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Nonlinear Model Predictive Control of a coagulation chemical dosing unit for water treatment plants ⋆

Oladipupo Bello ** **Yskandar Hamam** *** **Karim Djouani** ****

Electrical Engineering Department/F'SATI,
Tshwane University of Technology, Pretoria, South Africa
** *(e-mail: engroobello@gmail.com)*
*** *(e-mail: hamama@tut.ac.za)*
**** *(e-mail: djouanik@tut.ac.za)*

Abstract: The need for processes to be operated under tighter performance specifications and satisfy constraints have motivated the increasing applications of nonlinear model predictive control (MPC) by the process industry. Nonlinear MPC conveniently meets the higher product quality, productivity and safety demands of complex processes by taking into account the nonlinearities and constraints in the processes. This paper examines the application of a nonlinear MPC to a multi-variable coagulation chemical dosing unit for water treatment plants. A nonlinear model of the dosing unit based on mechanistic modelling and identified by nonlinear autoregressive with external input (NLARX) estimator was developed. The simulation of the MPC based control system showed very good performance for set-point tracking and disturbance rejection. The closed loop performance of the nonlinear MPC (NMPC) compares favourably with the unconstrained and linearised nonlinear MPC (LTIMPC). The results of this study shows the suitability of nonlinear MPC for process control in the water treatment industry.

1. INTRODUCTION

Coagulation in water treatment plants is a complex and nonlinear process requiring addition of optimum quantity of chemical reagents to raw water to meet the desired standards. One of the key issues in coagulation process is that water quality parameters vary unexpectedly and cannot be manipulated easily. These variations act as perturbation or disturbance to the control loop of the system. The control objective is therefore targeted at manipulating the flow of the coagulants and pH adjustment chemicals to track the set-point signals in the presence of these possibly fast acting disturbances. The traditional control system for coagulation control has been found to have a number of limitations such as inaccurate process model to describe the behaviour of the system, slow responses to longer system delay time, variations in water quality parameters and loop interaction effects within the system.

One of the commonly used control strategies is the feedforward control. It involves adjusting the levels of chemical coagulants added to a process stream as a result of sensory information measured from the raw water variable(s). This is achieved by changing the feed rate of the coagulant metering pump according to the measured flow rate of the raw water [American Water Works Association & American Society of Civil Engineers, 2005]. This approach however becomes inappropriate, when the flow rates vary rapidly and there are large changes in other water quality variables. To address these problems in the feedforward control strategy, several models such as multi-linear regression equations, artificial neural networks and fuzzy inference system algorithms have been proposed to predict the accurate amount of coagulants under varied conditions to replace the influent flowmeter response.

For instance, Evans et al. [1998] proposed a feedforward controller based on adaptive neuro-fuzzy networks for Huntington water treatment works in North West England. In Baxter et al. [2002], the integration of neural network models with the supervisory control and data acquisition (SCADA) system through a number of process optimisation interfaces to optimise the chemical costs and doses online in real-time is presented according to variations in influent water quality parameters. In Fletcher et al. [2002], a feedforward control was developed using models based on nonlinear transformation of variables, multilayer perceptron (MLP) and radial basis function (RBF) network to improve coagulation process. The findings of these research works are positive. However, the application of data-based models with feed-forward controllers to control coagulation process depends on the availability of a perfect model and accurate data from the plant operational records.

Another option in the literature for coagulation control is the application of feedback control strategy. This involves the use of sensors such as streaming current detector to measure the surface charge of the water after the coagulation process, compares the process value with the set point and adjusts the coagulant dosage pump accordingly to correct any deviation from the expected results. It is characterised by a system delay or dead time. During the seasons when the raw water quality changes frequently and widely, the control system may not function effectively re-

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sulting in under dosing or over dosing of coagulation chemicals. In a study on feedback control strategy by Adgar et al. [2005], the authors investigated the application of feedback control on coagulation process on a twin pilot plant using streaming current detector and pH sensor to improve the existing manually flow-proportional coagulant dosage control strategy. Analysis of the data collected during experiments on the pilot plant demonstrated that there is a strong interaction between the streaming current detector and pH measurements. Based on this observation, they proposed a new decoupling control scheme that reduces the interaction between the pH and coagulant dosage loops. The new control strategy was found to be less susceptible to disturbance when compared with the separate feedback control loops. In another study performed by Paz & Ocampo [2009], the author compared the performances of PID and linear model predictive control (MPC) controller for a SISO model of a coagulant dosage system. However, the study does not take into consideration the effect of pH on the coagulation control process.

