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Application of Neural Networks for Optimal-Setpoint Design and MPC Control in Biological Wastewater Treatment

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Abstract This paper proposes and compares six different methods for designing an optimal set point for the dissolved oxygen concentration in a biological wastewater treatment process. Since knowledge of the true nonlinear model of a wastewater treatment plant is unlikely, we develop neural-network autoregressive exogenous models for the online prediction of the dissolved oxygen concentration and ammonia concentration. We take advantage of the fact that data is predicable during dry weather conditions, and use a nonlinear optimization procedure that utilizes the dry-weather predictive models to decide on a nominal setpoint, which will be an optimal one for the dry-weather conditions. We also propose a simpler setpoint-finding algorithm that can move the setpoint dynamically during weather events, responding appropriately to significant changes in the influent. A constrained nonlinear neural-network model predictive control then tracks the setpoint. Simulations with the Benchmark Simulation Model #1 compare several variations of the proposed methods to a fixed-setpoint PI control, demonstrating improvement in effluent quality or reduction in energy use, or both (depending on the particular variation and the weather conditions).

Keywords BSM1 · Neural Network Control · Model Predictive Control · Biological Wastewater Treatment

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1 Introduction

Typical biological wastewater treatment plants include at least one aerated tank, in which an activated sludge process reduces organic matter and assists in nitrification. Since current technology measures only dissolved oxygen (DO), the control system attempts to track a DO setpoint by manipulating the amount of aeration. Contemporary control systems research aims at reducing pollution or reducing energy consumption, or both (while keeping the bacteria alive and meeting environmental regulations). Note that advanced methods also change the setpoint, so that the system can better react changes in influent during weather events.

Due to the large number of unmeasured states and uncertainly in the wastewater plant model, many researchers have proposed model predictive controllers (MPCs) for tracking the setpoint. A linear prediction model with feedforward action can react to large variations of the influent [1],[2],[3],[4], An MPC with a nonlinear prediction model can further improve performance, typically using either neural networks [5],[6] or fuzzy models [7]. Applying control methods for both the setpoint decision and tracking control is referred to as two-level hierarchical control, with the setpoint decision constituting the higher level. Proposed approaches include PI controllers for both lower level and upper level [8], MPC as the higher level and PI as the lower level [9], PI as the higher level and MPC as the lower level [10], and MPC for both levels [11]. The method in [12] uses a low order adaptive control for the lower level and an adaptive method based on one-step-ahead-predictions of the DO and ammonium for the upper level.

Rather than use a feedback-control approach for setpoint design, some have utilized optimization techniques. Genetic algorithms (GAs) in the higher level have been tried in [13] and [14]. In [13], a PI controller in the lower level follows an ammonia set-point determined by GA optimization in the higher level. The method in [15] proposes a unique approach that divides the control structure into three layers: the supervisory control layer, the optimizing control layer and, and the low-level control layer. The method utilizes MPC, extended Kalman filters, and grey-box parameter estimation.

Since humans are fairly adept at operating wastewater plants, another strategy is to encode decision-making in fuzzy logic rules. The method in [16] uses a fuzzy controller to control the DO setpoint and the ratio of aerobic and anoxic zones. The method in [17] studies control of the external carbon dosage as well as the DO setpoint control. DO and nitrate were controlled in [18] using a supervisory and fuzzy control. Fuzzy logic in [19] controls both the DO set-point and the air flow. The work in [20] uses MPC-plus-feedforward control in the lower level and compares three different controllers (MPC, affine function and fuzzy) in the upper level. A fuzzy controller adapts the DO set points of three aerated tanks in [21]. A low order adaptive control as the lower level and a fuzzy control with optimal membership functions as the higher level is introduced [22].

The control of biological wastewater treatment can still be considered an open problem in the literature due to the difficulty of meeting environmental standards during weather events when the influent changes dramatically. The aforementioned papers use the Benchmark Simulation Number #1 (BSM1) model of a wastewater treatment plant to develop and test control strategies. To our knowledge no paper has yet shown acceptable effluent quality during all three of the supplied 14-day weather data sets that come with BSM1 (dry, rainy, and stormy weather).

This paper presents a new method for designing the DO setpoint utilizing one-step-ahead prediction and nonlinear optimization. Three Neural Network Autoregressive eXogenous (NNARX) models train online to provide the required predictions. Setpoint decisions for dry weather can be made using nonlinear optimization. For weather events, we propose using an algorithm that changes the setpoint dynamically. The resulting DO setpoint then becomes the desired reference for a neural-network MPC (NNMPC). Simulations show reduction of pollution or energy (or both) compared to PI control during tests on the three weather-data sets.

2 The BSM1 Model of the Activated Sludge Process

The Benchmark Simulation Model 1 (BSM1) is a standard mathematical model of the wastewater treatment process, presented by the International Association of Water Quality (IAWQ) and COST (European Cooperation in the field of Scientific and Technical Research). The plant layout consists of five bioreactors, two anoxic tanks followed by three aerated tanks, and a clarifier. Each bioreactor uses activated sludge model number 1 (ASM1) to describe the biochemical reactions, using thirteen states (see Table. 1). The standard outputs for evaluating performance and energy consumption are the Effluent Quality Index (EQI) and the Overall Cost Index (OCI), respectively. BSM1 comes with two PI control loops implemented; a DO loop in the fifth tank (controlling DO with aeration) and a nitrate/nitrite loop (controlling nitrogen in the second tank using recycle flow to the first tank). Control systems researchers often just replace the existing PIs with more advanced controls, although in our work we also add an additional control loop (control of nitrate in the fifth tank using a recycle flow). The control objective may be either minimizing EQI, or OCI, or both, while avoiding violation of limits given in Table 2.

The dry weather data set shows regular daily variations in flow rate and chemical oxygen demand. The rainy weather file has a long rain event in the second week, with a significant increase in flow rate and no change in chemical oxygen demand load. In the stormy set, the first storm event results in an excessive increase in the chemical oxygen demand (COD) load, while the second, more gradual, storm event results in a less significant change in the chemical oxygen demand.

