MODEL PREDICTIVE CONTROLLER FOR WATER TREATMENT PROCESS

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Abstract— Water treatment processes incur relatively long transport delays, simply because the process variable is controlled by the addition of chemicals where a reaction time is allowed before the process variable can be sampled. This process dead time makes it difficult to control water treatment plants using standard feedback techniques mainly because the control action takes some time to affect the controlled variable. The feedforward control when used exhibits low performance and instability when the flow rates vary rapidly and when there are large changes in other water quality variables.

During the rainy seasons, raw water quality changes frequently and widely posing a challenge in the water coagulation process where the application of optimum amount of chemicals is required in order to meet the laid down standards. The process being continuous and with no feedback, the consumers may receive water that does not meet the set down quality standards. This paper focuses on the application of Model Predictive Control (MPC) to control of turbidity in the water treatment plants. The system monitors the incoming water quality and prescribes an optimized coagulation chemicals dosage for the process before large changes in turbidity values can be seen in the outlet.

Keywords—Coagulation, Model Predictive Control (MPC), Process dead time, Turbidity

I. INTRODUCTION

Turbidity is a measure of the degree to which the water loses its transparency due to the presence of suspended or dissolved particles which are generally invisible to the naked eye. These particles scatter light making the water appear cloudy or murky. The higher the quantity of suspended solids in the water, the murkier it seems and the higher the turbidity. Turbidity particles harbor harmful contaminants like viruses and bacteria. It is therefore a requirement that all drinking water utilities conduct several turbidity tests daily. Turbidity is a key water quality variable, which is typically measured in Nephelometric Turbidity Units (NTU). The World Health Organization, establishes that the turbidity of drinking water should not be more than 5 NTU, and should ideally be below 1 NTU.

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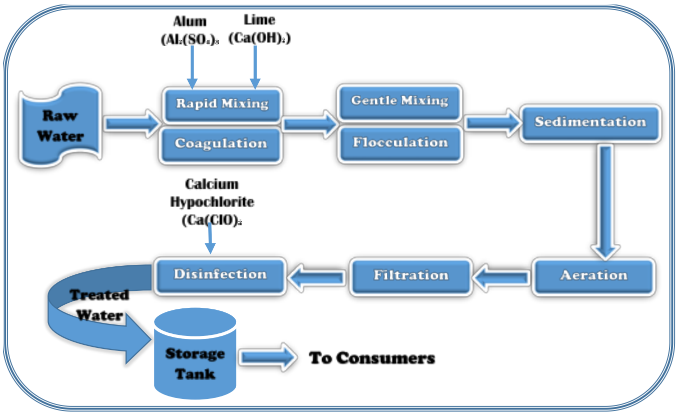

Figure 1: Water Treatment Process

Raw water in a water treatment plant goes through mixing, coagulation, sedimentation, filtration, and disinfection processes as shown in Figure 1. Coagulation removes suspended dirt and other particles from water. Alum, Aluminum Sulphate and other chemicals are added to form tiny sticky particles called “floc” which attract the dirt particles. The combined weight of the dirt and floc become heavy enough to sink to the bottom during sedimentation. Water turbidity is directly related to the suspended particles contents in the raw water and the amount of Alum added.

During the rainy seasons the raw water quality changes frequently and widely posing a challenge in the water coagulation process where the application of optimum amount of chemicals is required in order to meet the laid down standards. In such a case, the control system should function effectively to avoid under dosing or over dosing of coagulation chemicals in order to meet the required standards and save on chemical cost.

Feed forward or predictive control which involves adjusting the levels of coagulation chemicals added to a process stream as a result of sensory information from the raw water variable(s) has been widely applied to water treatment. Basically, this is achieved by changing the feed rate of the metering pumps according to the measured flow rate of the raw water [1, 2, 3]. This approach however becomes inappropriate, when the flow rates vary rapidly and there are large changes in other water quality variables. The coagulant dosage controller therefore exhibits low performance and instability.

With a feedback controller, the effect of disturbance is not neutralized very fast i.e. the control action starts immediately for set point change but not for changes in disturbance, therefore in case of sudden turbidity changes the corrective action will not be timely. The feed forward controller uses both set point and amount of disturbance to calculate the control action, therefore corrective action can be made before large turbidity values can be seen at the output. However, for the feed forward to be accurate, then the process model must be accurate. If the knowledge of how much disturbance must be compensated is unavailable, then this configuration will not work because there could be under or over compensation. Including a feedback trim along with feed forward will take care of modelling inaccuracies.

