



Averaging Level Control for Urban Drainage System

Yongjie Wang and Finn Aakre Haugen

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Yongjie WANG*, Finn Aakre HAUGEN

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***Corresponding Author: Yongjie WANG.** Faculty of Technology, Natural Sciences and Maritime Sciences. Department of Electrical engineering, Information Technology and Cybernetics. University of South-Eastern Norway (USN), Porsgrunn, Norway, E-mail: Yongjie.Wang@usn.no

Co-Author:

Finn Aakre HAUGEN. Faculty of Technology, Natural Sciences and Maritime Sciences. Department of Electrical engineering, Information Technology and Cybernetics. University of South-Eastern Norway (USN), Porsgrunn, Norway. E-mail: Finn.Haugen@usn.no

1 Background

We present results from a research project which is about potential use of automatic control on an existing urban drainage system (UDS) in Norway. Figure 1 illustrates the drainage system in covering areas with total volume up to 110 million m³/year wastewater flow. A 42 km long tunnel transports combined sewage overflow (CSO) to the largest Water Resource Recovery Facility (WRRF) in Norway named VEAS. An equalization magazine downstream the tunnel works as a buffer tank of the wastewater before it enters the VEAS plant, being processed and discharged into the Oslo Fjord.

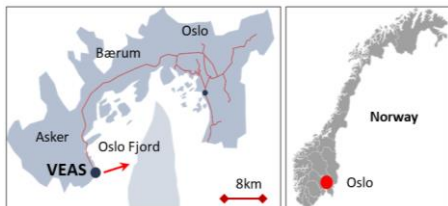


Figure 1. VEAS tunnel for transporting wastewater from Oslo area to the treatment plant. [1]

2 Aims

This work aims at testing model-based control and estimation algorithms using a simulated buffer tank as an equalization magazine:

- (1). Mathematical modelling of the buffer tank.
- (2). Averaging level control using model-based control.
- (3). Inflow estimation using Kalman filter (KF).

3 Materials and methods

The programming language is Python 3.8.0 [2]. Optimization is based on COBYLA solver [3].

Buffer tank

A laboratory buffer tank as shown in Figure 2 is used.

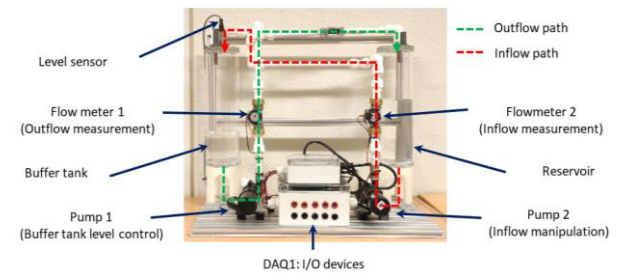


Figure 2. Laboratory buffer tank.

The flow from each pump is locally controlled based on inline flow meter readings.

Mathematical modelling

The mathematical model of the system can be derived from mass balance of the water tank, given in continuous state-space form as (1):

$$\begin{cases} \dot{h} = \frac{1}{A}(F_{in} - F_{out}) + w \\ y = h + v \end{cases} \quad (1)$$

where,

- h [cm], the process state variable, the water level inside the tank.
- y [cm], the process output, the water level measurement.
- F_{out} [cm³/s], the control variable of the pump to manipulate the outflow from the buffer tank.
- A [cm²], the tank cross-sectional area.
- F_{in} [cm³/s], inflow into the tank, which in the real VEAS case is unknown.
- w, v , process disturbance and measurement noise.

Parameter estimation

KF is used for the inflow estimation in this work. The state vector is augmented with inflow disturbance as is given in (2):

$$\begin{cases} \dot{h} = \frac{1}{A}(F_{in} - F_{out}) \\ \dot{F}_{in} = 0 \end{cases} \quad (2)$$

where, F_{in}^i [$\text{cm}^3/(\text{s}\cdot\text{s})$] is the first order derivative of the inflow. Only the state h measurement is used to update the KF in this work.

Control algorithms

(1). Model predictive control (MPC)

MPC is a control algorithm based on the process model and estimated state and parameter, to solve an optimal control problem over a finite horizon at each time step.

(2). Proportional-Integral (PI) control

Skogestad's method [4] is adopted as the parameter tuning method.

4 Results

Simulation results are presented in Figure 3. By comparing of results from PI and MPC control, one can see that:

- (1). The process can benefit from both control algorithms on averaging level control, given constrained control signal with upper/lower limits (u_{max}, u_{min}) and maximum flow change rate ($\Delta u/\Delta t$).
- (2). The MPC outperforms PI with much "smoother" control signal (flow change rate $\Delta u/\Delta t$). This is due to the moving horizon method and optimization algorithm applied.

5 Conclusions and future development

The work presents a demonstration of using model-based control algorithms for averaging level control of a wastewater tunnel basin using a small-scale buffer tank. The conclusions are:

- Inflow estimation can be done with the water level as the only measurement.
- Averaging level control using model-based control algorithms, especially MPC, is successful, with unknown/unexpected inflow.

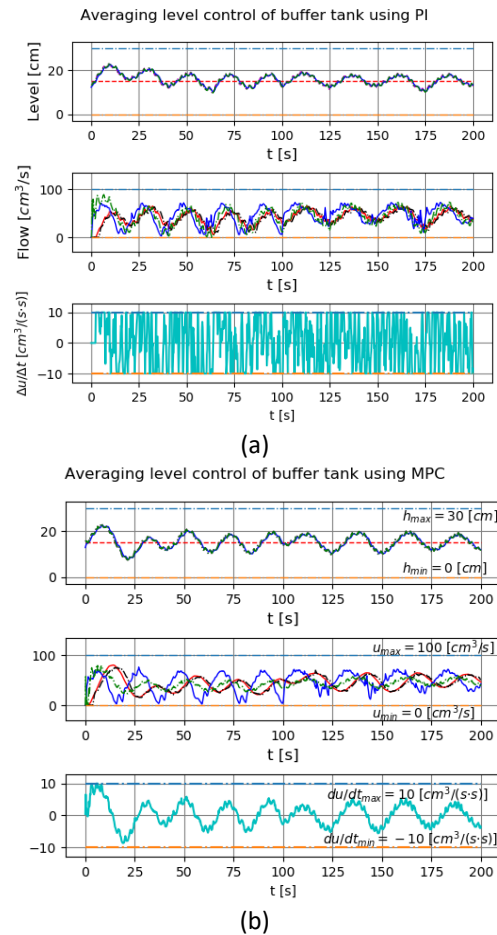


Figure 3. Results of averaging level control using PI (a) controller and MPC (b).

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