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Full Length Research Paper

Multilevel input signal for multivariable state-space identification of wastewater treatment plant

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The purpose of this work is to identify a linear time-invariant dynamic model of wastewater treatment plants with multilevel pseudo random signals as an excitation input. The plants naturally aim to remove suspended substances, organic material and phosphate. An activated sludge process becomes the best technology available to control the discharge of pollutants. For this purpose, state-space models that emphasize on subspace-based method such as numerical subspace state-space system identification (N4SID) and 'robust' N4SID besides predictive estimation models are explored. The performance of identified models perturbed by multilevel input signal is validated by variance accounted for and compared to pseudo random binary input signal. It was proved that the estimated model with multilevel input offers good predicted behavior's as compared to two-level input signal. Benchmark simulation model (BSM1) was applied as data generator for identification procedures.

Key words: Multilevel input signal, multivariable subspace state-space identification, wastewater plant.

INTRODUCTION

In general, a multiple-input-multiple-output (MIMO) system has more complex internal structure. Due to this reasons, the state-space model is most commonly used to describe a MIMO physical system due to its simple mathematical equation form as compared to polynomial models. This invites system identification approach that deals with a problem in estimating a model of dynamic systems based on input and output data. Basically, there are two approaches for linear identification, and they include optimization-based referred to predictive error method (PEM) and subspace-based method, such as numerical subspace state-space system identification (N4SID), multivariable output-error state-space model identification (MEOSP) and canonical variate analysis (CVA). Zhu (2001) states that a good identification test needs some priori knowledge of the process, such as the dominant time constant, bandwidth of the dynamics, nonlinearity and disturbance characteristics. This can be done through a step test, staircase test, impulse test or even white noise experiment. For a step test, the process is operating in open-loop without the presence of any controller where each input is stepped separately and the step responses are recorded.

Furthermore, a perturbation signal is commonly used at the input in obtaining informative data. According to Ljung (1987) and Sodestrom and Stoica (2001), perturbation signal must be persistently exciting so that the bandwidth of the perturbation signal may span with respect to the system. Zhu (2001) explains some minimum requirements that needed to be obeyed by the test signal to guarantee for a unique estimation solution. Nevertheless, crucial problem in identification comes in defining the behavior of the perturbation signal. Basically, two aspects need to be considered in selecting the tests signal, and they include the shape of the signal and the power spectrum. For a linear system, pseudo random binary sequences (PRBS) are commonly used in identification due to similarity of white noise

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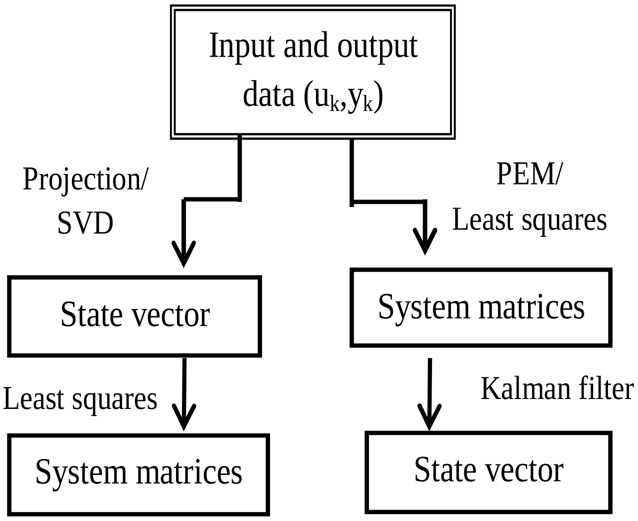

Figure 1. Subspace and PEM methods in system identification.

autocorrelation function besides easy implementation. However, the resulting data of two levels PRBS may not provide sufficient information in perturbing a nonlinear signal. Furthermore, the estimation of the linear kernel may be bias for a large magnitude of PRBS. On the other hand, multilevel pseudo random signal (MPRS) allows the user to highlight nonlinear system behavior while manipulating the harmonic contents of the signal and hence reducing the effect of nonlinearities (Godfrey, 1993). In this paper, the theoretical frameworks of multilevel signal suggested (Braun et al., 1999; Jose and Basilio, 2003) are explored.

No doubt, a wastewater treatment plants (WWTP) are strongly known with the complexity of the model structure and the wide number of states and parameters. WWTP aims to remove suspended substances, organic material and phosphate before releasing to the recipients. Ololade et al. (2009) investigates the quality of surface water and underground water due to the impact of indiscriminate dumping of household wastes. Meanwhile, the effectiveness of aquatic plants in removing nutrients from wastewater was investigated by Christine et al. (2011), while the use of activated carbon from local raw material was analyzed by Fayomi and Popoola (2011). Referring to Lindberg (1997) and Rahmat et al. (2011), nitrogen is an essential nutrient for biological growth and acts as one of the main constituents in all living organisms. However, higher nitrogen in effluent wastewater invites a numbers of problems. As a result, two biological processes called nitrification (ammonium removal) and denitrification (nitrate removal) are proposed. Due to the complexity factors besides that emphasized on both processes were suggested. There are numbers of works on wastewater identification, such as Lindberg (1997) that presents a multivariable model for describing nitrification and denitrification using subspace identification where PRBS and white noise were used in exciting the plant. Similarly, a linear identification for dissolve oxygen and nutrient removal was applied to cost simulation (Wahab et al., 2009). Meanwhile, PEM with generalized binary noise input signal has been used as model estimator and excitation input signal of nitrate removal in cascade control structure as discussed in the work of Hongbin et al. (2010) and Hongbin and ChangKyoo (2011). However, Oscar et al. (2003) introduced multilevel random signal to identify ASWWTP-USP wastewater plant. This leads to the application of multilevel pseudorandom test signal in multivariable identification for benchmark simulation model (BSM1).

