

Performance evaluation of a wiener model predictive control for a coagulation chemical dosing unit in water treatment plants

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ABSTRACT

Coagulation process control is an essential operation in water treatment plants. It is a challenging control problem due to the nonlinear and physicochemical nature of the coagulation process. The paper presents the application of the Wiener model predictive control (WMPC) algorithm to a coagulation chemical dosing unit for water treatment plants in order to keep the surface charge and pH level of the dosed water at the reference trajectory set by the operator of the plant. Wiener models with different nonlinear estimators are compared and evaluated. A Wiener model with a wavelet network estimator presented the highest goodness of fit (98%), and was thus selected as the best prediction model. Simulation results show that the proposed control strategy has good set-point tracking, as well as noise and disturbance rejection performances.

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1. Introduction

The coagulation process control is a challenging problem in the water and wastewater, paper and pulp, beverage and brewery industries where the need for clean water is imperative to achieve the organisation goals and objectives. This could be attributed to the complex and nonlinear behaviour of the process [1, 11]. Several approaches have been proposed in the literature for the control of the process in the water treatment plants in particular. Traditionally, visual inspection and reference table are methods used by plant operators to evaluate the quality of the finished water. The operators observe the water and make adjustment to increase, maintain or decrease the coagulant dosages based on

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their personal judgment and experience. This approach does not support production of adequate and cost effective water treatment operation. Moreover, jar tests are basically routine laboratory procedures to establish the optimum dosage of coagulation chemicals for water treatment. A typical jar test apparatus consists of a six variable-speed paddle gang stirrers with impellers, 1.5 litres square glass beakers or jars and sample tap or draw-off siphoning tube. The jar tests could be suitably used to select primary and secondary coagulants, perform mixing energy and time studies, estimate the settling velocities for sedimentation, basin sizing and evaluate sludge recycling effect. However, jar tests are time-consuming and labour intensive. It does not have the ability to be incorporated into an online monitoring and automatic control scheme for coagulation process [9].

Another common approach is to develop prediction process models for coagulation chemical dosages using data collected from water treatment plants. The input variables of these models are obtained from the operational and physical water quality parameters of the raw water flowing into the plant. These parameters are measured by means of appropriate sensors before the water enters the rapid mixing tank or dosing point. These models are developed using statistical or regression analysis techniques [7]. Alternatively, intelligent techniques such as artificial neural networks, adaptive neuro-fuzzy inference scheme, fuzzy logic and genetic programming techniques are suitably used to model the nonlinear relationship between the input and output variables of the prediction models [2, 11, 12, 15–18]. Previous studies have shown that these intelligent techniques exhibit lesser prediction errors when compared to the regression based model [7]. With the development of these empirical models, feedforward controllers are implemented to control the flowrates of the dosing pumps with satisfactory results [3]. Automatic control actions of the coagulation chemical dosage system could also be provided using the feedback controllers. In this approach, streaming current detector and pH meter are required to achieve feedback of the measured variables to the control system. The streaming current detector provides a direct measurement of the average colloidal surface charge while the pH meter measures the pH or degree of hydrogen ions concentration in the raw water. For effective implementation of a feedback control scheme, the average colloidal surface charge and pH of the water after coagulation must be controlled to follow the reference trajectory set by the plant operators and have robust performance when operational disturbances are acting on the process [1], [13] and [7].

Model predictive control (MPC) is a widely used control algorithm in the process industries. It involves the use of a dynamic model to predict and optimise process performances. MPC has capability to handle system constraints effectively and could be used with multiple-input, multiple output systems where the traditional control scheme may prove inadequate. Most processes are nonlinear in nature, whereas most MPC software available are based on linear dynamic model. Thus, the MPC may not work effectively with highly nonlinear processes. One of the identified approaches to approximate any nonlinear process with high precision is to use Wiener model. Wiener model has a structure that consists of the cascade connection of a linear invariant (LTI) system followed by a static or memoryless nonlinearity. The application of the Wiener model to nonlinear processes have been discussed and reported in [8, 14]. The most commonly used nonlinearity blocks will be applied in this study to identify a Wiener model from the input-output data generated from a nonlinear first principles simulation model of the coagulation process in a rapid

mixing tank reactor. The simulation model is developed based on the operational data collected from the Rietvlei water treatment plant, South Africa. The identification results of the nonlinearity blocks are compared to determine the best estimator among them. The best identified Wiener model is applied in the MPC algorithm. The performances of the Wiener model predictive control scheme are examined in terms of its ability to track changes in reference trajectory and reject disturbances after a simulation period of 48 hours.