Water treatment processes incur relatively long transport delays, simply because the process variable is controlled by the addition of certain chemicals and a reaction time is allowed before the process variable can be sampled. It therefore, becomes part of the design requirement to allow enough distance between the chemical dosing and sampling points, and the time delay is then a function of the water flow within this distance as well as the flow in the sample line [4]. This process dead time makes it difficult to control water treatment plants using standard feedback techniques mainly because the control action takes some time to affect the controlled variable, and therefore the control action that is applied based on the actual error tries to correct a situation that originated some time before [5].

Conventional Proportional-Integral-Derivative (PID) control algorithms are the most commonly used and well established class of controllers in water treatment processes. However, the use of PID control for coagulation has been found to have a number of limitations such as an inaccurate dynamic system model to describe the behaviour of the system, slow response of the PID controller to longer system delay or dead time, daily and seasonal variations in water quality parameters and loop interaction effects within the system. Using ordinary single-loop PID control the dead-time forces the bandwidth of the control system to be relatively low.

In a paper, [6] proposed a fuzzy model predictive control (FMPC) strategy to regulate the output variables of a coagulation chemical dosing unit. A multiple-input, multiple-output (MIMO) process model in form of a linearized Takagi–Sugeno (T–S) fuzzy model was derived while the process model was obtained through subtractive clustering from the plant's data set. The simulation results showed that the FMPC has good set-point tracking and adequate disturbance rejection ability required for efficient coagulation control and process optimization in water treatment operations. Despite the attractive nature of fuzzy logic control, difficulties such as knowledge acquisition from experienced operators, and a large set of rules involved in developing the rule base, have been identified as limitations to this approach.

The application of linear MPC has been studied on the coagulant dosage system for water treatment plants by [7]. The authors used a linear model of the system for their study. The study focused on a single-input, single-output (SISO) model rather than solving nonlinear and multivariable control problem.

This paper therefore examines the application of MPC to maintain the treated water turbidity (controlled variable) at the specified set point by adjusting the control variables of a multiple input, single output (MISO) model of the coagulation chamber unit.

While MPC is suitable for almost any kind of problem, it displays its main strength when applied to problems with a large number of manipulated and controlled variables; constraints imposed on both the manipulated and controlled variables; changing control objectives and/or equipment; sensor/ actuator) failure and time delays as is the case of the water treatment system. The MPC strategy works to keep the output variables close to their reference trajectories while taking into consideration the operating constraints. Moreover, the MPC techniques can consider many process constraints in an intrinsic ay, since the control signal is computed through an optimization procedure making it a powerful tool for this application.

II. PLANT DESCRIPTION

The data used for this work was collected from Turasha treatment works. Turasha treatment works is fully owned and managed by Nakuru Rural Water and Sanitation Company (NARUWASCO) under the county government of Nakuru. It is located in Langa-Langa area in Gilgil sub-county of Nakuru county. Construction of the infrastructure started in the year 1989 and it was completed and commissioned in 1992 having a capacity of $19200m^3$/day. However, it is currently operating below its capacity because of increased human activity along the catchment of its source River Turasha and siltation of its reservoir dam both in Nyandarua county. The water from the treatment works serves the entire Gilgil town and parts of Nakuru town. It has typical raw water average flow rate of $730m^3$/hour and turbidity levels of up to 1000 NTU against the recommended below 5 NTU levels.

It was essential to collect historical water treatment plant data that traverses one year so as to cover every one of the seasons. From the collected data, the turbidity of the treated water depends non-linearly on the amount of coagulant added and the turbidity level of the raw water necessitating the decomposition of the input-output relationship into interacting variables.