STATE-SPACE IDENTIFICATION METHODS

In this paper, the state-space estimation models emphasized on subspace identification method (SIM) that offers an attractive approach to input and output measurement for a MIMO system. Initially, a weighted projection of the row space of Hankel matrices is considered. From this projection, the observability matrix, Γ_i and/or the state sequence, X_i were retrieved. It then followed by determining the system matrices. Basically, input and output data is given and SIM will estimates the matrices with respect to the number of order within a similarity transformation and Kalman filter gain. A sequence of state vectors can be determined directly from the input and output data in SIM but not in PEM. The different approach between subspace methods and PEM is summarized as shown in Figure 1 and the details of SIM algorithms can be referred to the work of Overschee and Moor (1999).

This work focused on a state-space model of combined deterministic-stochastic system as shown in Equation 1.

$$x_{k+1} = Ax_k + Bu_k + Ke_k$$

$$y_k = Cx_k + Du_k + e_k \tag{1}$$

where $u_k \in \Re^m$ is the m-dimensional input, $x_k \in \Re^n$ is the n-dimensional state, $y_k \in \Re^l$ is the l-dimensional output, K is the steady state Kalman gain and $e_k \in \Re^l$ is an unknown innovation with covariance matrix $E[e_k e^T_k] = Re$.

Notice that the model is in relation with stochastic state space model as:

$$x_{k+1} = Ax_k + Bu_k + v_k$$

$$y_k = Cx_k + Du_k + \omega_k \tag{2}$$

where $v_k \in \Re^m$ and $\omega_k \in \Re^l$ are the process and the measurement noise with covariance matrices $E[v_k v^T_k] = Q$, $E[\omega_k \omega^T_k] = R$, $E[v_k \omega^T_k] = S$. The process noise represents the disturbances entering the system and the measurement noise represents the uncertainty in the system observations. In

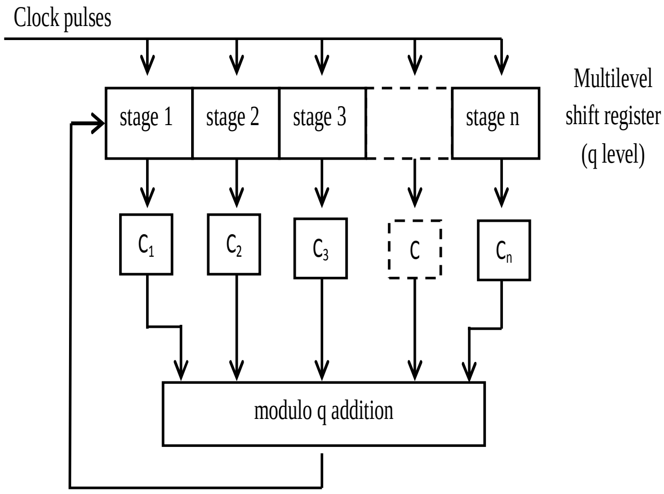

Figure 2. A generator of a *q*-level pseudo random binary sequence using shift register and modulo q addition.

conjunction, the algorithm for combined deterministic-stochastic for 'robust' N4SID can be referred to in Equations 3 to 8.

1. The oblique, O_i and orthogonal projections, Z_i and Z_{i+1} are calculated as:

$$O_i = Y_f / U_f \, W_p, \quad Z_i = Y_f \Big/ \begin{pmatrix} W_p \\ U_f \end{pmatrix}, \quad Z_{i+1} = Y_f^- \Big/ \begin{pmatrix} W_p^+ \\ U_f^- \end{pmatrix} \tag{3}$$

where *f* and *p* denote future and past, while W_p indicates the joint past. Noted that the superscript '+' stands for 'add one block row' while the superscript '-' stands for 'delete one block row'.
2. The SVD of the weighted oblique projection are then determined as in Equation 4. Here, $\Pi_{U_f^{\perp}}$ denotes the orthogonal projection of matrix *U*.

$$O_i \Pi_{U_f^{\perp}} = U S V^T \tag{4}$$

3. Next, the model's order and the SVD is partitioned in obtaining U_1 and S_1. These values are then used in calculating the extended observability matrices, Γ_i and Γ_{i-1} where:

$$\Gamma_{i-1} = \Gamma_i \text{ and } \Gamma_i = U_1 S_1^{1/2} \tag{5}$$

4. To find the matrices of A and C, solve:

$$\left(\frac{\Gamma^{\dagger}_{i-1} . Z_{i+1}}{Y_{i|i}} \right) = \begin{pmatrix} A \\ C \end{pmatrix} . \Gamma^{\dagger}_{i-1} . \kappa . U_f + \begin{pmatrix} \rho_\omega \\ \rho_v \end{pmatrix} \tag{6}$$

where $\bullet^{\dagger}$ denotes the Moore-Penrose pseudo inverse of matrix $\bullet$ and ρ denotes the residuals.
5. Similarly, Equation 7 is solved to find matrices of B and D.

$$B,D = \arg\min_{B,D} \left\| \left(\frac{\Gamma^{\dagger}_{i-1} . Z_{i+1}}{Y_{i|i}} \right) - \begin{pmatrix} A \\ C \end{pmatrix} . \Gamma^{\dagger}_i . Z_i - \kappa(B,D) . U_f \right\|_F^2 \tag{7}$$

where $\|\bullet\|_F$ denotes the Frobenius norm of a matrix.

