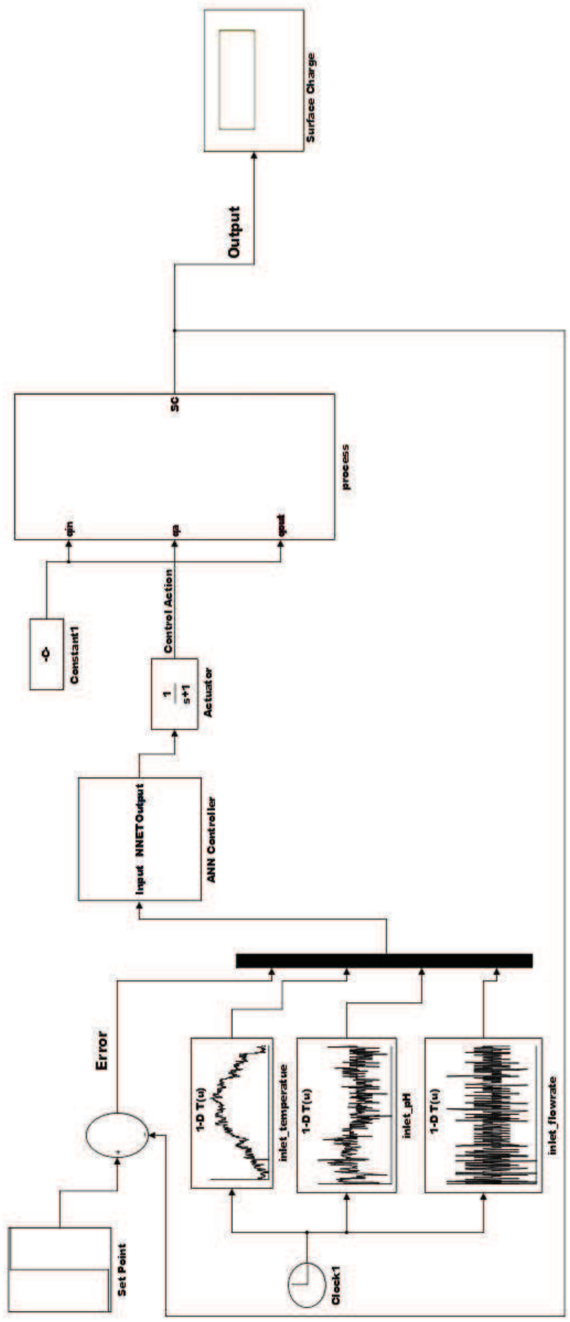

Figure 5. System control in MATLAB

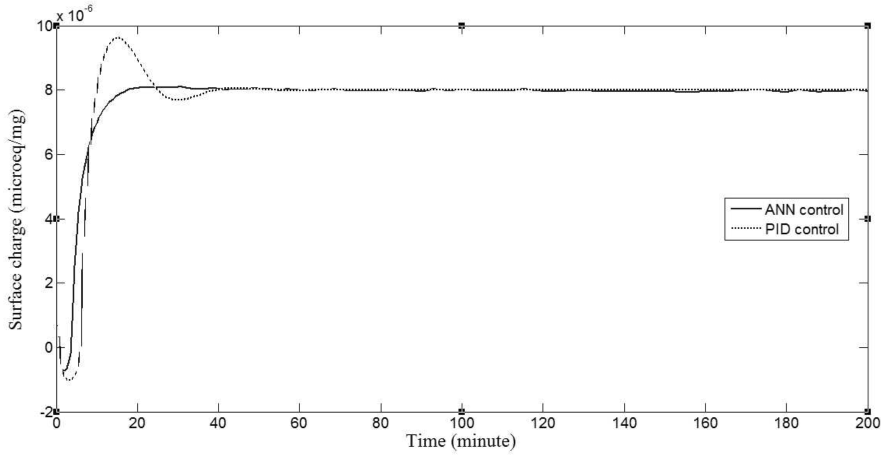

Figure 6. Simulation output with PID and ANN based control (case 1)

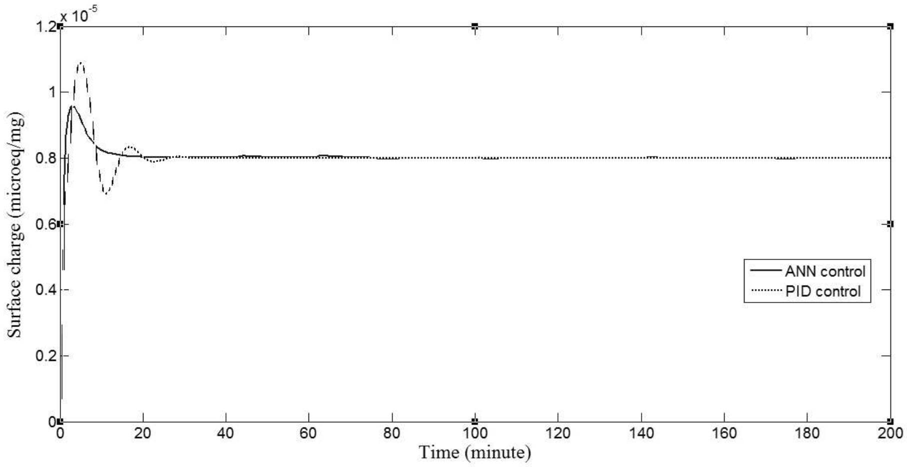

Figure 7. Simulation output with PID and ANN based control (case2)