2. Materials and methods

2.1. Description of the Rietvlei water treatment plant

The Rietvlei water treatment plant was built between 1932 and 1934, near Irene, City of Tshwane, South Africa. The production capacity of the plant is approximately 40 million litres per day. Fig. 1 illustrates the process train of the Rietvlei water treatment plant. A pumping station and transport system is available to lift water from the dam and convey it to the treatment plant. Raw water then flows through the intake pipe into the coagulation chemical dosing unit. The chemical dosing unit consists of a concrete mixing tank with inlet and outlet channels. Four metering pumps are used for dosing the chemicals into the influent raw water of which two dosing pumps are active while the other two are on a standby or redundant position. One of the dosing pumps feeds a polyelectrolyte solution while the other feeds a ferric chloride solution into the concrete mixing tank. The polyelectrolyte solution known as suffloc 3835, is a blend of epichlorohydrin/dimethylamine (polyamine) and aluminium chlorohydrate. The adoption of organic polyelectrolytes as part of the water treatment process in South African waterworks is widely established due to their higher efficiency and lower cost when compared to the traditional or inorganic coagulants. The pumps are controlled by programmable logic controllers (PLC) that are connected to the supervisory control and data acquisition (SCADA) system of the plant. The dosage quantities of coagulation chemicals depend on the influent flowrate of the raw water flowing into the water treatment plant. Calcium hydroxide (hydrated lime) in slurry form is also added to the mixing tank using a diaphragm pump to stabilise the water and adjust the pH value to a set point value between 8.1 and 8.3.

The chemically dosed water flows out slowly and evenly from the rapid mixing tank into a series of baffled or flocculation channels to grow the flocs. The water from the baffled channels then flow into the Dissolved Air Floatation/Filtration (DAFF) unit. The filtered water from the DAFF then flows into the Granular Activated Carbon (GAC) filtration unit to eliminate any foul odour, taste and colour caused by the natural organic matter. Thereafter, the water from the GAC flows into the chlorination chamber. Here, chlorine gas is added to the water to disinfect the clean water before it is pumped to the storage reservoirs and distributed to end users [4, 5].

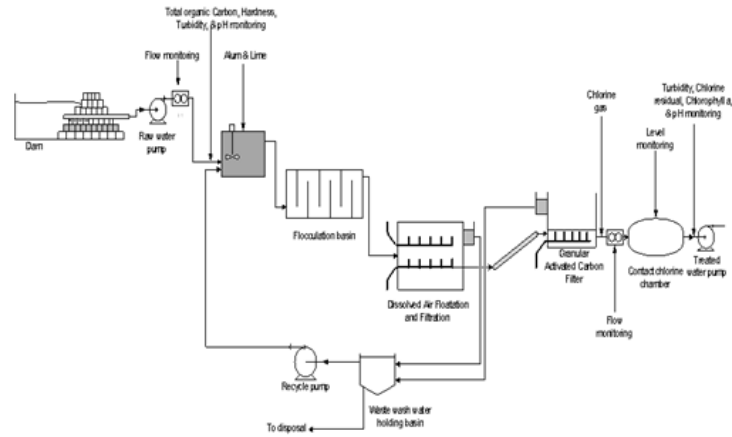
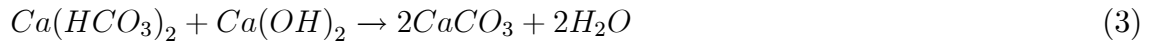
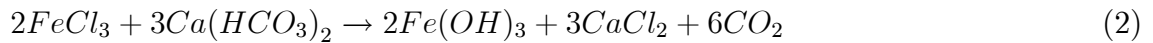
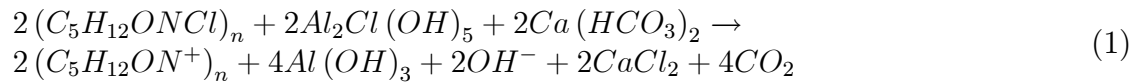


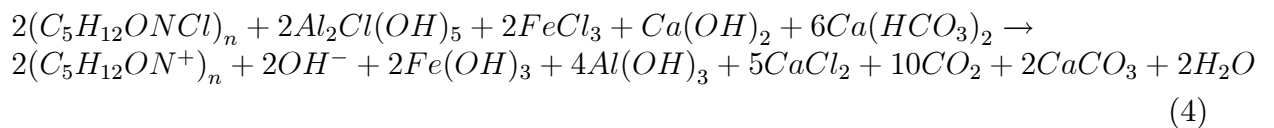
Fig. 1 – Process flow diagram of the Rietvlei water treatment plant, City of Tshwane.