6. Finally, with *E* as, an expected value operate the covariance matrices are then it is calculated as:

$$\begin{pmatrix} Q & S \\ S^T & R \end{pmatrix} = E_j \left[\begin{pmatrix} \rho_\omega \\ \rho_v \end{pmatrix} . \begin{pmatrix} \rho_\omega^T & \rho_v^T \end{pmatrix} \right] \tag{8}$$

For dynamic linear multivariable system identification, SIM offers an advance computational simplicity and effectiveness in calculating a good state-space model without any prior knowledge of the system. These algorithms are numerically robust and do not involve nonlinear optimization techniques. Alternatively, PEM that has excellent statistical properties is explored. The prediction error filter produces an error vector which is then used to define a nonlinear least squares criterion of fit. This criterion is then minimized. However, PEM model can sometimes be overwhelmingly difficult, especially when it deals with highly order system. Ljung (1987) and Sodestrom and Stoica (2001) worked on PEM. Here, estimated approach using 'robust' N4SID is highlighted and the performances in identification are then compared to N4SID and PEM.

DEVELOPMENT OF MULTILEVEL PSEUDORANDOM INPUT SIGNALS

The generation of MPRS is based on multilevel maximum length signals. The signal is periodic, deterministic and is similar to white noise autocorrelation function. MPRS exist for the number of levels, q and the length, N of signal is represented by $q^{nr}-1$, where n_r is an integer. The sequences will repeat itself after N digits. The shift register configuration of MPRS is as shown in Figure 2. Basically, the sequences can be generated by a *q*-level shift register with feedback to the first stage consisting of the modulo *q* sum of the outputs of the other stages that are multiplied by coefficients [C_1, ..,C_n]. Definitely, the integers lie within the range of [0, q−1]. The number of levels *m* should be at least one greater than the nonlinearity order of the model. The important properties of *q*-level MPRS were discussed (Vergara et al., 2005; Vergara, 2006).

In developing the MPRS, several steps as discussed (Jose and Basilio, 2003) were considered. Initially, the excitation signal bandwidth, ω_s that places the power of the input signal in the frequency range is calculated as shown in Equation 9. It needs the fast dominant time constant, τ^H_{dom} and the slowest dominant time constant, τ^L_{dom} that can be measured form preliminary step test on the system. Meanwhile, α_s and β_s that are related to the high and low frequency content are selected. The typical values of α_s = 2 or 3 and β_s = 5.

$$\omega_{low} \leq \omega_s \leq \omega_{up} \tag{9}$$

where, $\omega_{low} = \dfrac{1}{\beta_s \tau_{dom}^{H}}$ and $\omega_{up} = \dfrac{\alpha_s}{\beta_s \tau_{dom}^{L}}$

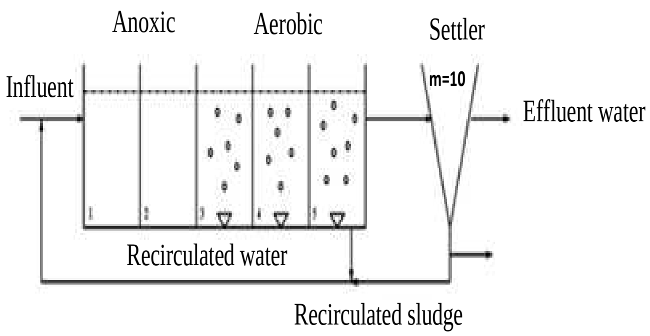

Figure 3. The Plant Layout of the BSM1.

The switching time, T_{sw} can be calculated as:

$$T_{sw} \leq \frac{2.78\tau_{dom}^{\ L}}{\alpha_s} \tag{10}$$

It was viewed that the signal must have a minimum number of levels, depending on the highest order of nonlinearity degree. Meanwhile, the low frequency limit as in Equation 13 can be obtained by measuring the length of the signal N, that is given in Equations 11 and 12. Also, with respect to N, the signal cycle time, T_{cyc} can be determined as in Equation 14.

$$N \geq \frac{2\pi\beta_s\tau_{dom}^{\ H}}{T_{sw}} \tag{11}$$

$$N = q^{nr} - 1 \tag{12}$$

$$\frac{2\pi}{t_{sw}(q^{n_r}-1)} \leq \omega_{low} \tag{13}$$

$$T_{cyc} = (N)(Tsw) \tag{14}$$

Other characteristics, such as the delay of signal, the number of non suppressed harmonics and mapping choices can be further referred to in the work of Jose and Basilio (2003).

BENCHMARK SIMULATION MODEL 1 (BSM1)

ASP becomes a common concepts for biological process in which microorganism are oxidized to organic matter. There are several models describing the biological processes in the bioreactor, but the most widely used is the IAWQ Activated Sludge Model No. 1 (ASM1) (Henze et al., 1987). Thirteen state variables and eight dynamic processes include anoxic growth of heterotrophs, aerobic growth of heterotrophs and autotrophs, decay of heterotrophs and autotrophs, ammonification of soluble organic nitrogen, hydrolysis of entrapped organics and finally hydrolysis of entrapped organic nitrogen are involved. In wastewater, there are several forms of nitrogen components like ammonia (NH_3), ammonium (NH^{4+}), nitrate (NH^{3-}), nitrite (NO^{2-}) and organic (Wahab et al., 2009).

The plant layout of BSM1 is as shown in Figure 3. The bioreactor consists of five reactors where the first two compartment are anoxic zones (pre-nitrification) followed by three aerobic ones (nitrification) and a secondary settler. The plant is designed for an average influent dry-weather flow rate of 18,446 m^3/day and an average biodegradable COD in the influent of 300 g/m^3. The biological reactor volume and the settler volume are both equal to 6,000 m^3. The wastage flow rate is equal to 385 m^3/day. Meanwhile, the secondary settler is modeled as a 10 layers non-reactive unit. The settler has an area of 1,500 m^2. The height of each layer is equal to 0.4 m, for a total height of 4 m. Therefore, the settler volume is equal to 6,000 m^3. The model proposed by Takács et al. (1991) was chosen to resemble the behavior of the secondary settler. In addition, three dynamic input files include dry, rain and storm events that has realistic variations in influent flow rate and composition have been developed for uniform testing and evaluation. In default benchmark control strategy, dissolved oxygen (DO) and nitrate (SNO) concentrations are commonly used as measurement signals with control handle of air flow rate and internal recirculation flow rate, respectively. Copp (2002) and Alex et al. (2008) did much work on BSM1.