Table 1: State variables of BSM1 model

State in Tank (i)	Variable	Units
S_I	Soluble inert organic matter	g m^{-3}
X_I	Particulate inert organic matter	g m^{-3}
S_S	readily biodegradable substrate	g m^{-3}
X_S	Slowly biodegradable substrate	g m^{-3}
$X_{B,H}$	Active heterotrophic biomass	g m^{-3}
$X_{B,A}$	Active autotrophic biomass	g m^{-3}
X_P	Particulate products arising from biomass decay	g m^{-3}
S_O	Oxygen	g m^{-3}
S_{NO}	Nitrate and nitrite nitrogen	g m^{-3}
S_{NH}	nitrogen	g m^{-3}
S_{ND}	Soluble biodegradable organic nitrogen	g m^{-3}
X_{ND}	Particulate biodegradable organic nitrogen	g m^{-3}
S_{ALK}	Alkalinity	mol m^{-3}

Table 2: Effluent quality limits

Variable	Definition	Value
N_{tot}	Total nitrogen concentration	$< 18gNm^{-3}$
COD_t	Total Chemical Oxygen Demand	$< 100gCODm^{-3}$
S_{NH}	Ammonium concentration	$< 4gNm^{-3}$
TSS	Suspended solid concentration	$< 30gSSm^{-3}$
BOD_5	Biological oxygen demand over a 5-day period	$< 10gBODm^{-3}$

Effluent Quality Index (EQI)

In practice, the amount of time the EQI exceeds regulated limits would determine fines to be paid. The calculation performs a weighted sum of different "pollution" compounds in Table 2:

$$\mathrm{EQI} = \frac{1}{1000.T}\int_{t=7\mathrm{days}}^{t=14\mathrm{days}} (B_{\mathrm{TSS}}.\mathrm{TSS}(t) + B_{COD}.\mathrm{COD}(t) + B_{NKj}.S_{NKj}(t) + B_{NO}.S_{NO}(t) + B_{BOD_5}.\mathrm{BOD}_5(t)).Q_e(t)dt, \quad (1)$$

where Q_e is the outlet flow rate and each B_i is a weighting factor.

Overall Cost Index (OCI)

The OCI defines as the weighted sum of aeration energy (AE), the pumping energy (PE), the sludge production to be disposed (SP), the consumption of external carbon source (EC) and the mixing energy (ME) as follows:

$$\mathrm{OCI} = \mathrm{AE} + \mathrm{PE} + 5.\mathrm{SP} + \mathrm{ME}, \quad (2)$$

with

$$
\begin{aligned}
\mathrm{AE} =& \frac{8}{T.1.8.1000}\int_{t=7\mathrm{days}}^{t=14\mathrm{days}}\sum_{i=1}^{5} V_i.K_{\mathrm{La,i}}(t).dt, && (3)\\
\mathrm{PE} =& \frac{1}{T}\int_{t=7\mathrm{days}}^{t=14\mathrm{days}}(0.004.Q_0(t)+0.008.Q_a(t)+0.05.Q_w(t)).dt, && (4)\\
\mathrm{SP} =& \frac{1}{T}.(\mathrm{TSS}_a(14\mathrm{days})-\mathrm{TSS}_a(7\mathrm{days})+\mathrm{TSS}_s(14\mathrm{days})\\
&-\mathrm{TSS}_s(7\mathrm{days})+\int_{t=7\mathrm{days}}^{t=14\mathrm{days}}\mathrm{TSS}_w.Q_w.dt), && (5)\\
ME =& \frac{24}{T}\int_{t=7\mathrm{days}}^{t=14\mathrm{days}}\sum_{i=1}^{5}\begin{cases}0.005.V_i dt & \text{if } K_{\mathrm{La,i}} < 20\mathrm{day}^{-1}\\ 0 & \text{otherwise}\end{cases}, && (6)
\end{aligned}
$$

where TSS_a is the amount of solids in the reactor, TSS_s is the amount of solids in the settler, TSS_w is the amount of solid in the wastage, and V is the volume of the tank.

3 Proposed Methods

3.1 Overview of NNARX Models

The setpoint design and setpoint tracking control use three NNARX models. In our method the DO setpoint changes in real time in order to respond to changing influent disturbance, while the nitrate-nitrite setpoint remains at a fixed value at 1(mgl^{-1}). The setpoint traking uses NNARX1, which provides a one step-ahead prediction of the DO offset in the fifth tank. Note that a multi-step prediction simply calls NNARX1 multiple times. NNARX2 estimates a static model of the process from steady state values, providing the nominal DO level. NNARX1 and NNARX2 together generate the one-step-ahead prediction of the DO output $y_{\mathrm{ref},1}$. NNARX3 predicts the one-step-ahead value of $S_{NH,5}$ to generate $y_{\mathrm{ref},2}$. The setpoint design uses a nonlinear optimization to find a trade-off between $y_{\mathrm{ref},1}$ and $y_{\mathrm{ref},2}$.

3.2 NNARX1:One-step-ahead prediction of $S_{O,5}$

The algorithm uses a Multilayer Perceptron (MLP) with one hidden layer and a linear output

$$\hat{S}_{O,5,t} = \mathbf{w}_1^T \sigma(\mathbf{H}_1^T \mathbf{q}_1), \tag{7}$$

where $\mathbf{w}_1 \in R^m$ is a column vector of output weights, $\mathbf{H}_1 \in R^{p\times m}$ is a matrix of hidden weights

$$\mathbf{H}_1^T = \begin{bmatrix} h_{11} & \dots & h_{1p}\\ \vdots & \dots & \vdots\\ h_{m1} & \dots & h_{mp}\end{bmatrix} = \begin{bmatrix}\mathbf{h}_1^T\\ \vdots\\ \mathbf{h}_m^T\end{bmatrix}. \tag{8}$$

The vector $\mathbf{q}_1 \in R^p$ contains the inputs: delayed dissolved oxygen concentration, oxygen transfer coefficient, and the inlet flowrate.

$$\mathbf{q}_1(t) = [S_{O,5}(t-1), \dots, S_{O,5}(t-n_a), K_{\mathrm{La},5}(t-1), \dots, K_{\mathrm{La},5}(t-n_b), Q_o(t-1), \dots, Q_o(t-n_c)], \quad (9)$$

where n_a and n_b and n_c are the maximum lags in the output and inputs, respectively. The MLP contains three hidden units and training occurs with the Levenberg-Marquardt adaptation method.