2.2. Theoretical Modelling

The general chemical reactions in the mixing tank reactor in Fig. 2 are written as [5] :



Chemical reactions in (1), (2) and (3) take place simultaneously. Therefore, the overall chemical equation becomes :



The reaction invariants (4) are $[(C_5H_{12}ON^+)_n]$, $[Al^{3+}]$, $[Fe^{3+}]$, $[Ca^{2+}]$, $[H^+]$, $[HCO_3^-]$, $[OH^-]$, $[SO_4^{2-}]$ and $[CO_3^{2-}]$. However, $[SO_4^{2-}]$ and $[CO_3^{2-}]$ ions present in the system do not take part in the neutralisation reactions. Therefore, the electroneutrality equation of the reaction for equation (4) is expressed as :

$$[(C_5H_{12}ON^+)_n] + [Al^{3+}] + [Fe^{3+}] + [Ca^{2+}] + [H^+] = [HCO_3^-] + [OH^-] \quad (5)$$

Rewriting (5) gives :

$$[HCO_3^-] - [(C_5H_{12}ON^+)_n] - [Al^{3+}] - [Fe^{3+}] - [Ca^{2+}] = [H^+] - [OH^-] \quad (6)$$

Let the difference of the ionic concentrations be expressed as :

$$X = [HCO_3^-] - [(C_5H_{12}ON^+)_n] - [Al^{3+}] - [Fe^{3+}] - [Ca^{2+}] \quad (7)$$

Where

$$X = [H^+] - [OH^-] \quad (8)$$

Assuming that there is perfect mixing in the tank reactor, the relationship between the ionic concentrations of the effluent and input concentrations using the material balance equations can be expressed as :

$$V \frac{d[(C_5H_{12}ON^+)_n]}{dt} = [((C_5H_{12}ON^+)_n)_{in}] q_a - [(C_5H_{12}ON^+)_n] q_{out} \quad (9)$$

$$V \frac{d[Al^{3+}]}{dt} = [Al_{in}^{3+}] q_a - [Al^{3+}] q_{out} \quad (10)$$

$$V \frac{d[Fe^{3+}]}{dt} = [Fe_{in}^{3+}] q_b - [Fe^{3+}] q_{out} \quad (11)$$

$$V \frac{d[Ca^{2+}]}{dt} = [Ca_{in}^{2+}] q_c - [Ca^{2+}] q_{out} \quad (12)$$

$$V \frac{d[HCO_3^-]}{dt} = [HCO_{3,in}^-] q_{in} - [HCO_3^-] q_{out} \quad (13)$$

Where $[(C_5H_{12}ON^+)_n]$ is the polyamine ionic concentration at the mixing tank outlet, $[((C_5H_{12}ON^+)_n)_{in}]$ the polyamine ionic concentration at the mixing tank inlet, $[Al^{3+}]$ is the aluminium ionic concentration at the mixing tank outlet, $[Al_{in}^{3+}]$ aluminium ionic concentration at the mixing tank inlet, $[Fe^{3+}]$ is the ferric ionic concentration at the mixing tank outlet, $[Fe_{in}^{3+}]$ ferric ionic concentration at the mixing tank inlet, $[Ca^{2+}]$ calcium ionic concentration at the mixing tank outlet, $[Ca_{in}^{2+}]$ calcium ionic concentration at the mixing tank inlet, $[HCO_3^-]$ bicarbonate ionic concentration of the effluent stream, $[HCO_{3,in}^-]$ bicarbonate ionic concentration of influent stream, q_a flow rate of sudfloc 3835 solution, q_b flow rate of ferric chloride solution, q_c flow rate of hydrated lime, q_{out} flow rate of the effluent stream, q_{in} flow rate of the influent stream, V volume of mixing tank, $[H^+]$

hydrogen ions concentration, $[OH^-]$ hydroxide ions concentration and k_w dissociation constant of water.

Adding (9) to (12) and then subtract the sum from (13) gives :

$$V \frac{d[HCO_3^-]}{dt} - V \frac{d[(C_5H_{12}ON^+)_n]}{dt} - V \frac{d[Al^{3+}]}{dt} - V \frac{d[Fe^{3+}]}{dt} - V \frac{d[Ca^{2+}]}{dt} = [HCO_3^-]_{in} q_{in} - [((C_5H_{12}ON^+)_n)_{in}] q_a - [Al^{3+}]_{in} q_a - [Fe^{3+}]_{in} q_b - [Ca^{2+}]_{in} q_c + [(C_5H_{12}ON^+)_n]_{out} q_{out} + [Al^{3+}]_{out} q_{out} + [Fe^{3+}]_{out} q_{out} + [Ca^{2+}]_{out} q_{out} - [HCO_3^-]_{out} q_{out} \quad (14)$$

The material balance expression of the mixing tank reactor yields :

$$V \frac{dX}{dt} = [HCO_3^-]_{in} q_{in} - [((C_5H_{12}ON^+)_n)_{in}] q_a - [Al^{3+}]_{in} q_a - [Fe^{3+}]_{in} q_b - [Ca^{2+}]_{in} q_c - X \cdot q_{out} \quad (15)$$

Thus, (4.15) is expressed as :

$$V \frac{dX}{dt} = [HCO_3^-]_{in} q_{in} - \left([((C_5H_{12}ON^+)_n)_{in}] + [Al^{3+}]_{in} \right) q_a - [Fe^{3+}]_{in} q_b - [Ca^{2+}]_{in} q_c - X \cdot q_{out} \quad (16)$$