RESULTS

MPRS signal

It was observed that the dominant time constants of the ASP, τ_{dom}^{H} = 3.5 days and τ_{dom}^{L}= 0.0135 days. α_s= 2 and β_s=3 were used. Meanwhile, the signal bandwidth of 0.095 rad/day ≤ ω_s ≤ 148.15 rad/day and the switching time was set to T_{sw} = 0.017 day. Minimum length of the signal was calculated to 3509.2. It then verified that the signal with q = 17 and n_r = 3 meets the low frequency requirements with the maximum number of harmonics. AGF (17) with primitive polynomial of degree 3 is selected. For a good MPRS excitation, 77% of the total power should be inside within the bandwidth, ω_s.

System identification procedures

For nitrogen removal, ammonium is oxidized to nitrate under aerobic condition while the nitrate formed was converted to gaseous nitrogen under anoxic condition. For this purpose, a multivariable control structure covers the process of nitrate (SNO_2) in the second anoxic tank and dissolve oxygen (DO_5) in the last aerated tank were explored. The input signals are the internal recirculation rate (Q_{intr}) and the oxygen transfer coefficient (KLa_5) in the second anoxic and the last aerobic tank, respectively. However, influent flow rate (Q_{in}), influent ammonium (S_{nh}) and influent soluble substrate (S_S) were used as measurable disturbances as to improve the quality of identified model. The signals used in the identification procedure are summarized in Figure 4.

Identification can be performed by perturbing the plant inputs while the response on the plant outputs is recorded. KLa_5 and Q_{intr} were excited using MPRS input signals. Their amplitudes and frequencies are chosen in optimizing the information within the bandwidth of each reactor. Two different operating conditions include constant

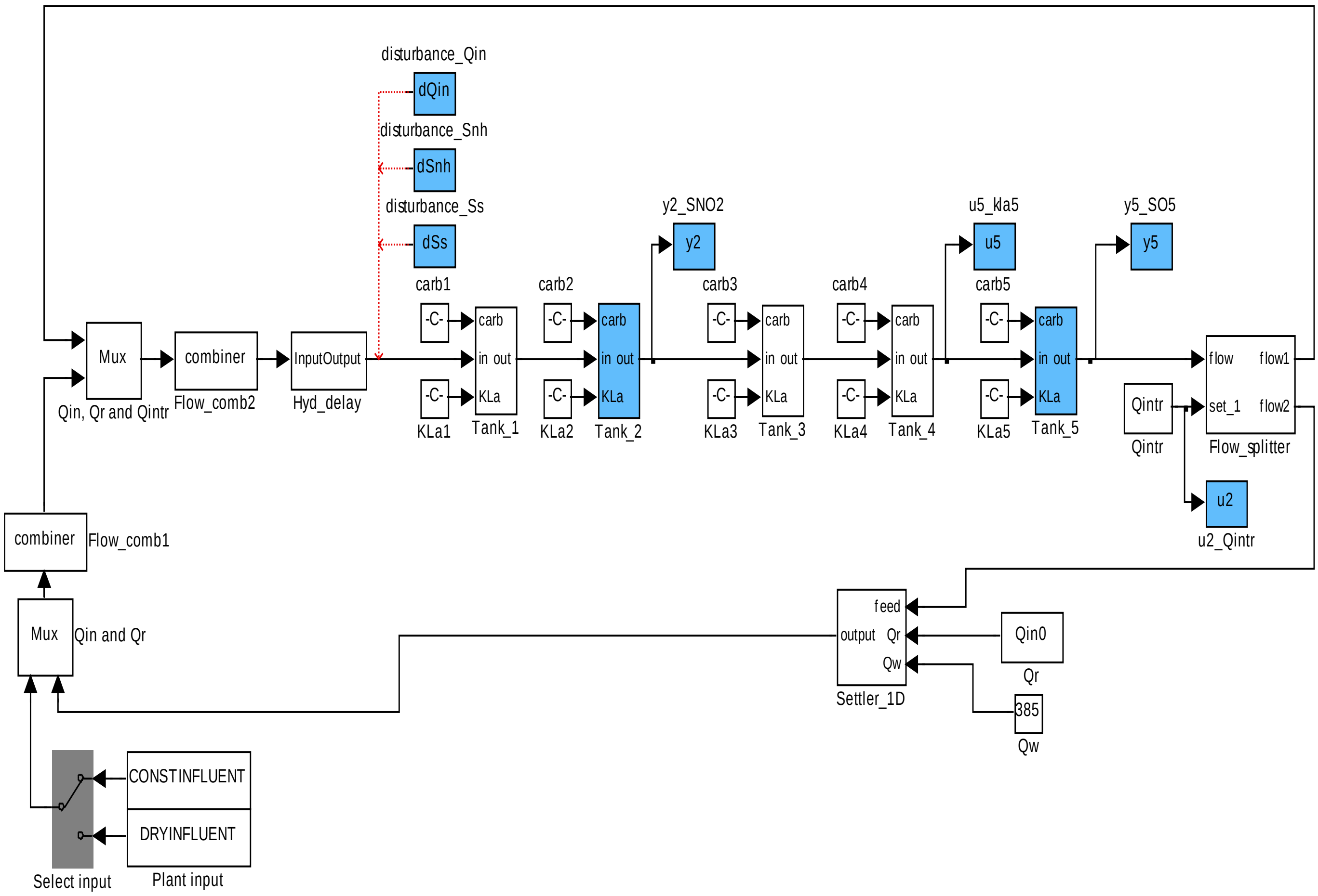

Figure 4. Signals for state-space identification.

and dry influent flows are applied in testing the estimated model. For a better identification result, the raw data set is pre-treatment. Initially, the sample mean was subtracted from data set and it is aimed to remove the offsets for non zero operating point. All data signals are then normalized to ensure that the input and output data are in comparable scales. Finally, the data set is detrended in removing the linear trends from input and output data.