3.3 NNARX2:One-step-ahead prediction of $S_{O,5,p}$

Another MLP predicts an optimal set point $\hat{S}_{O,5,p}$ using a steady-state analysis at $S_{O,5,\mathrm{ss}}$ and $K_{\mathrm{La},5,\mathrm{ss}}$ and $Q_o(t-1)$

$$\hat{S}_{O,5,p} = \mathbf{w}_1^T \sigma(\mathbf{H}_1^T \mathbf{q}_{\mathrm{ss}}), \quad (10)$$

with inputs

$$\mathbf{q}_{\mathrm{ss}}(t) = [S_{O,5,\mathrm{ss}}, \dots, S_{O,5,\mathrm{ss}}, K_{\mathrm{La},5,\mathrm{ss}}, \dots, K_{\mathrm{La},5,\mathrm{ss}}, Q_o(t-1), \dots, Q_o(t-1)]. \quad (11)$$

3.4 NNARX3:One-step-ahead prediction of $S_{NH,5}$

This section tackles the issue of identifying appropriate DO setpoint changes due to changes in ammonium concentration. The dissolved oxygen concentration in the aerobic zone should be high enough for an efficient nitrification process during a high load of ammonium and should be low enough to prevent an unnecessary increase in the aeration energy consumption during a low load of ammonium. Thus, we wish to move the setpoint in the direction of ammonium changes in the last tank, so that the set point will be small if $S_{NH,O}$ is low and the set point will high if $S_{NH,O}$ is high. An additional MLP learns to predict the future value of $\hat{S}_{NH,5,t}$

$$\hat{S}_{NH,5,t} = \mathbf{w}_2^T \sigma(\mathbf{H}_2^T \mathbf{q_2}), \quad (12)$$

where the inputs are the delayed ammonium concentration in the last tank, the oxygen transfer coefficient in the last tank, and the inlet ammonium concentration

$$\mathbf{q_2}(t) = [S_{NH,5}(t-1), \dots, S_{NH,5}(t-n_a), K_{\mathrm{La},5}(t-1), \dots, K_{\mathrm{La},5}(t-n_b), S_{NH,o}(t-1), \dots, S_{NH,o}(t-n_c)]. \quad (13)$$

3.5 Applied Control Strategies

We use the two standard BSM1 control loops and propose adding in a third loop (Fig. 1). The loops are:

Loop 1) The control of the Dissolved Oxygen $S_{O,5}$ concentration in the last aerated tank by manipulating the oxygen transfer coefficient $K_{\mathrm{La},5}$. constrained to a maximum of 360day^{-1}. The set point for this loop changes over time to react to influent changes. The control utilizes an NNMPC (see Section. 3.6).

Loop 2) The control of nitrate (S_{NO}) level in the second anoxic tank to a fixed set point of 1mgL^{-1} by manipulating the internal recycle flow rate Q_a. This flow rate has an upper limit of 92230m^{3}day^{-1}. A low-order Lyapunov-based adaptive control regulates this loop (Appendix A).

Loop 3) The control of nitrate (S_{NO}) level in the last aerated tank to a set point of 7mgL^{-1} by manipulating the waste flow rate Q_w. This flow rate has an upper limit of 18446m^{3}day^{-1}. A low-order Lyapunov-based adaptive control regulates this loop (Appendix A).

3.6 Dissolved oxygen NNMPC control

The control structure for the DO loop (Fig 1) uses NNARX1 as a model to predict

$$\hat{\mathbf{y}} = \left[\hat{y}(t), \hat{y}(t+1), \ldots, \hat{y}(t+N_y)\right]^T = \left[\hat{S}_{O,5,t}, \hat{S}_{O,5,t+1}, \ldots, \hat{S}_{O,5,t+N_y}\right]^T. \tag{14}$$

The MPC minimizes the cost functional

$$J = E^T(t)E(t) + \lambda_1 \Delta\mathbf{u}^T(t)\Delta\mathbf{u}(t) + \lambda_2 \sum F_{\mathrm{con}}(\mathbf{y}), \tag{15}$$

where λ_1 and λ_2 are weighting parameters (the larger λ_1 leads to a smoother control signal at the cost of sluggish disturbance rejection), the first term sums the squared error $E(t) = \hat{\mathbf{y}} - \mathbf{y}_{ref}$ over the prediction horizon N_y, and the

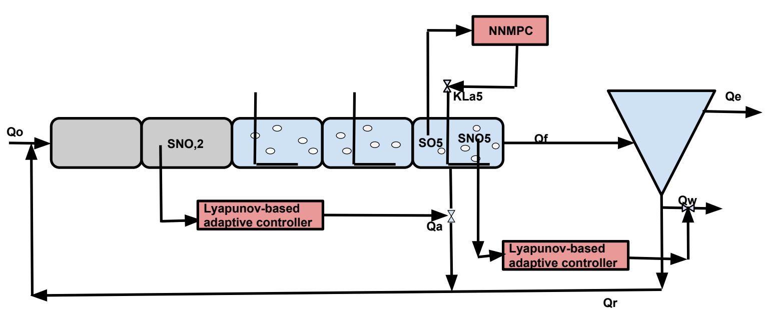

Fig. 1: Applied control strategies

second term is defined over the control horizon Nu. The vector $\hat{\mathbf{y}}$ shows the future outputs and $\mathbf{u}$ contains future control inputs

$$\mathbf{u} = \left[K_{\text{La},5}(t), K_{\text{La},5}(t+1), \ldots, K_{\text{La},5}(t+N_u) \right]^T . \tag{16}$$

The vector $\mathbf{y}_{ref}$ contains present and future evaluations of the setpoint. If the future values of the setpoint are not known, we can simply consider $y_{ref}(t) \ldots y_{ref}(t+N_y) = y_{ref}$, where y_{ref} gives the optimal setpoint as in Section. 3.7.

Since MPC formulates the control as an optimization problem, the design can easily handle constraints. We use hard constraints on the control inputs as

$$u_{\min} \leq \mathbf{u} \leq u_{\max}, \tag{17}$$

but for limiting outputs we use penalty terms in the objective function

$$F_{con}(\hat{\mathbf{y}}) = \begin{bmatrix} f_{\text{con}}(\hat{y}(t)) \\ f_{\text{con}}(\hat{y}(t+1)) \\ \ldots \\ f_{\text{con}}(\hat{y}(t+N_y)) \end{bmatrix}, \tag{18}$$

where, as in [23], we use

$$f_{\text{con}}(y) = \frac{\exp(\frac{2S.(\hat{\mathbf{y}}-y_{mid})\text{sign}(\hat{\mathbf{y}}-y_{mid})}{y_{max}-y_{min}})}{\exp(S)}, \tag{19}$$