III. METHODOLOGY

A. Coagulation chamber model

Using the collected data from Turasha treatment works, the coagulation chamber model was developed and simulated in the MATLAB R2015b environment system identification toolbox. The measurements of several variables of the process are taken and a model is constructed by identifying a model that matches the dynamics that underlies the measured data with minimal loss of accuracy. The steps towards system identification is summarized in the figure2 below**.**

Figure 2: The identification procedure by Ljung (1987)

The basic requirements for the identification procedure are:

i. ***Data*****:** Historical/ experimental data

$$f(N) = \{y(1), u(1), y(2), u(2) \ldots, y(N), u(N)\} \quad (1)$$

This data was collected from the normal operating records of the Turasha Treatment works.

ii. ***Model Set:*** a model set ***M***, specifying the class of candidate models among which (an) optimal model(s) will be selected. I

iii. ***Identification criterion*****:** Having f(N) and ***M***- determines which model(s) to select from ***M*****.** The prediction error identification method was used. In prediction error identification methods, the model set **M** is a specified set of predictor models and the identification criterion is based on prediction errors.

Consider the data sequence:

$$Z^N = \{y(1), U(1), y(2), u(2) \ldots, y(N), u(N)\} \quad (2)$$

and a parametrized model set ***M***, induced by the parametrization $\widetilde{M}$ with parameter set Θ. Every model $\widetilde{M}(\theta)$, $\theta \in \Theta$, in the model set ***M*** can predict the output *y*(*t*) based on y^{t}-1, u^{t}, and for every time instant *t* = 1, 2, · · · , *N and* the actual prediction error can be determined by comparing prediction and actual measurement *y*(*t*).As a result, every parameter $\theta \in \Theta$ gives rise to a prediction error

$$\varepsilon(t,\theta) = y(t) - \tilde{y}(t|t-1;\theta) \qquad t = 1,2,\ldots,N (3)$$

The prediction error that is made serves as a signal that indicates how well a model is able to describe the dynamics that underlies a measured data sequence. An accurate model generates "small" prediction errors.
From the collected data, the simulation parameters units are stated in Table I.

TABLE I
UNITS FOR COAGULATION MODEL VARIABLES

Variable	**Units**
Raw water turbidity	Nephelometric Turbidity Units (NTU)
Raw water flow rate	Cubic meters per Hour (m^3/h)
Alum concentration	Milligram per liter (mg/l)
Treated water turbidity	Nephelometric Turbidity Units (NTU)

The response of the simulated models using various techniques of system identification is as shown in Figure 2:

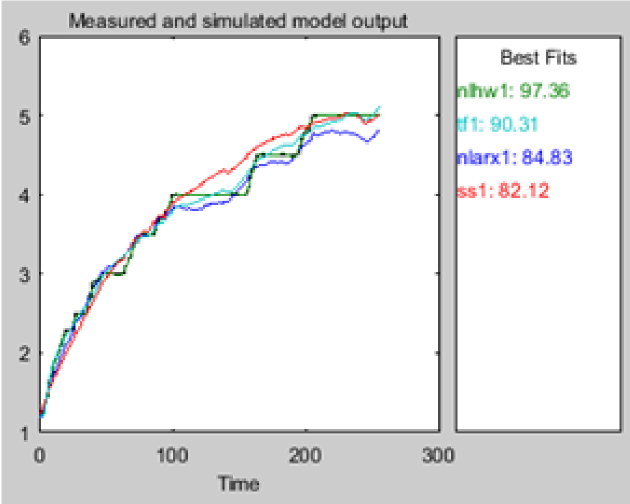

Figure 3: Comparison of models from system identification

Where:
nlhw1: Nonlinear Hammerstein Weiner model
tf1:Transfer function model
nlarx1: Nonlinear autoregressive external input model
ss1: State space model
From Figure 3, it is clear that the Hammerstein-Wiener model has the capability of representing the dynamics of a system with the highest fit to estimation data. It achieves this bya linear transfer function and capture the nonlinearities using nonlinear functions of the inputs and outputs of the linear system as shown in Figure 4.