In addition, it is an important role to choose the best order of estimated model. For subspace identification, a gap in the spectrum of the singular values decomposition (SVD) was detected while the estimation errors were compared in PEM. Figure 5 shows an example of SVD for constant influent. As a result, n=4 was chosen for both constant and dry influent flow. The preprocessed data of perturbation input signals and the disturbances are as shown in Figures 6 and 7. The process is assumed to be at steady state conditions for input values of u_{ss}= [55338 84]. The state-space estimation models; N4SID, 'robust' N4SID and PEM are investigated. For constant influent, the identification procedure was carried out off-line with the first 60000 data while the remaining 25000 data were applied in validation purposes. Similarly, simulation was continued for dry influent but with different samples where 800 data are used in identification and 650 data in validation. Due to a good performance in estimating a linear model, identification and validation data for constant and dry influent that estimated by 'robust' N4SID are presented in Figure 8 and 9. The solid lines denote the real data while the dotted lines represent the predicted data.

Identified result

The estimated model using 'robust' N4SID with MPRS excitation input signal that emphasized on dry influent that has realistic variations in influent flow rate and composition was expressed in Equation 15. Meanwhile, the poles' were located at 0.9678 ± 0.1583i, 0.9718 and 0.9470 as shown as in Figure 10. It can be observed that the poles are nearer to unit circle that are mostly referred to the slower dynamic system.

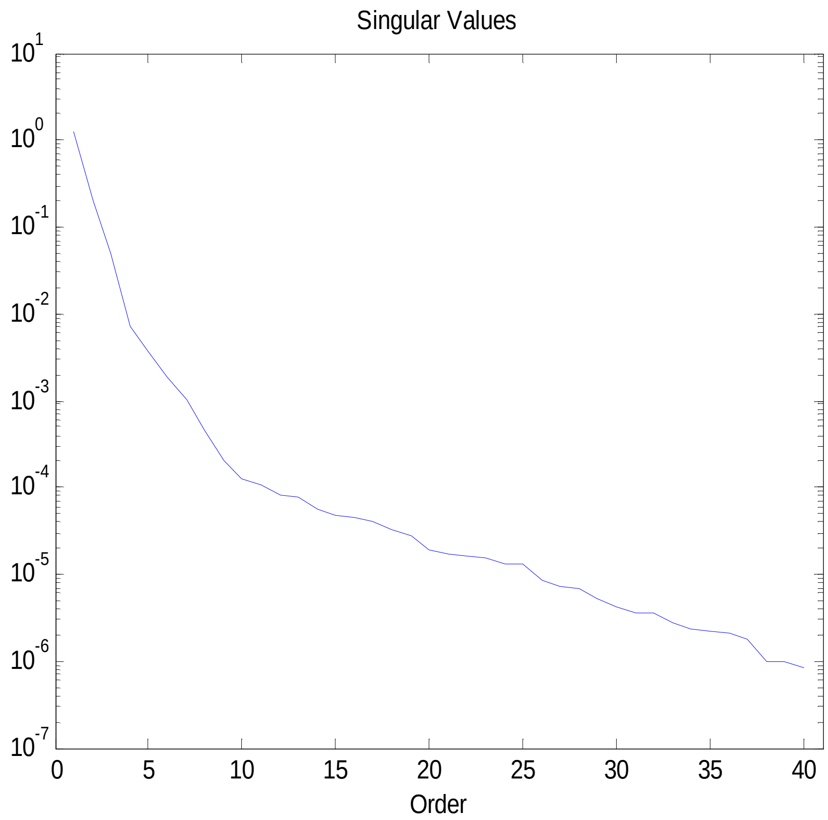

Figure 5. A singular value decomposition.