The dissociation equation for water is

$$[H^+] \cdot [OH^-] = k_w = 10^{-14} \quad (17)$$

Substituting (8) into (17) gives a quadratic expression :

$$[H^+]^2 - X [H^+] - k_w = 0 \quad (18)$$

The solutions of the equation (4.18) are written as :

$$\begin{aligned} \text{If } X > 0, \text{ then } [H^+] &= \frac{X + \sqrt{X^2 + 4k_w}}{2} = \frac{X}{2} \cdot \left(\sqrt{1 + \frac{4k_w}{X^2}} + 1 \right) \\ \text{If } X = 0, \text{ then } [H^+] &= \sqrt{k_w} \\ \text{If } X < 0, \text{ then } [H^+] &= \frac{X - \sqrt{X^2 + 4k_w}}{2} = -\frac{X}{2} \cdot \left(\sqrt{1 + \frac{4k_w}{X^2}} + 1 \right) \end{aligned} \quad (19)$$

The concentration of the hydrogen ions $[H^+]$ may be expressed in the logarithmic function as :

$$pH = -\log [H^+] \quad (20)$$

The expression for the surface charge of the raw waters is obtained as described in section 3.1.

$$\sigma = [(2/\pi) n\varepsilon\kappa T]^{1/2} \sinh 1.15 (pH_0 - pH) \quad (21)$$

Where σ is the surface charge , κ is the Boltzmann constant, T is the temperature, ε refers to the relative dielectric permittivity, pH_0 P_H at point of zero charge and n ionic strength.

From (12), (20) and (21), the dynamics of the chemical dosing unit is formulated. The surface charge and pH are the controlled output variables while the coagulant flow rate (q_a), co-coagulant flow rate (q_b) and pH adjustment chemical flow rate (q_c) are the control input variables of the model.

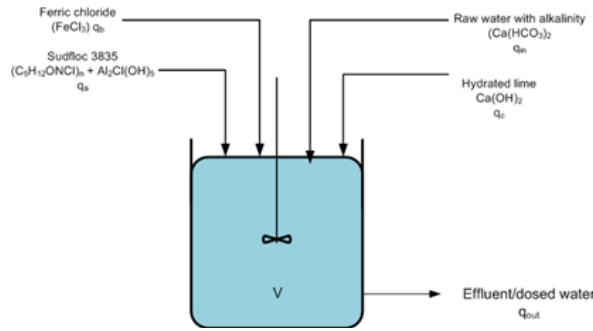


Fig. 2 – Mixing tank reactor for the coagulation chemical dosing unit.

2.3. Identification with Wiener models

Wiener model consists of a linear dynamic system G followed by a static nonlinearity f as shown in Fig. 3. The input u and the output y are measurable, while the states of the models are denoted by x which can be observed. For the linear dynamic system of the Wiener model structure, it could be written as :

$$x(t) = G(q, \theta) u(t) \quad (22)$$

Similarly, the nonlinearity part is expressed as

$$y(t) = f(x(t), \eta) u(t) \quad (23)$$

By combining (22) and (23) together, the output of the Wiener model structure is :

$$y(t) = f(G(q, \theta) u(t) + v(t), \eta) + e(t) \quad (24)$$

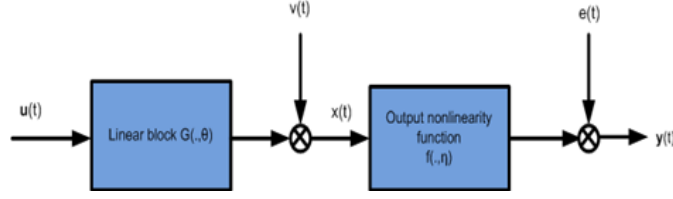


Fig. 3 – Wiener model structure.

The linear dynamic system that shows the relationship between the input and the output could be represented in the discrete state-space form as [10] :

$$\begin{aligned} \xi(k+1) &= A\xi(k) + Bu(k) \\ y(k) &= C\xi(k) + Du(k) \end{aligned} \tag{25}$$

where ξ is the state vector, consisting of n state variables. a , B and C are system matrices. The nonlinear block is static and thus a real-valued function of the state variables. The general structure of the nonlinear block can be expressed using the function expansion with basis functions and parameters :

$$y = \sum_{i=1}^{n_b} f_i B_i(x) \tag{26}$$

where $B_i(x)$ is the basis function. The commonly used basis functions for the nonlinear blocks are :

Power Series :

$$B_i(x) = x^i \quad i = 0, 1, 2, \dots, n_b \tag{27}$$

where n_b is the number of input time steps.