with S showing the sharpness of the function f, and y_{mid} providing the average of $y_{\min}$ and $y_{\max}$. This penalty term remains constant when the predicted outputs $\hat{\mathbf{y}}$ are between the bounds $y_{\min}$ and $y_{\max}$, but it increases when predicted outputs are near those bounds. Since first and second derivatives exist for this penalty term, numerical optimization can use the Levenberg-Marquardt (L-M) search direction

$$\mathbf{u}(t+1) = \mathbf{u}(t) + \mu_t \Delta\mathbf{u}(t) \tag{20}$$

$$\left(\frac{\partial^2 J}{\partial \mathbf{u}^2} + \lambda_{LM}(t)\mathbf{I}_N \right) \Delta\mathbf{u}(t) = -\left(\frac{\partial J}{\partial \mathbf{u}} \right), \tag{21}$$

where $\frac{\partial^2 J}{\partial \mathbf{u}^2}$ is the Hessian, $\frac{\partial J}{\partial \mathbf{u}}$ is the gradient of the cost function, $\mathbf{I}_N$ is the $N \times N$ identity matrix, and $\lambda_{LM}(t)$ is the Levenberg-Marquardt parameter. Note the Hessian matrix must be positive definite in order to have a convex optimization. The Cholesky factorization allows us to investigate the positive definiteness of the Hessian matrix, [23] (if the Hessian is not positive definite, $\lambda_{LM}(t)$ must be increased until it is).

Taking the gradient of cost function gives

$$\frac{\partial J}{\partial \mathbf{u}} = 2\left(\frac{\partial E(t)}{\partial \mathbf{u}} \right)^T E(t) + 2\lambda_1 \left(\frac{\partial \Delta\mathbf{u}(t)}{\partial \mathbf{u}} \right)^T \Delta\mathbf{u}(t) + \lambda_2 \frac{\partial \sum F_{\text{con}}(\hat{\mathbf{y}})}{\partial \mathbf{u}}, \tag{22}$$

For the first term, one can show that

$$\frac{\partial E}{\partial \mathbf{u}} = \frac{\partial \hat{\mathbf{y}}(t)}{\partial \mathbf{u}}, \tag{23}$$

provided by the NNARX1 formulation in (7) and

$$\frac{\partial \Delta \mathbf{u}(t)}{\partial \mathbf{u}} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ -1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \dots & -1 & 1 & 0 \\ \dots & 0 & -1 & 1 \end{bmatrix}. \tag{24}$$

For the third term, we can write

$$\frac{\partial \sum F_{\text{con}}(\hat{\mathbf{y}})}{\partial \mathbf{u}} = \left(\frac{\partial \hat{\mathbf{y}}(t)}{\partial \mathbf{u}}\right)^T \text{diag}\left(\frac{2\text{S.sign}(\hat{\mathbf{y}} - \text{y}_{\text{mid}})}{\text{y}_{\max} - \text{y}_{\min}}\right) \text{F}_{\text{con}}(\hat{\mathbf{y}}), \tag{25}$$

with

$$\text{diag}(\frac{2\text{S.sign}(\hat{\mathbf{y}} - \text{y}_{\text{mid}})}{\text{y}_{\max} - \text{y}_{\min}}) = 2\text{S} \\ \times \begin{bmatrix} \frac{sign(\hat{y}(t) - y_{mid})}{y_{\max} - y_{\min}} & 0 & \dots & 0 \\ 0 & \frac{sign(\hat{y}(t+1) - y_{mid})}{y_{\max} - y_{\min}} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & \frac{sign(\hat{y}(t+N_y) - y_{mid})}{y_{\max} - y_{\min}} \end{bmatrix}. \tag{26}$$

The Hessian of the cost function comes from

$$\frac{\partial^2 J}{\partial \mathbf{u^2}} = 2(\frac{\partial E}{\partial \mathbf{u}})^T(t)(\frac{\partial E}{\partial \mathbf{u}})(t) + 2\lambda_1(\frac{\partial \Delta \mathbf{u}}{\partial \mathbf{u}})^T(t)(\frac{\partial \Delta \mathbf{u}}{\partial \mathbf{u}})(t) + \lambda_2 \frac{\partial^2 \sum F_{\text{con}}(\hat{\mathbf{y}})}{\partial \mathbf{u^2}},$$

where the second derivative of the third term is

$$\frac{\partial^2 \sum F_{\text{con}}(\hat{\mathbf{y}})}{\partial \mathbf{u^2}} = (\frac{\partial E}{\partial \mathbf{u}})^T \text{diag}(\frac{(2\text{S})^2}{(\text{y}_{\max} - \text{y}_{\min})^2} \text{F}_{\text{con}})(\frac{\partial \text{E}}{\partial \mathbf{u}}), \tag{27}$$

with

$$\text{diag}(\frac{(2\text{S})^2}{(\text{y}_{\max} - \text{y}_{\min})^2} \text{F}_{\text{con}}) = \frac{(2\text{S})^2}{(\text{y}_{\max} - \text{y}_{\min})^2} \\ \times \begin{bmatrix} f_{\text{con}}(\hat{y}(t)) & 0 & \dots & 0 \\ 0 & f_{\text{con}}(\hat{y}(t+1)) & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & f_{\text{con}}(\hat{y}(t+N_y)) \end{bmatrix}. \tag{28}$$

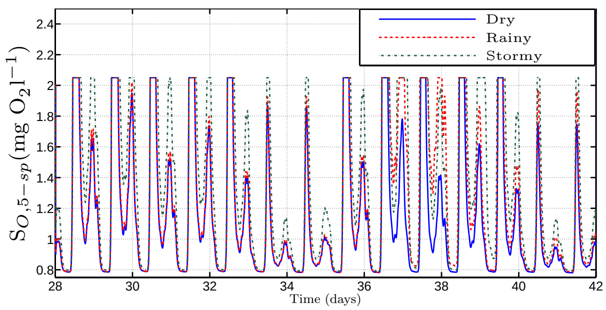

Fig. 2: Comparison of obtained optimal set points using Method3 .

3.7 Finding the optimal set point

Our proposed algorithm considers two possible desired future output values, $y_{\text{ref},1}$ and $y_{\text{ref},2}$, appropriate for following the dissolved oxygen concentration $\hat{S}_{O,5}$ and the ammonium concentration $\hat{S}_{NH,5}$, respectively.