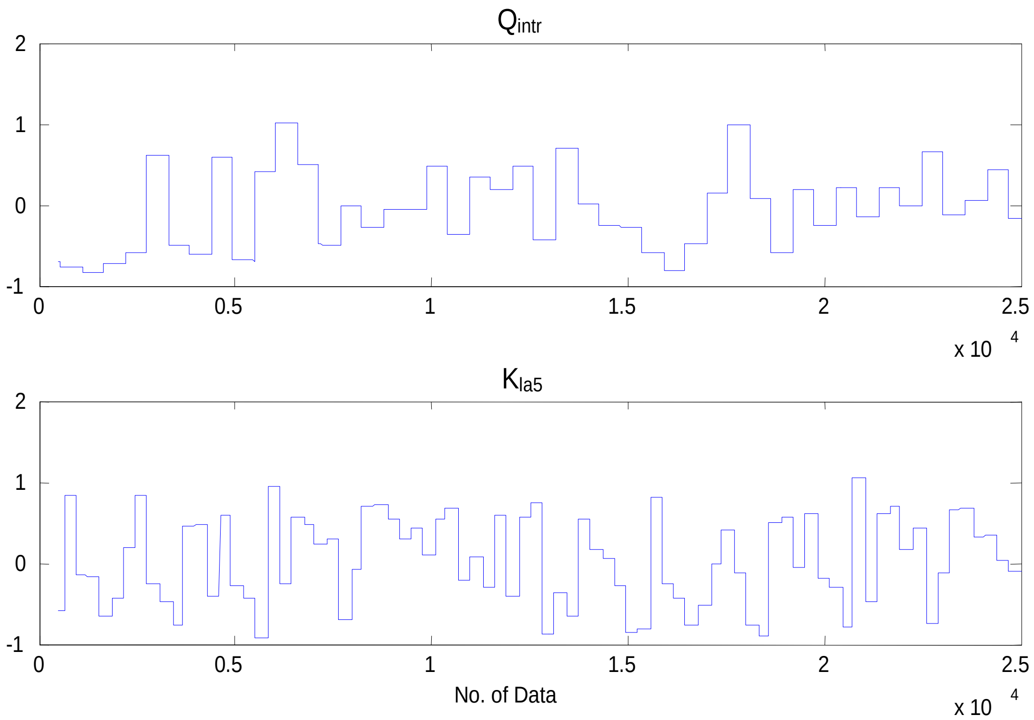

Figure 6. MPRS signals for Q_{intr} and K_{la5}.

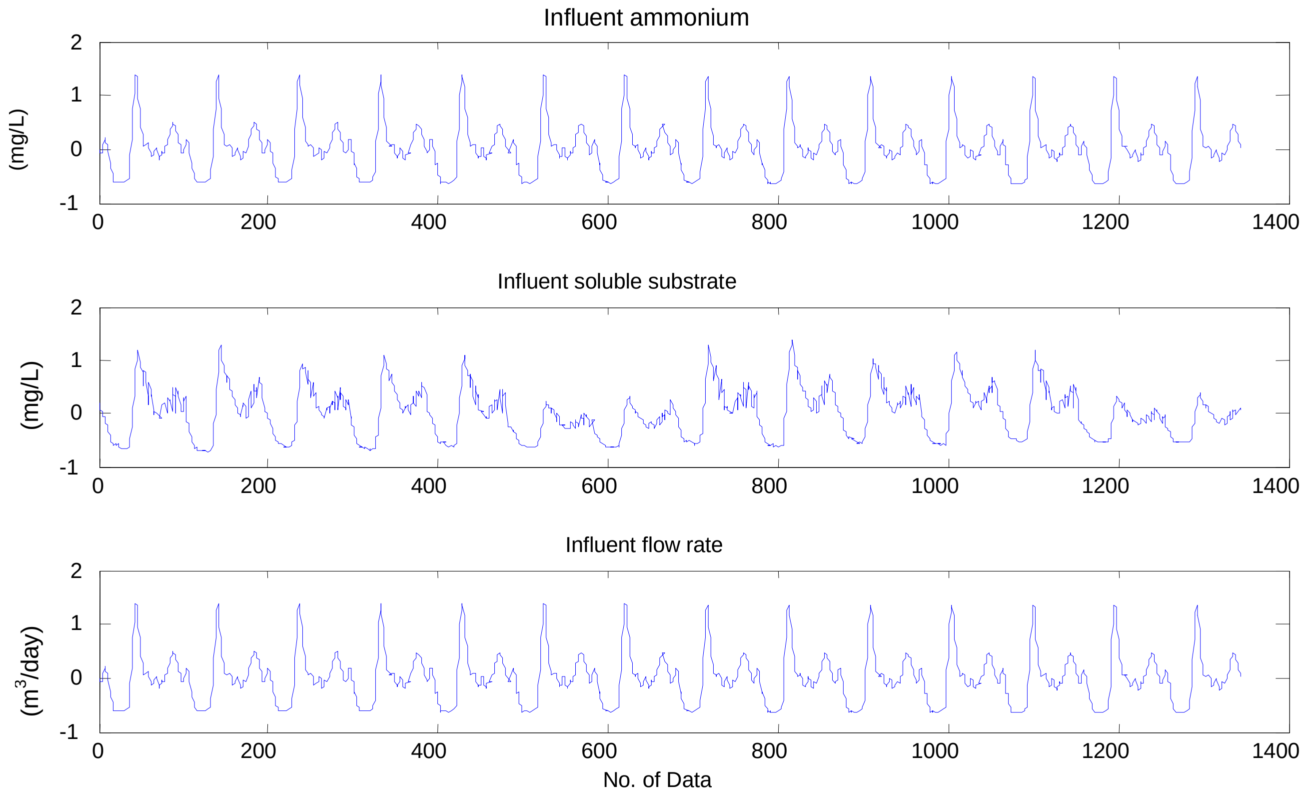

Figure 7. Disturbances used in dry influent identification.