The combination of feedforward and feedback control to correct the effect of measured disturbances and errors in the system is another strategy that has been proposed. In Hua et al. [2009], a feedforward fuzzy logic controller and feedback controller to determine optimum chemical dosage and to control the coagulant dosage system of a water treatment plant was developed. However, in spite of the attractive nature of fuzzy logic control, the proposed controller has some difficulties, such as knowledge acquisition from experienced operators and large set of rules involved in testing the controller.

This paper therefore examines the application of nonlinear MPC to maintain the controlled variables at the specified reference values or set-points by adjusting the control variables of a multi-input multi-output (MIMO) model of a coagulation chemical dosing unit. The nonlinear MPC is proposed due to its ability to handle nonlinear and multivariable process satisfactorily. It has the ability to predict future events and can take appropriate actions to meet control objective of the plant. It can handle large time delay and higher order dynamics of system model. Nonlinear MPC can accommodate constraints place on the actuator's inputs without driving it to saturation. The coagulation chemical dosing unit at the Rietvlei water treatment plant, South Africa is considered for the study. The study shows the efficacy of nonlinear MPC to control nonlinear and complex process in water treatment plants where traditional control strategies are inadequate or exhibit poor performance.

The paper is organised as follows. Section 2 gives the description of the water treatment plant and the control problem. The process modelling of the chemical dosing unit and model predictive control is discussed in Section 3. The results of different simulation scenarios are presented in Section 4. The concluding remarks are highlighted in the last Section.

2. PLANT DESCRIPTION

Rietvlei water treatment plant was constructed between 1932 and 1934 near Irene, City of Tshwane in South Africa. Fig. 1 shows how the water treatment plant takes raw

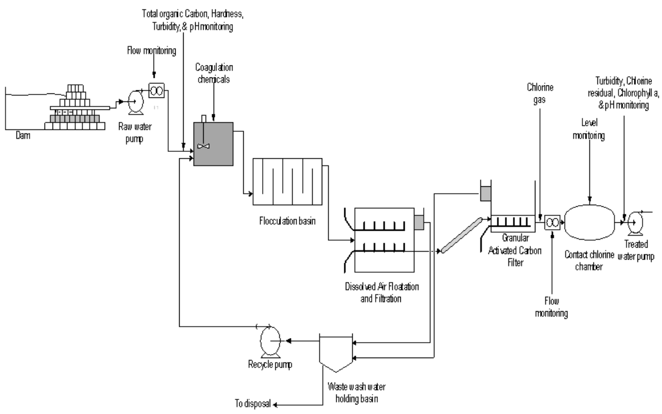

Fig. 1. Description of process train at the Rietvlei water treatment plant

waters from the dam through the inlet tower followed by a train of unit processes such as coagulation, flocculation, dissolved air flotation and filtration, granular activated carbon filtration, chlorination and finally distribution to consumers [American Water Works Association & American Society of Civil Engineers, 2005, City of Tshwane, S.a]. The reagents for chemical dosing unit in the plant are sudfloc 3835, ferric chloride and hydrated lime. The sudfloc 3835 (mixture of polyamine polymer and aluminium chlorohydrate) and ferric chloride are the primary and secondary coagulants respectively. They neutralise the negative surface charge of the raw waters and destabilised the colloids particles to form flocs that are filtered out as sludge. The hydrated lime is added to adjust the pH level of the waters in the mixing tank so that effective coagulation could take place. The chemical solutions are applied to the mixing tank with the aid of dosing pumps.

The challenge in the water coagulation process is the application of optimum amount of these reagents to the raw waters undergoing treatment in order to meet the laid down standards, satisfy varying water quality and demands. Thus, the control strategy objective is to ensure that the controlled variables of the effluent waters track the reference trajectories of the dosing unit and simultaneously rejects any disturbances arising from variations in operational conditions. This is to be achieved by manipulating the flow rates of the chemical reagents applied to the raw waters in the mixing tank taking into considerations the constraints on the manipulated inputs to prevent the dosing pumps from exceeding their limits.

3. METHODS/MATERIALS

3.1 Nonlinear model of the chemical dosing unit

The coagulation chemical dosing unit involves a nonlinear and physicochemical process. The dynamics of the process model is presented as follows.

The mass balance equations for the mixing tank are [Evangelou, 1998, Gardia & Godoy, 2011, Bello et al., 2013]:

$$V\frac{d\left[(C_5H_{12}ON^{+})_n\right]}{dt} = \left[\left((C_5H_{12}ON^{+})_n\right)_{in}\right]q_a -$$