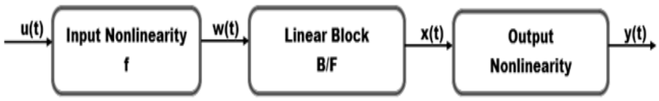

Figure 4: The Hammerstein-Wiener model representation

Where,

⇒ *f* is a nonlinear function that transforms input data *u*(*t*) as *w*(*t*) = *f*(*u*(*t*))

⇒ *w*(*t*), an internal variable, is the output of the Input Nonlinearity block and has the same dimension as (*u*(*t*)

⇒ *B/F* is a linear transfer function that transforms *w(t)* as *x(t) = (B/F) w(t)*

⇒ *x(t)*, an internal variable, is the output of the Linear block and has the same dimension as *y(t)*

For *ny* outputs and *nu* inputs, the linear block is a transfer function matrix containing entries:

$$\frac{B_{j,i}(q)}{F_{j,i}(q)} \qquad (3)$$

where *j* = 1, 2...,ny and *i* = 1, 2..., nu.

⇒ *h* is a nonlinear function that maps the output of the linear block *x*(*t*) to the system output *y*(*t*) as *y*(*t*) = *h*(*x*(*t*))

Further to the selection of the Hammerstein-Wiener model, the wavelet nonlinear estimator/ function gives a better fit than its counterparts i.e. sigmoid, polynomial and piecewise as shown in Figure 5.

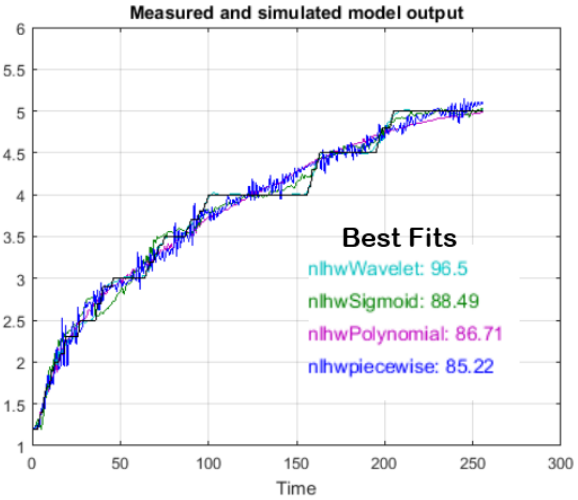

Figure 5: Comparison of the nonlinear estimators/functions with the measured output dataset

The time response plot between the identify model and collected data having a 95.17% fit is shown in Figure 6 below clearly indicating the capability of the Hammerster Weiner model.

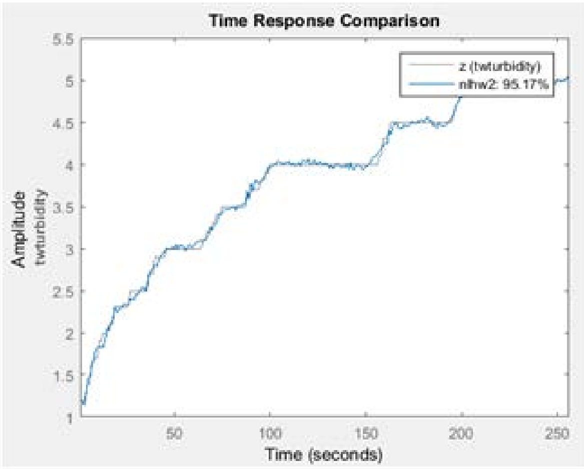

Figure 6: Time Response comparison of nonlinear Hammerstein Weiner model and collected data

B. *Model Predictive Control (MPC)*

In predictive control, the prediction of the future values of the process outputs and the states from the current time is performed. However, the real plant/process cannot be made to operate in the future time steps from the current time, but the model of the process being controlled can be easily simulated to obtain the process outputs and the states for the future time steps.

The process outputs and the states predicted for the future time steps by using the process model is used to formulate an optimization problem which is an optimal control problem. The nature of the optimization problem can vary from tracking a set point to more complex economic objectives. In this project the set point tracking objective is applied to get the optimization problem.

Model Predictive Control solves an optimization problem specifically, a quadratic program (QP) – at each control interval. This QP problem includes the following features:

- The objective or cost function - A scalar nonnegative measure of controller performance to be minimized.
- Constraints - Conditions the solution must satisfy, such as physical bounds on MVs and plant output variables.
- Decision/ solution - The MV adjustments that minimizes the cost function while satisfying the constraints.

The solution determines the manipulated variables (MVs) to be used in the plant until the next control interval i.e. it uses the knowledge of the system model at time *k* to design an input sequence:

$$u(k)|k, u(k+1|k), u(k+2|k), u(k+3|k), \dots, u(k+N|k) \qquad (4)$$

over a finite horizon N from the current state *x(k)*. It then implements a fraction of that input.