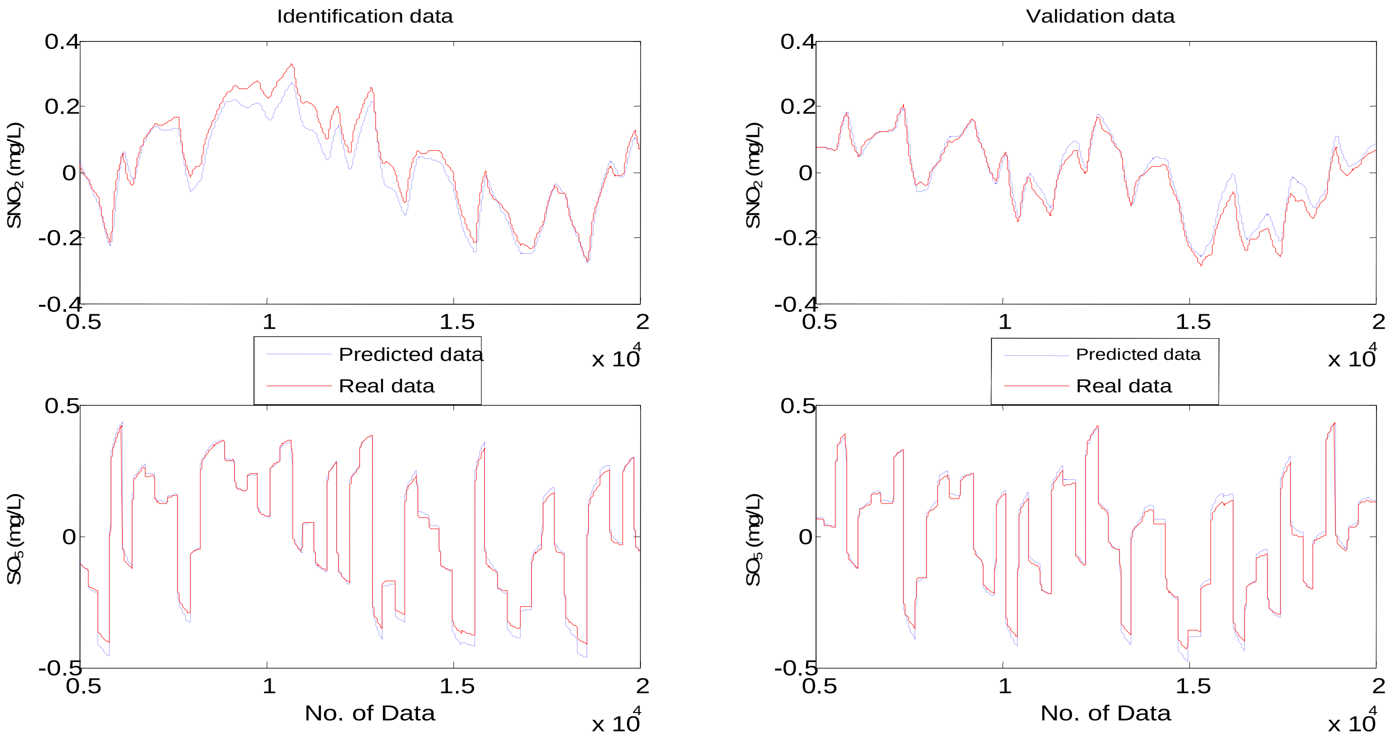

Figure 8. Identification and validation data for constant influent with 'robust' N4SID.

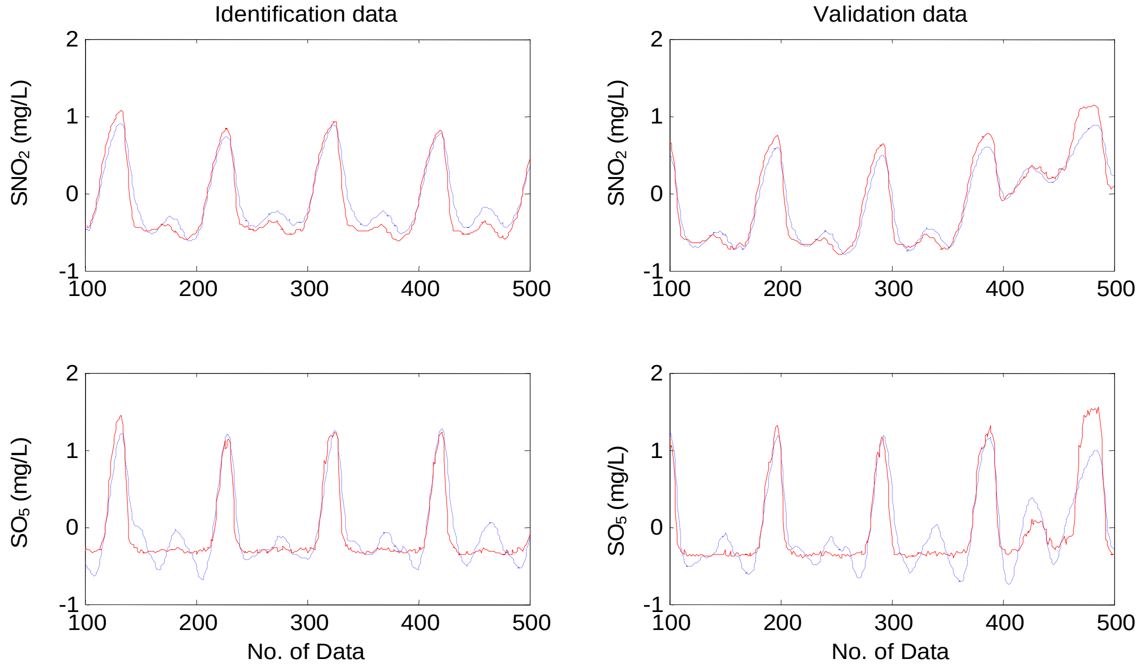

Figure 9. Identification and validation data for dry influent with 'robust' N4SID.