The output from NNARX2 essentially provides a prediction of $\hat{S}_{O,5,p}$ using a local model; thus the value of $\hat{S}_{O,5,p}$ generally provides a only direction to search for the true global optimal setpoint. The search continues until the predicted optimal setpoint is within tolerance tol_{sp} of the current setpoint, in which case we conclude we have likely found the setpoint. The search algorithm, initialized with $y_{\text{ref},1} = y_0$, becomes

$$
\begin{aligned}
&\texttt{if abs}(\hat{S}_{O,5,t} - \hat{S}_{O,5,p}) < \text{tol}_{\text{sp}} \\
&\quad y_{\text{ref},1} = \hat{S}_{O,5,p} \\
&\quad \dot{y}_d = 0 \\
&\texttt{else} \\
&\quad \dot{y}_d = \dot{y}_{\max} \times \texttt{sign}(\hat{S}_{O,5,p} - \hat{S}_{O,5,t}) \\
&\quad y_{\text{ref},1} = \hat{S}_{O,5,t} + \dot{y}_d \times \Delta t
\end{aligned} \tag{29}
$$

The second (possible) setpoint calculation uses the predicted ammonium concentration from (12)

$$
y_{\text{ref},2} = \hat{S}_{NH,5,t} + \dot{\hat{S}}_{NH,5,t} \Delta t. \tag{30}
$$

We choose a compromise between these two desired values as the actual setpoint

$$
y_{\text{ref}} = (y_{\text{ref},1} + G y_{\text{ref},2})/(1 + G), \tag{31}
$$

where G is a positive constant which provides a relative weighting.

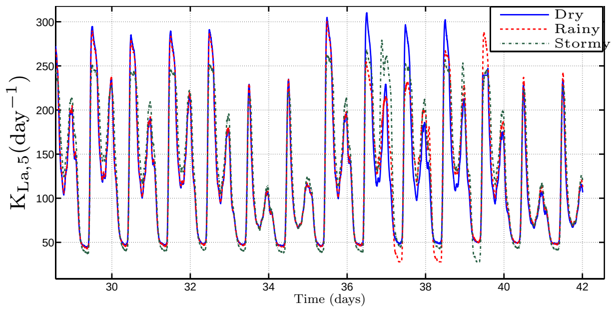

Fig. 3: Comparison of obtained control inputs using Method3.

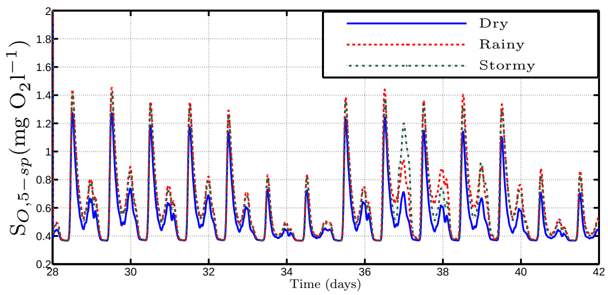

Fig. 4: Comparison of obtained optimal set points using Method4 .

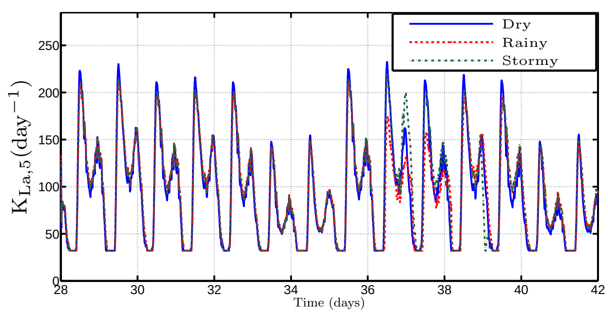

Fig. 5: Comparison of obtained control inputs using Method4.

4 Results and Discussions

4.1 Simulation tests

The simulations test six different setpoint decision methods for deciding the output setpoint y_{ref} (for DO concentration in the fifth tank $S_{O,5}$). The first method uses the standard constant setpoint from BSM1. The second uses an optimization using a Jacobian linearized 65×65 model and data obtained during dry weather conditions; since dry weather conditions show a predictable behaviour, depending on time of day and the day of the week, the variables

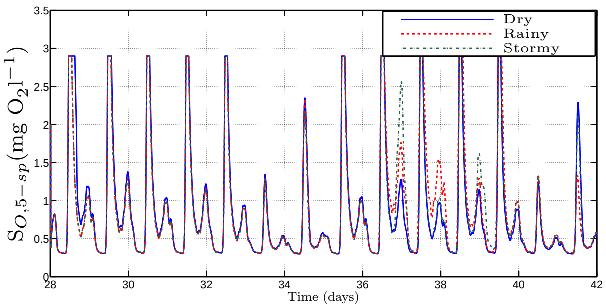

Fig. 6: Comparison of obtained optimal set points using Method5.

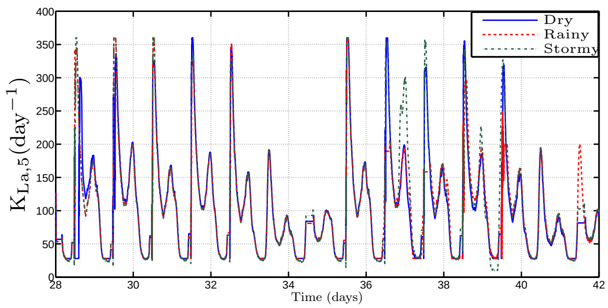

Fig. 7: Comparison of obtained control inputs using Method5.

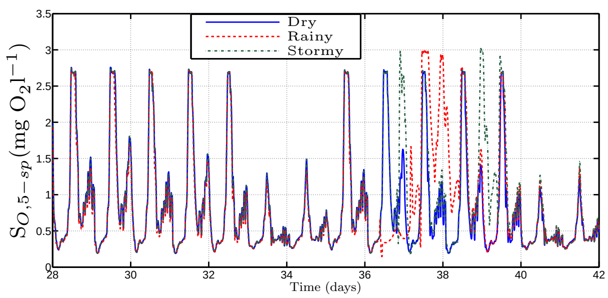

Fig. 8: Comparison of obtained optimal set points using Method6.

needed for optimization are predictable to some degree of accuracy (i.e we have full knowledge of inlet flow rate and inlet concentrations). The resulting solution can then still be used for weather events (although the solution is no longer optimal). The third through sixth methods try our proposed ideas with different combinations of algorithms and optimizations to produce $y_{\text{ref},1}$, $y_{\text{ref},2}$ and G. We utilize Matlab's Optimization Toolbox. The details of the six methods are:

Method 1) The control regulates a fixed set point $y_{\text{ref}} = 2\text{mgL}^{-1}$.