Chebyshev polynomials :

$$B_j(x_j) = \begin{cases} 0 & \text{if } (x \leq x_{i-1}) \\ \left(\frac{x-x_{i-1}}{x_i-x_{i-1}} \right) & \text{if } (x_{i-1} \leq x \leq x_i) \\ \left(\frac{x_{i+1}-x}{x_{i+1}-x_i} \right) & \text{if } (x_i \leq x \leq x_{i+1}) \\ 0 & \text{if } (x_{i+1} \leq x) \end{cases} \tag{28}$$

Piecewise polynomial :

$$B_k = \frac{1}{1 + e^{-(\eta_{o_k} + x\eta_{1_k})}} \tag{29}$$

where η_{o_k} and η_{1_k} are internal parameters of the sigmoid function that determines the position of the transition from 0 to 1 and how fast.

Wavelets :

$$B_{i,j}(k) = \frac{1}{\sqrt{2^i}} \psi\left(\frac{x - 2^i j}{2^i}\right) \quad (30)$$

where i is a scaled parameters, j is the dilation parameter and ψ is the mother wavelets.

The goal of identification using Wiener model is to estimate the two parameters, θ and η , using the measurements of the input u and the output y to achieve the best model for the process under consideration. When the parameters θ and η , and the given input u are known, then the predicted output, $\hat{y}(k, \theta, \eta)$ could be estimated. In order to estimate the quality of a model, the predicted output $\hat{y}(k)$ and measured output y are compared using a prediction error criterion. The prediction error criterion for this purpose is stated as :

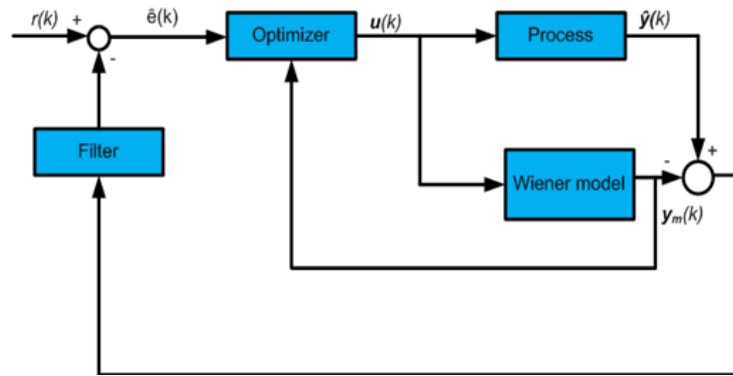


Fig. 4 – Block diagram of WMPC scheme.

$$V_N(\theta, \eta) = \frac{1}{N} \sum_{k=1}^N (y(k) - \hat{y}(k, \theta, \eta))^2 \quad (31)$$

where N is the number of data.

The implication of (31) is that the best model has the minimal value of $V_N(\theta, \eta)$ which depends on the optimal estimate of these two parameters [10].

2.4. Wiener model predictive control scheme

MPC scheme based on the Wiener model is presented in this study. MPC basically uses the dynamic model of the plant to predict and optimise the future behaviour of the process. At each control interval, the MPC algorithm computes a sequence of future input control moves over a control horizon M , in order to optimise the future response of the plant. The optimisation of the plant behaviour is achieved by minimising an objective function based on a desired output trajectory over a prediction horizon P . Only the first value of the input control move sequence is applied into the plant others are discarded,

then the horizon is moved one step towards the future, and the optimisation process is repeated. The objective function can be written as :

$$J = \sum_{i=0}^P \|\hat{y}_{k+i|k} - r_{k+i}\|_{Q(i)}^2 + \sum_{i=0}^{M-1} \|u_{k+i|k}\|_{S(i)}^2 + \sum_{i=0}^{M-1} \|\Delta u_{k+i|k}\|_{R(i)}^2 \quad (32)$$

where $\hat{y}_{k+i|k}$ represents the prediction, made at time k , of the output at time $k+i$, r_{k+i} is the value of the reference at time $k+i$ and $u_{k+i|k}$ and $\Delta u_{k+i|k}$ are the control input and control input increment, computed at time k , at time $k+i$ respectively. $Q(i)$, $S(i)$ and $R(i)$ are positive semi-definite diagonal weighting matrices, and $\|x\|_w = \sqrt{x^T W x}$ is the weighting 2-norm of vector x . The prediction horizon P , control horizon M , the weighting matrices are design parameters of the MPC that are tuned to obtain desired performances.

In formulating the MPC algorithm, constraints on the process due to the limited range and dynamic response of actuators, operational, safety, economic or environmental factors are taking into consideration. The constrained optimisation problem solved in the MPC algorithm is stated as [8] :

$$\underbrace{\min}_{\Delta u} J(k) \quad (33)$$

subject to :

$$\begin{aligned} u_{\min}^i &\leq u_k^i \leq u_{\max}^i \\ \Delta u_{\min}^i &\leq \Delta u_k^i \leq \Delta u_{\max}^i \\ y_{\min}^i &\leq y_k^i \leq y_{\max}^i \end{aligned} \quad (34)$$

where i represent the i th component of the corresponding vector. The WMPC scheme in Fig. 4 is implemented by using the identified Wiener model as a replacement for the internal model employed in the standard MPC algorithm for predicting the future response and optimisation.