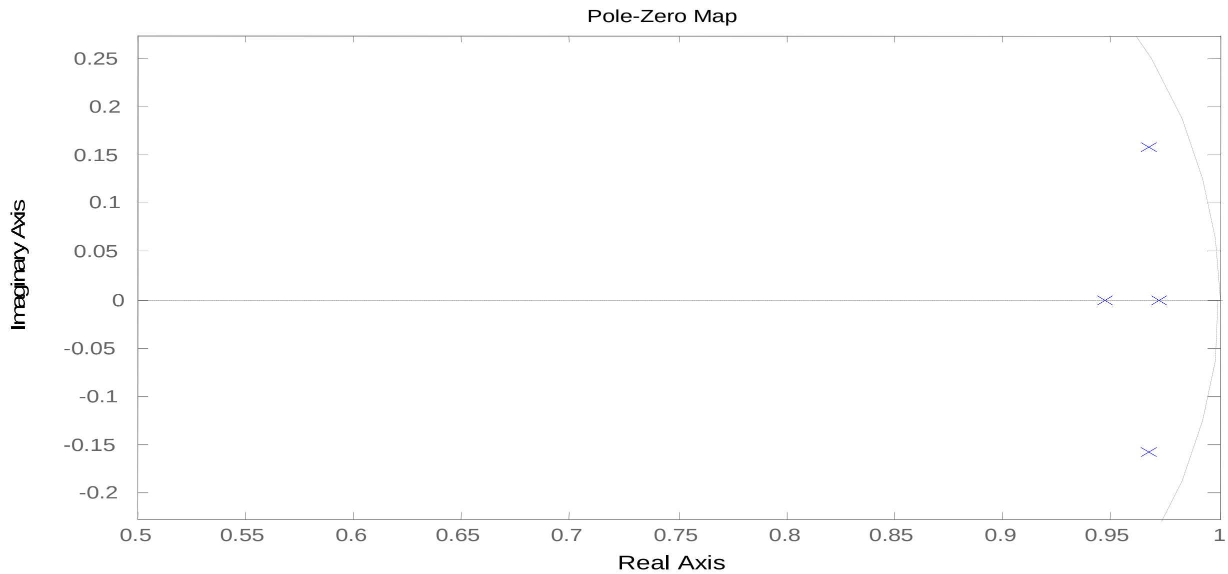

Figure 10. Poles' location of dry influent estimated model.

are nearer to unit circle that are mostly referred to the slower dynamic system. are as shown in Figures 8 and 9. The solid lines denote the real data while the dotted lines represent the predicted data. validation. Due to a good performance in estimating a linear model, identification and validation data for constant and dry influent estimated by 'robust' N4SID'.

Comparison with PRBS

To show the advantages of MPRS as an excitation input

Table 1. VAF analysis for constant influent.

Identification and validation data	PRBS				MPRS			
	Best fit (%)		VAF (%)		Best fit (%)		VAF (%)	
	SNO_2	SO_5	Identification	Verification	SNO_2	SO_5	Identification	Verification
N4SID	91.05	97.84	98.7155	98.7362	80.55	93.38	98.0705	96.1588
'robust' N4SID	97.7285	90.7285	93.5026	92.1231	94.5434	99.5434	96.0052	98.7438
PEM	94.18	96.24	98.8800	98.8585	82.05	93.74	98.1909	96.1675

Table 2. VAF analysis for dry influent.

Identification and validation data	PRBS				MPRS			
	Best fit (%)		VAF (%)		Best fit (%)		VAF (%)	
	SNO_2	SO_5	Identification	Verification	SNO_2	SO_5	Identification	Verification
N4SID	76.19	56.49	88.8516	83.7800	85.58	72.17	91.6393	83.7435
'robust' N4SID	92.2937	61.8152	79.1916	78.6576	92.6643	77.0410	85.9251	84.7905
PEM	62.3	64.24	75.1650	72.2481	77.53	73.85	85.6741	80.1245

signals for a nonlinear identification, the performance of identified models are then compared to PRBS with the same identification behaviors. In this case, 13 of shift registers were used and hence the length of PRBS sequences was set to 8191.

Validation data

Definitely, model validation aims to investigate the performance of identified model in estimating the, physical behavior of the system. The model is cross-validated on validation data. Meanwhile, variance accounted for (VAF) was used to identify the quality of the models. The best-identified models are indicated by smaller deviations obtained between measured and predicted output. Tables 1 and 2 represent the VAF analysis for constant and dry influents. It was observed that slight improved VAF was recorded for constant influent for the three state-space methods with MPRS test signal. In contrast, the effect of nonlinearities in estimating linear models for dry influent was reduced with MPRS where a good model obtained compared to PRBS input signal. This is in line with N4SID, 'robust' N4SID and PEM estimation methods.

$$A = \begin{bmatrix} 0.9653 & -0.0423 & -0.0451 & -0.0091 \\ 0.0134 & 0.9698 & -0.1031 & -0.0722 \\ 0.0301 & 0.0756 & 0.9563 & -0.1778 \\ -0.0064 & 0.0067 & 0.0831 & 0.9629 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.0021 & 0.0072 & 0.1616 & -0.0834 & 0.2431 \\ 0.0003 & 0.0210 & 0.4007 & -0.4018 & -0.0357 \\ -0.0005 & -0.0533 & -0.0942 & -0.1345 & -0.0028 \\ 0.0021 & -0.0482 & -0.1252 & -0.0573 & 0.3869 \end{bmatrix}$$

$$C = \begin{bmatrix} -0.2761 & 0.0516 & -0.0722 & 0.0022 \\ -0.1967 & -0.2133 & -0.1568 & -0.1434 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (15)$$

Conclusions

Identification is a process to find models from collected data. A crucial problem in identification comes in defining the behavior of the perturbation signal. It was shown that MPRS and PRBS were used as an excitation signals to identify LTI discrete-time MIMO state-space model for nitrate in the second anoxic tank and dissolves oxygen in the last tank of an activated sludge process. The performances of model estimation using PEM, N4SID and 'robust' N4SID are investigated. It was observed that a tricky problem arises in resulting good estimation models since both nitrate and dissolve oxygen deal in different time scales. The best identification results were obtained for the MPRS with 17 levels and harmonics of multiple 2 suppressed as compared to binary input signal. The harmonic contents of the signal are manipulated, and hence, minimizing the effect of nonlinearities in estimating a linear model, so that multilevel input signal offers a good option as perturbation signal definitely for a nonlinear systems in obtaining more informative data in signal excitation. Besides, it would be more interesting to identify MIMO systems with respect to variables' operational time where multi-rate sampling strategy may prefer to be considered in selecting the sampling time. As a result, the quality of identified model and its effect on control performances would be improved. A good identified model then leads to superior performances of control design in satisfying a stricter effluent demands in optimizing nitrate and ammonium removal.

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