For this applications, the controller must keep the selected plant outputs(turbidity) at or near the specified reference values. MPC controller uses the following scalar performance measure:

$$J_y(z_k) = \sum_{u=1}^{n_y} \sum_{i=1}^{p} \left\{ \frac{w_{i,j}^y}{s_j^y} \left[r_j(k+i|k) - y_j(k+i|k) \right] \right\} \qquad (5)$$

Where,

- k — Current control interval.
- p — Prediction horizon (number of intervals).
- n_y — Number of plant output variables.
- z_k— QP decision, given by:
  $z_k^T = [u(k|k)^T u(k+1|k)^T u(k+p-1|k)^T \varepsilon_k]$ (6)
- $y_j(k+i|k)$ — Predicted value of *j*th plant output at *i*th prediction horizon step
- $r_j(k+i|k)$ — Reference value for *j*th plant output at *i*th prediction horizon step
- s_j^y— Scale factor for *j*th plant output
- $w_{i,j}^y$— Tuning weight for *j*th plant output at *i*th prediction horizon step

The values n_y, p, s_j^y and $w_{i,j}^y$ are controller specifications, and are constant. The controller receives $r_j(k+i|k)$ values for the entire prediction horizon. The controller uses the state observer to predict the plant outputs.

Specifying the prediction and control horizons

For a plant with delays, it is good practice to specify the prediction and control horizons such that

$$P{-}M \gg t_{d,\,max}/\Delta t \qquad (7)$$

where,

- *P* is the prediction horizon (How far ahead the model predicts the future).
- *M* is the control horizon.
- $t_{d,\,max}$ is the maximum delay
- Δt is the controller sample time

Results

The coagulation chamber model has three inputs and one output

Inputs

- Alum concentration – the concentration of alum in the feed stream (mg/L)
- Turbidity of raw water – feed turbidity (NTU)
- Raw water flow rate (m^3/h) – assumed to be constant

Output

- Treated water turbidity (NTU)

The control objective is to maintain the turbidity of the treated water at its set point (<=5 NTU) by adjusting the Alum concentration feed. The control system should meet the said objective and also keep the input and output variables within safe and acceptable operational limits. Linearization was necessary inorder to use the identified Nonlinear Hammerstein Weiner model since the standard MPC works with linear systems. The resulting model was used in MPC design to give the set point tracking response shown in figure 7 below. The controller parameterswere:
Sample time 0.1
Prediction horizon 17
Control horizon 3

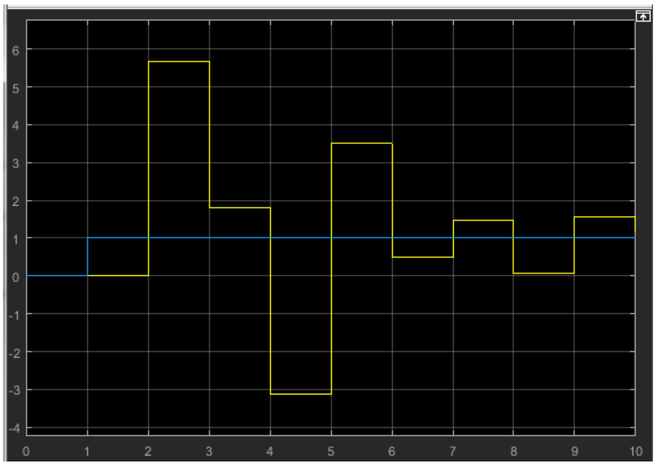

Figure 7: Set point tracking performance

Figure 7 shows the Controller has oscillations about the set point.

C. CONCLUSION

This study considers the set point tracking of the standard MPC when applied to the coagulation chemical dosing unit of drinking water treatment plants. Simulation tests of the control system has been examined under the linearized Nonlinear Hammerstein Wiener model. The study shows that the MPC based control strategy is inadequate for the linearized model and ineffective to maintain the output variables at constant level. There is need to develop a Nonlinear MPC which is capable of handling nonlinear models and/or nonlinear inequality constraints and study the performance when applied to the Nonlinear Hammerstein Wiener model of the coagulation chamber.

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