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ICUD-0399 Model predictive control for urban drainage: testing with a nonlinear hydrodynamic model

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Summary

We applied Model Predictive Control to a realistic nonlinear hydrodynamic model of the urban drainage system in the Danish city Aarhus. We reported the closed loop behavior of the MPC, and measured control performance in terms of overflow reductions at different locations. The coupling to the hydrodynamic model revealed some of the nonlinear effects, like backwater, normally not taken into account in literature on advanced real-time control of urban drainage systems.

Keywords

hydrodynamics, integrated urban water management, model predictive control, overflow risk, real-time control, urban drainage

Introduction

We consider the northern catchment area of the Danish city Aarhus. A MIKE URBAN (MU) model supplied by the utility models the urban drainage system. It mimics the global rule-based control strategy with several connected PID loops in a coordinating control layer (Mollerup 2016). The PIDs have fixed operator chosen flow setpoints controlling different actuators in different parts of the system (Frier 2013). In this study, we add a Model Predictive Control (MPC) on top of the existing coordinating control layer to optimize the flow setpoints.

With the MIKE 1D (M1D) API (mikepoweredbydhi.com), it is possible to externally extract and manipulate MU model variables during simulation with the M1D engine from a .NET environment, e.g. MATLAB. Hence, we can test more advanced real-time control strategies for a given MU model, than the PIDs and rule-based control already configurable in MU.

Methods and Materials

We solve a Quadratic Programming problem to minimize overflows in the system. Our linear MPC model uses the overflow modeling technique from (Halvgaard 2017). We configure our MPC model and optimization problem with an MPC framework, currently under development at DHI. The MPC framework connects to the MU model through the M1D API. With this connection, we can both retrieve sensor information for the MPC at each simulation time step, and update the
MU model with new MPC setpoints in a receding horizon manner. During closed loop simulation the MU model acts as the real sewer system and provides simulated measurements.

**Fig. 16. Coupled MPC and MU model simulation.**

Fig. 1 shows the connections between the MPC and an MU model. The dashed red frame is the MU model that contains the coordinating control layer and the hydrodynamic model in the dashed green frame. The PIDs manipulate the actuators in the model and receive setpoints from the MPC (the dashed blue frame). The MU model feeds back measurements of the sewer system state for updating the internal MPC model. The MPC also gets predictions of runoffs to the controlled areas, in our case from a MU simulated runoff model forced with historic rain event data (gray box). The dashed black frame manages the operator chosen MPC objectives.

**Results and Discussion**

**Fig. 17. Closed loop MPC simulation of a single rain event (24 hours starting 13/7/14 22:00) using the MU model with six different controllable parts of the system (TB, HB, MB, KB, CB, and JP) with**
prioritization weights (1e1, 1e5, 1e4, 1e3, 1e4, 1e2). Each plot shows simulated M1D engine variables (red) and MPC variables (blue) that ideally should match. The dashed lines are constraints. The resulting overflow volume reductions for each area compared to normal operation (gray) without MPC and fixed PID setpoints in the existing coordinating control layer are (10.7%, 9.0%, 0%, 35.6%, 0%, 75.3%), respectively. Inflow predictions are not shown.

So far, we tested the MPC on a rain event with a 3.7-year return period measured in Aarhus. The MPC objective is to prioritize and minimize overflows in the sewer system. An MPC performance evaluation should look at individual overflow locations and not only the total overflow volume. As reflected in the choice of objective weights, the MPC prioritized overflows at TB while protecting MB. In this simulation, we achieved a 24.6% total overflow volume reduction compared to the existing control strategy. Each row in Figure 2 shows closed loop simulation results for each of six modelled parts of the system. The first column shows controllable flows for each part. The measured flows (red) from the M1D model should follow the MPC setpoints (blue). There are several reasons why the two curves often do not align:

1) The MPC does not model backwater effects. In some situations, e.g. for the HB location, the MPC might suggest unrealistically high flow setpoints while downstream conditions inhibit or even reverse the otherwise controllable flow.

2) We used perfect inflow forecasts based on the historic runoffs. The MPC uses these fixed upstream flows to predict flow constraints as well. The predicted constraints are however uncertain due to unmodelled flow delays within the lumped parts of the system.

3) The MPC performance depends highly on the underlying control layer design. In some parts of the system, large flow delays between actuators and downstream sensor significantly reduces PID control performance.

The second column shows the MPC model states, i.e. the volumes for each part of the system and their overflow volume constraint. The MPC volume is intentionally never above this constraint and overflows when reaching this constraint, while the actual lumped area might have a higher total volume.

The third column shows overflows in all areas.

Conclusions

We showed a closed loop simulation of our MPC framework controlling the sewer system of Aarhus during a single rain event. We coupled the MPC to a realistic nonlinear hydrodynamic model and measured performance in terms of overflow volume reductions. This coupling is crucial for reporting realistic control performance results, but it is often neglected in literature. The simulated total overflow volume reduction for the event was 24.6% compared to the existing control strategy. Future work includes performance evaluation of the MPC with a range of historical rain events and testing the MPC in the operational system.

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References