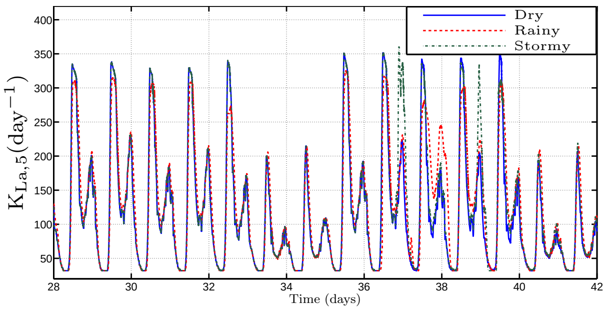

Fig. 9: Comparison of obtained control inputs using Method6.

Method 2) A multi-objective optimization problem finds a constant y_{ref} using dry-weather data

$$\begin{aligned} &\text{minimize} && \text{EQI}(y_{\text{ref}}), \text{OCI}(y_{\text{ref}}) \\ &\text{subject to} && N_{tot} \leq 18, \text{COD}_t \leq 100, S_{NH} \leq 4, \\ &&& TSS \leq 30, \text{BOD}_5 \leq 10. \end{aligned}$$

Method 3) The setpoint is a weighted addition of static setpoint $y_{\text{ref},1} = 2$ and time-varying setpoint $y_{\text{ref},2}$ generated with (30) during all weather conditions. An optimization finds the relative weighting G based on dry-weather data

$$\begin{aligned} &\text{minimize} && \text{OCI}(G) \\ &\text{subject to} && N_{tot} \leq 18, \text{COD}_t \leq 100, S_{NH} \leq 4, \\ &&& TSS \leq 30, \text{BOD}_5 \leq 10, \\ &&& 0 \leq G \leq G_{\max}. \end{aligned}$$

where $G_{\max}$ is an arbitrary limit that prevents excessive optimization time.

Method 4) The algorithm (30) generates $y_{\text{ref},2}$ during all weather conditions while an optimization problem finds constant G and constant $y_{\text{ref},1}$ using dry weather conditions

$$\begin{aligned} &\text{minimize} && \text{EQI}(G, y_{\text{ref},1}) \\ &\text{subject to} && N_{tot} \leq 18, \text{COD}_t \leq 100, S_{NH} \leq 4, \\ &&& TSS \leq 30, \text{BOD}_5 \leq 10, \\ &&& 0 \leq G \leq G_{\max}. \end{aligned}$$

Method 5) The algorithm (30) generates $y_{\text{ref},2}$ during all weather conditions while a multi-objective optimization finds constant G and constant

Table 3: Comparison of Effluent Qualities in Dry Weather: Time-varying optimal set point can reduce EQI

Controller type	$N_{tot,ave}$(mg Nl^{-1})	COD_{ave}(mg CODl^{-1})	$S_{NH,ave}$(mg Nl^{-1})	TSS_{ave}(mg SSl^{-1})	$BOD_{5,ave}$(mg l^{-1})	EQI (kg poll.unitsd^{-1})
PI with Method1	16.9245	48.2201	2.5392	13.0038	2.7568	7552.3603
NNMPC with Method1	15.3492	50.3587	1.1230	14.6517	2.8805	7.1908e+03(**-4.7874%**)
NNMPC with Method2	13.9659	50.0016	1.7145	14.3520	2.8504	6.6521e+03(**-11.9203%**)
NNMPC with Method3	14.2173	51.2343	1.0055	15.3008	2.9249	6.8281e+03(**-9.5899%**)
NNMPC with Method4	13.1447	50.4217	1.7993	14.6500	2.8739	6.3721e+03(**-15.63%**)
NNMPC with Method5	13.6185	50.2065	1.7646	14.4942	2.8636	6.5265e+03(**-13.5833%**)
NNMPC with Method6	13.7934	50.3346	1.3167	14.6049	2.8730	6.6089e+03(**-12.4923%**)

$y_{\text{ref},1}$ using dry weather conditions

$$\begin{aligned} \text{minimize} \quad & \text{EQI}(G, y_{\text{ref},1}), \text{OCI}(G, y_{\text{ref},1}) \\ \text{subject to} \quad & N_{tot} \leq 18, \text{COD}_t \leq 100, S_{NH} \leq 4, \\ & TSS \leq 30, \text{BOD}_5 \leq 10, \\ & 0 \leq G \leq G_{\max}. \end{aligned}$$

Method 6) Algorithms (29) and (30) generate $y_{\text{ref},1}$ and $y_{\text{ref},2}$, respectively, during all weather conditions. A multi-objective optimization finds a constant G using dry weather data

$$\begin{aligned} \underset{G}{\text{minimize}} \quad & \text{EQI}(G), \text{OCI}(G) \\ \text{subject to} \quad & N_{tot} \leq 18, \text{COD}_t \leq 100, S_{NH} \leq 4, \\ & TSS \leq 30, \text{BOD}_5 \leq 10, \\ & 0 \leq G \leq G_{\max}. \end{aligned}$$

4.2 Results

Compared to standard PI control, during dry weather conditions our results show a reduction of EQI by -4.7874% for the NNMPC with Method 1, by -11.9203% for Method 2, by -9.5899% for Method 3, by -15.63 for Method 4, by -13.5833% for Method 5 and by -12.4923% for Method 6 (Table. 3). Note that Method 4, Method 5 and Method 6 do especially well, also reducing $N_{tot,ave}$. Method 2, Method 4 and Method 5 strategies result in less consumed aeration energy, but use more pumping energy. Although Method 2, Method 4 and Method 5 strategies result in a large amount of pumping energy, a larger reduction of AE, SP resulted in an improvement in OCI by -8.7428%, -9.2386% and -9.6588%, respectively (Table. 4). The highest reduction of EQI is for Method 4 because this method considers EQI as the only objective function. Method 3 results in the smallest OCI because this method considers OCI as the only objective function. By considering EQI and OCI simultaneously, Method 5 and Method 6 can improve both OCI and EQI, compared to other methods.