Table 1 – Process modelling variables.

Variable	Symbols	Values and units
Polyamine and aluminium ions concentration	$[(C_5H_{12}ON^+)_n + [Al^{3+}]]$	0.0001 mol/L
Ferric ions concentration	$[Fe^{3+}]$	0.0001 mol/L
Calcium ions concentration	$[Ca^{2+}]$	0.0001 mol/L
Bicarbonate ion concentration	$[HCO_3^-]$	0.0001 mol/L
Hydrogen ion concentration	$[H^+]$	10^{-7} mol/Litre
Coagulant flow rate	q_a	0.14 Litres/s
Hydrated lime flow rate	q_b	0.7 Litres/s
Influent water flow rate	q_{in}	462.96 Litres/s
Tank Volume	V	8000 Litres
Dissociation constant of water	K_w	10^{-14}
Temperature	T	298 K
electron charge	e	1.6×10^{-19} C
Ionic strength	n	50×10^6 mol/cm ³
Relative dielectric permittivity	ε	80
Boltzman constant	κ	$1.38 \times 10^{23} JK^{-1}$
Faraday constant	F	96,490 Ceq^{-1}
Universal gas constant	R	8.314 $Jmol^{-1}K$

3. Results and discussions

3.1. Simulation model results

The simulation model of the coagulation chemical dosing unit described in the previous section was developed and simulated in MATLAB 7.10 environment. The simulation parameters are stated in Table 1. The input variables to the simulation models were the data collected from the water treatment plant for a period of 690 days. The response of the simulation model is presented in Fig. 5.

The simulation results show that surface charge values are within the range of $-1 \times 10^{-5} \mu eq/mg$ and $+7 \times 10^{-5} \mu eq/mg$ and the pH values fall between the range of 7 and 8.5. Based on these results, a suitable control scheme is proposed for the dosing unit to ensure that its output variables follow the desired set-points.

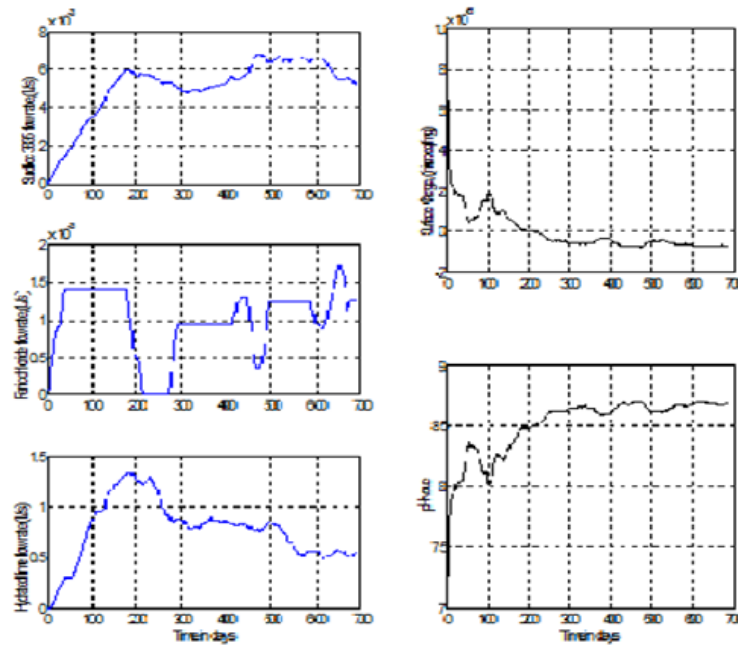


Fig. 5 – Input and output datasets.

3.2. Performance of the estimators

The following four nonlinearity blocks were used in the Wiener model for the system identification of the coagulation process : piecewise linear, polynomial, sigmoid, and wavelet network. The results of each nonlinear block are compared with each other and the measured output data of the dosing unit. The estimation results of the nonlinear blocks are shown in Fig. 6. It is observed from the results that the wavelet network had the highest goodness of fit and hence the best estimators among them. In view of this finding, the wavelet estimator is thus used as nonlinear estimator for the Wiener model of the process.

3.3. Performance of the WMPC scheme

The WMPC scheme proposed in the previous section was implemented using the MPC toolbox in the MATLAB 7.10/Simulink software. Simulation constraints were placed on the manipulated variables to take into consideration the minimum and maximum flow rate of the metering pumps discharging the sudfloc 3835 (q_a), secondary coagulant (q_b) and hydrated lime (q_c) into the rapid mixing tank. A lower limit of 0 L/s and an upper limit of 2 L/s were selected for these variables. The prediction horizon, was chosen as $P = 15$, while the control horizon as $M = 5$. Each of weighting matrices S , R and Q was selected as $\text{diag}(0.1, 0.1, 0.1)$.