Improving the effluent qualities during rain/storm events, while still preventing the excessive energy consumption, defines the main goal of the control

Table 4: Comparison of Operational Cost in Dry Weather: Time-varying optimal set point can reduce OCI

Controller type	AE (kWhd^{-1})	PE (kWhd^{-1})	SP ($kgSS$d^{-1})	OCI
PI with Method1	7.2414e+03	1.4954e+03	2.441e+03	2.11797e+04
NNMPC with Method1	7.2761e+03	1.6744e+03	1.6791e+03	1.7346e+04(**-18.1008%**)
NNMPC with Method2	6.7520e+03	2.3577e+03	2.0437e+03	1.9328e+04(**-8.7428%**)
NNMPC with Method3	7.0239e+03	1.8971e+03	1.5508e+03	1.6675e+04(**-21.2690%**)
NNMPC with Method4	6.6135e+03	2.2676e+03	2.0683e+03	1.9223e+04(**-9.2386%**)
NNMPC with Method5	6.7694e+03	2.1536e+03	2.0423e+03	1.9134e+04(**-9.6588%**)
NNMPC with Method6	6.9321e+03	1.9998e+03	1.9477e+03	1.8671e+04(**-11.8448%**)

Table 5: Comparison of Effluent Qualities in Rainy Weather: Time-varying optimal set point can reduce EQI

Controller type	$N_{tot,ave}$(mg Nl^{-1})	COD_{ave}(mg CODl^{-1})	$S_{NH,ave}$(mg Nl^{-1})	TSS_{ave}(mg SSl^{-1})	$BOD_{5,ave}$(mg l^{-1})	EQI (kg poll.unitsd^{-1})
PI with Method1	14.7465	45.4337	3.226	16.1768	3.4557	9037.7895
NNMPC with Method1	14.3350	47.0480	1.6276	15.9120	3.2328	8.7344e+03(**-3.3569**)
NNMPC with Method2	12.8333	47.6105	1.9540	16.3089	3.2500	8.1287e+03(**-10.0588%**)
NNMPC with Method3	13.3258	48.0942	1.3336	16.6981	3.2778	8.3941e+03(**-7.1222%**)
NNMPC with Method4	13.3248	46.4214	2.7770	15.3854	3.1919	8.2512e+03(**-8.7%**)
NNMPC with Method5	12.6661	47.6855	1.9185	16.3591	3.2532	8.0797e+03(**-10.6009%**)
NNMPC with Method6	12.7733	47.7606	1.7069	16.4233	3.2586	8.1257e+03(**-10.0920%**)

Table 6: Comparison of Operational Cost in Rainy Weather: Time-varying optimal set point can reduce OCI

Controller type	AE (kWhd^{-1})	PE (kWhd^{-1})	SP ($kgSS$d^{-1})	OCI
PI with Method1	7.1707e+03	1.9377e+03	2.3576e+03	21136.3723
NNMPC with Method1	7.2479e+03	1.9894e+03	2.2629e+03	2.0552e+04(**-2.7648%**)
NNMPC with Method2	6.6968e+03	3.0281e+03	2.3594e+03	2.1522e+04(**+1.8245%**)
NNMPC with Method3	7.0670e+03	2.1771e+03	2.0650e+03	1.9569e+04(**-7.4155%**)
NNMPC with Method4	6.5969e+03	2.5811e+03	2.6058e+03	2.2207e+04(**+5.0653%**)
NNMPC with Method5	6.7458e+03	2.5281e+03	2.3608e+03	2.1078e+04(**-0.2762%**)
NNMPC with Method6	6.8924e+03	2.4621e+03	2.3057e+03	2.0883e+04(**-1.1988%**)

system. In comparison to PI, during a rain event the reduction of EQI is -3.3569% for Method 1, -10.0588% for Method 2, -7.1222% for Method 3, -8.7% for Method 4, -10.6009% for Method 5 and -10.0920% for Method 6 (Table. 5). Method 2, Method 5 and Method 6 control strategies obtain a controller where EQI is reduced by -10% while Method 6 is able to reduce OCI by -1.1988% too. On the other hand, Method 2 control strategy obtains a controller where OCI is increased by $+1.8245\%$ and OCI has not changed remarkably for Method 5, (Table. 6.)

For stormy weather, Method 5 and Method 6 control strategies result in reasonable reduction of EQI and OCI (Table. 7 and Table. 8).

5 Conclusions

This paper develops NNARX-based methods of nonlinear control for wastewater treatment plants. We compare six different optimal setpoint finding methods for the BSM1 benchmark model of a biological wastewater treatment plant, and the results are compared with the default PI controller with all three sup-

Table 7: Comparison of Effluent Qualities in Stormy Weather: Time-varying optimal set point can reduce EQI

Controller type	$N_{tot,ave}$(mg Nl^{-1})	COD_{ave}(mg CODl^{-1})	$S_{NH,ave}$(mg Nl^{-1})	TSS_{ave}(mg SSl^{-1})	$BOD_{5,ave}$(mg l^{-1})	EQI (kg poll.unitsd^{-1})
PI with Method1	15.8676	47.6626	3.0622	15.2737	3.205	8.3027e+03
NNMPC with Method1	14.7446	48.6370	1.5178	15.5398	3.0661	7.9554e+03(**-4.1830%**)
NNMPC with Method2	13.9757	47.4103	2.7672	14.5577	2.9793	7.5220e+03(**-9.4030%**)
NNMPC with Method3	14.6134	47.8061	1.8644	15.7709	3.0077	7.8240e+03(**-5.7656%**)
NNMPC with Method4	13.5801	47.6784	2.7303	14.7533	2.9970	7.3870e+03(**-11.0289%**)
NNMPC with Method5	13.0721	48.9976	1.9346	14.8973	3.0844	7.3128e+03(**-11.9226%**)
NNMPC with Method6	13.4288	48.7576	1.6389	15.6055	3.0683	7.4460e+06(**-10.3183%**)

Table 8: Comparison of Operational Cost in Stormy Weather: Time-varying optimal set point can reduce OCI as well

Controller type	AE (kWhd^{-1})	PE (kWhd^{-1})	SP ($kgSS$d^{-1})	OCI
PI with Method1	7.2892e+03	1.7371e+03	2.6055e+03	22293.6884
NNMPC with Method1	7.3342e+03	1.8763e+03	1.9775e+03	1.9098e+04(**-14.3345%**)
NNMPC with Method2	6.7233e+03	2.7324e+03	2.4829e+03	2.1870e+04(**-1.9005%**)
NNMPC with Method3	7.1414e+03	1.9479e+03	1.9479e+03	2.0312e+04(**-8.8890%**)
NNMPC with Method4	6.6547e+03	2.4189e+03	2.4715e+03	2.1431e+04(**-3.87%**)
NNMPC with Method5	6.8742e+03	2.3803e+03	2.2183e+03	2.0346e+04(**-8.7365%**)
NNMPC with Method6	7.0731e+03	2.1749e+03	2.1738e+03	2.0117e+04(**-9.7637%**)

plied weather data sets. The first method uses a fixed set point of 2mgL^{-1} for the dissolved oxygen concentration, the 2nd method utilizes a fixed set point found by using a Multi-Objective-Optimization problem. Method 3, 4, 5, 6 use set points that are changing over time. Method 3 and Method 4 use a single objective function while Method 5 and Method 6 employ multi-objective functions. All obtained set points are used together with a NNMPC to control the dissolved oxygen concentration. Simulation results show that all six methods reduce pollution during all weather conditions compare to the standard BSM1 PI control. The 5th and 6th methods improve on other methods in two ways: both reducing the amount of control effort required during dry weather, and improving the effluent quality during rain/storm events without increasing control effort. Thus, the proposed strategies have the potential for environmental benefits in terms of both reducing energy usage during dry-weather operations and reducing pollution due to rain/storm events.