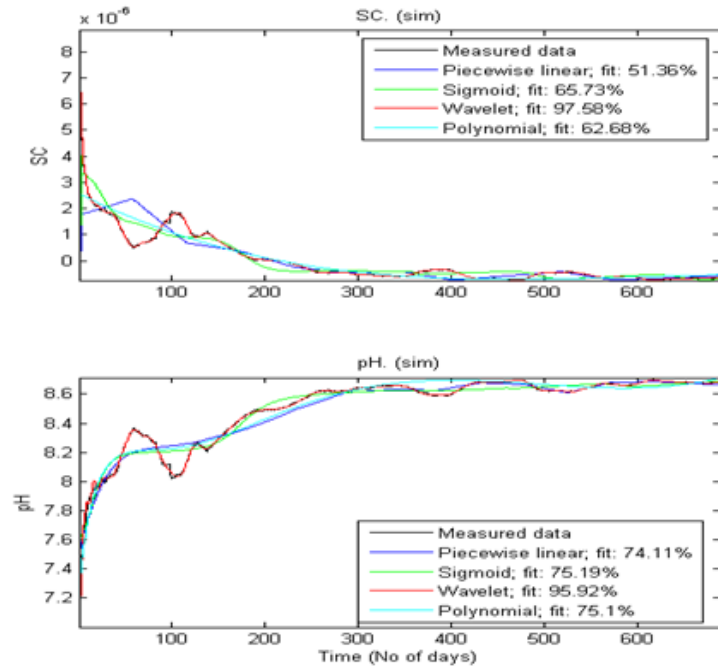


Fig. 6 – Comparison of the nonlinear estimators/functions with the measured output dataset.

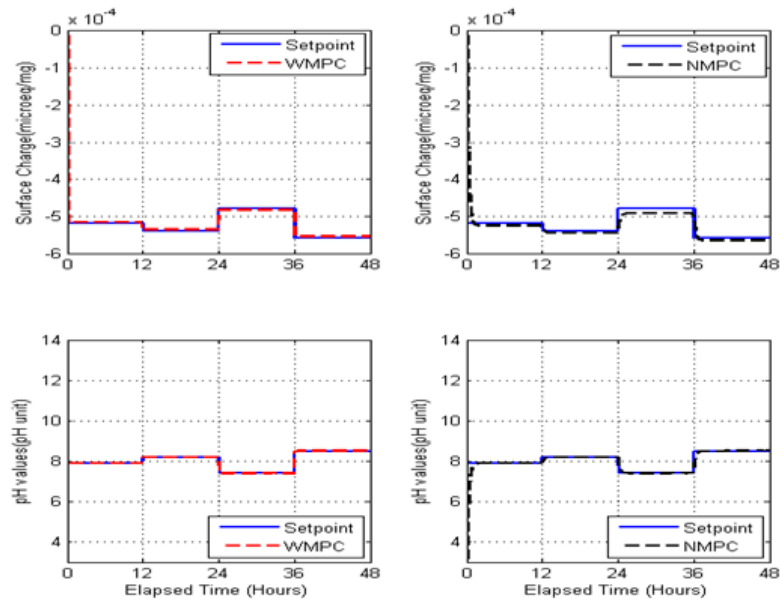


Fig. 7 – Set point tracking performance.

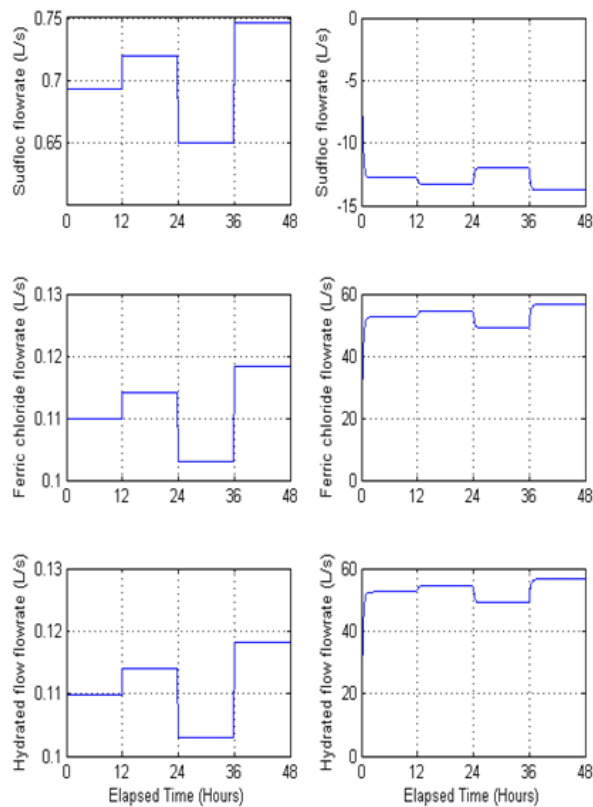


Fig. 8 – Control input moves.

In the first simulation experiment, the response of WMPC scheme to changes in the reference trajectory was examined. The system was simulated for a period of 48 hours while the set points were changed every twelve hours. The simulation results of the WMPC compared with the nonlinear model predictive control (NMPC) scheme are shown in Fig. 7. It can be observed that the WMPC scheme tracks the reference trajectory satisfactorily and its normalised root mean square error (RMSE) values in Table 2 are lower than that of NMPC. Fig. 8 shows the control input moves to achieve the set-point tracking performance of the two control schemes. The performance of the WMPC scheme when the system is subjected to disturbances in form of input and output noise signals and step signals on the manipulated input channels was investigated in the second simulation experiment. The simulation results when compared with the NMPC are shown in Fig. 9. The control input moves of the control schemes are shown in Fig. 10. The WMPC scheme behaved appropriately by rejecting the disturbances acting on the system without violating the constraints placed on the manipulated variables. In addition, the normalised RMSE values of WMPC are smaller than that of NMPC indicating a better performance of WMPC over NMPC.

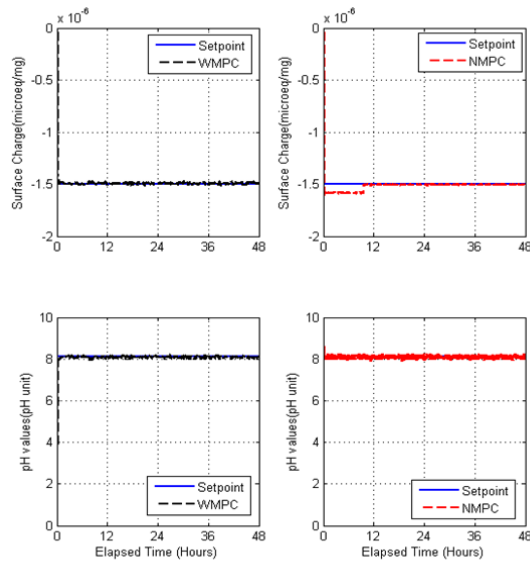


Fig. 9 – Noise and disturbance rejection performance.

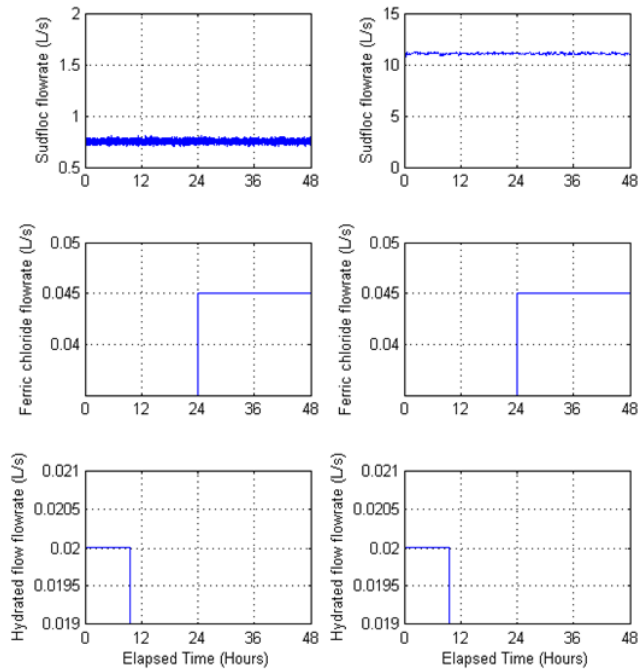


Fig. 10 – Control input moves.

Table 2 – .

Control scheme	Surface Charge (SC)	pH
WMPC(Setpoint)	0.01085	0.1495
NMPC(Setpoint)	0.02880	0.4254
WMPC(Disturbance)	0.03919	0.1335
NMPC(Disturbance)	0.04559	0.2421

Conclusion

The study has presented the Wiener model identification and predictive control of coagulation process in the water treatment plants. Input-output data from the simulation mode developed using the mechanistic modelling techniques were applied for the identification of the Wiener models of the coagulation chemical dosing unit. A comparison of the different Wiener models evaluated in the study showed that the Wiener model based on Wavelet network block had the best prediction capabilities. This Wiener model was thus proposed as the internal model of MPC algorithm instead of a standard linear model. Simulation results showed that the proposed Wiener based MPC algorithm could effectively handle the coagulation process control in water treatment operations. In continuation of this study, the subspace model identification may be examined and compared to the wavelet model identification technique. In addition, the use of genetic programming and other evolutionary computational modelling techniques could be investigated and applied in conjunction with the predictive control for coagulation process.

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