Appendix A

This stability analysis for each SISO control loop uses the same assumptions required for an analysis of a PI control: namely that nonlinearities, higher-order dynamics, cross-coupled dynamic terms, and disturbances are all bounded.

In our model-reference adaptive control approach the reference model is

$$\dot{y}_m(t) = -a_m y_m(t) + b_m u_c(t) \tag{A.1}$$

where u_c is the desired value of the manipulated variable.

Consider a first-order approximation of the system

$$\dot{y}(t) = -ay(t) + bu(t) + d(t), \tag{A.2}$$

where we assume terms in $d(t)$ are bounded i.e. $|d(t)| \leq d_{\max}$ where $d_{\max}$ is a finite positive constant.

Consider a control design

$$u(t) = \theta_1(t)u_c(t) - \theta_2(t)y(t) - Ke(t), \tag{A.3}$$

where positive constant K is the control gain and θ_1, θ_2 are adaptive parameters. For simplicity, we drop the argument (t) in further equations. The parameter errors are

$$z_1 = b\theta_1 - b_m, \quad z_2 = b\theta_2 + a - a_m,$$

and their derivatives are

$$\dot{z}_1 = b\dot{\theta}_1, \qquad \dot{z}_2 = b\dot{\theta}_2.$$

The error dynamics become

$$\begin{aligned}
\dot{e} =& \dot{y} - \dot{y}_m = -ay + bu + d + a_m y_m - b_m u_c, && \text{(A.4)}\\
=& -ay + b\theta_1 u_c(t) - b\theta_2 y(t) - bKe - a_m e \\
& + a_m y - b_m u_c + d, && \text{(A.5)}\\
=& -a_m e - bKe + y(t)(a_m - b\theta_2 - a) \\
& + u_c(t)(b\theta_1 - b_m) + d, \\
=& -a_m e - bKe - y(t)z_2 + u_c(t)z_1 + d. && \text{(A.6)}
\end{aligned}$$

Consider the adaptive control Lyapunov function

$$V(e, \theta_1, \theta_2) = \frac{1}{2}\left(e^2 + + \frac{1}{b\gamma}z_1^2 + \frac{1}{b\gamma}z_2^2\right), \tag{A.7}$$

where γ is a positive constant determining the rate of adaptation. The time derivative of V is

$$\begin{aligned}
\dot{V} &= e\dot{e} + \frac{1}{\gamma}z_1\dot{\theta}_1 + \frac{1}{\gamma}z_2\dot{\theta}_2, && \text{(A.8)}\\
&= -a_m e^2 - bKe^2 + de - eyz_2 + eu_c z_1 + \frac{1}{\gamma}z_1\dot{\theta}_1 + \frac{1}{\gamma}z_2\dot{\theta}_2, \\
&= -a_m e^2 - bKe^2 + de + \frac{z_1}{\gamma}(\gamma u_c e + \dot{\theta}_1) + \frac{z_2}{\gamma}(-\gamma ye + \dot{\theta}_2).
\end{aligned}$$

Applying the adaptive-parameter update laws with e-modification:

$$\dot{\theta}_1 = -\gamma(u_c e + \nu|e|\theta_1), \tag{A.9}$$

$$\dot{\theta}_2 = \gamma(ye - \nu|e|\theta_2), \tag{A.10}$$

results in

$$\dot{V} = -a_m e^2 - bKe^2 + de + \frac{z_2}{\gamma}(-\gamma\nu|e|\theta_2) + \frac{z_1}{\gamma}(-\gamma\nu|e|\theta_1),$$

which can be bounded

$$\begin{aligned}\dot{V} \leq & |e| \left(\begin{bmatrix} |z_1| \\ |z_2| \end{bmatrix}^T \begin{bmatrix} -\nu/b & 0 \\ 0 & -\nu/b \end{bmatrix} \begin{bmatrix} |z_1| \\ |z_2| \end{bmatrix} \right. \\ & \left. - |e|(a_m + bK) + \begin{bmatrix} -\nu b_m/b \\ -\nu(a_m - a)/b \end{bmatrix}^T \begin{bmatrix} |z_1| \\ |z_2| \end{bmatrix} + d_{\max} \right), \\ \leq & |e|(-\mathbf{z}^T \mathbf{K_1} \mathbf{z} - (\mathbf{a_m} + \mathbf{bK})|\mathbf{e}| - \mathbf{K_2}\mathbf{z} + \mathbf{d}_{\max}), \qquad (A.11) \\ \leq & |e|(-K_1 \|z\|^2 - (a_m + bK)|e| + k_{2,\max}\|\mathbf{z}\| + d_{\max}), \qquad (A.12)\end{aligned}$$

where we have positive constants $K_1 = \nu/b$ and $k_{2,\max} > \|\mathbf{K_2}\|$. Assuming we have chosen K such that $a_m + bK > 0$, then $\dot{V} < 0$ when $|e| > \delta_e$ or $\|\mathbf{z}\| > \delta_z$ where

$$\delta_e = \frac{1}{a_m + bK} \left(\frac{k_{2,\max}^2}{4K_1} + d_{\max} \right), \qquad (A.13)$$

$$\delta_z = \frac{k_{2,\max}}{2K_1} + \sqrt{\frac{k_{2,\max}^2}{4K_1^2} + \frac{d_{\max}}{K_1}}, \qquad (A.14)$$

and thus all signals are uniformly ultimately bounded on the $(|e|, \|\mathbf{z}\|)$ plane with an ultimate bound given by Lyapunov surface $V() = V(\delta_e, \delta_z)$.

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