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Reducing Energy Consumption in Wastewater Pump Stations using Model Predictive Control

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1 Motivation

Exploiting the flexibility in **converter driven loads** allows for **optimization** with regards to CO_2 - and/or energy reduction, efficiency, load shifting and others. Model predictive control can accommodate these in a control strategy that minimizes in an objective function. The aim is to develop a general framework for the control of multiple pumps in wastewater stations.

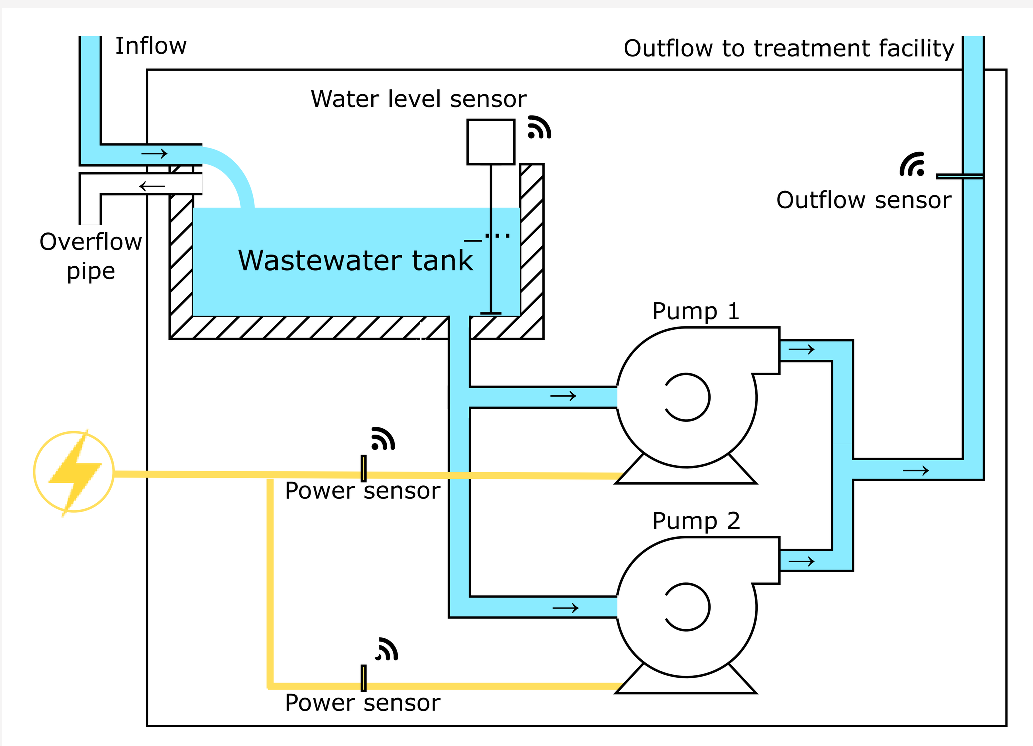

Figure 1: Schematic of wastewater pump station including most relevant variables.

2 System Description

The MPC is implemented in CasADi[A] and is formulated as:

$$\min_{\omega} \sum_{t=k+1}^{N+k} \lambda_1 \overbrace{E_t^T E_t}^{\text{Energy cost}} + \lambda_2 \overbrace{\dot{\omega}_t^T \dot{\omega}_t}^{\text{Control Effort}}$$

$$\ldots + \lambda_3 \overbrace{\left(h_t - h_{ref,t}\right)^2}^{\text{Height Reference}} + \lambda_4 \overbrace{(\overline{TR}_t^T \cdot \omega_t)}^{\text{Pump Selection}}$$

$$\ldots + \overbrace{\lambda_5 s_h + \lambda_6 s_P}^{\text{Slack Variables}}$$

$$\text{s.t.} \quad Q_{out,t} = \sum_{i \in \{1,3,4\}} f_{Q,i}(\omega_{i,t-1})$$

$$\underset{i \in \{1,3,4\}}{E_{i,t}} = f_{E,i}(\omega_{i,t-1})$$

$$P_t = f_P(Q_{out,t-1})$$

$$h_t = h_{t-1} + \frac{T_s}{A}(\hat{Q}_{in,t-1} - Q_{out,t-1})$$

$$\underline{\omega} \leq \omega_{i,t} \leq \overline{\omega}$$

$$\underline{P} - s_P \leq P_t \leq \overline{P} + s_P$$

$$\underline{h} - s_h \leq h_t \leq \overline{h} + s_h$$

The system (1) has the states power E, pressure P, outflow Q_{out} and tank level h and is subject to the inflow disturbance Q_{in} and pump speed input ω. $\hat{Q}_{in,t}$ is online estimated using a Kalman Filter and perfect forecast is assumed.
The system dynamics $f_{Q,i}$, $f_{E,i}$, $f_{P,i}$ are captured in a piece-wise linear function, ARX model and static function respectively found through system identification based on real world data from a pump station in Rønne, Bornholm.

3 Pump Selection

All three pumps follow an alternating schedule TR of 6h runtime. The controllers **optimal pump selection** supplements the active pump with further pump capacity in case of heavy inflow to meet all constraints (2).

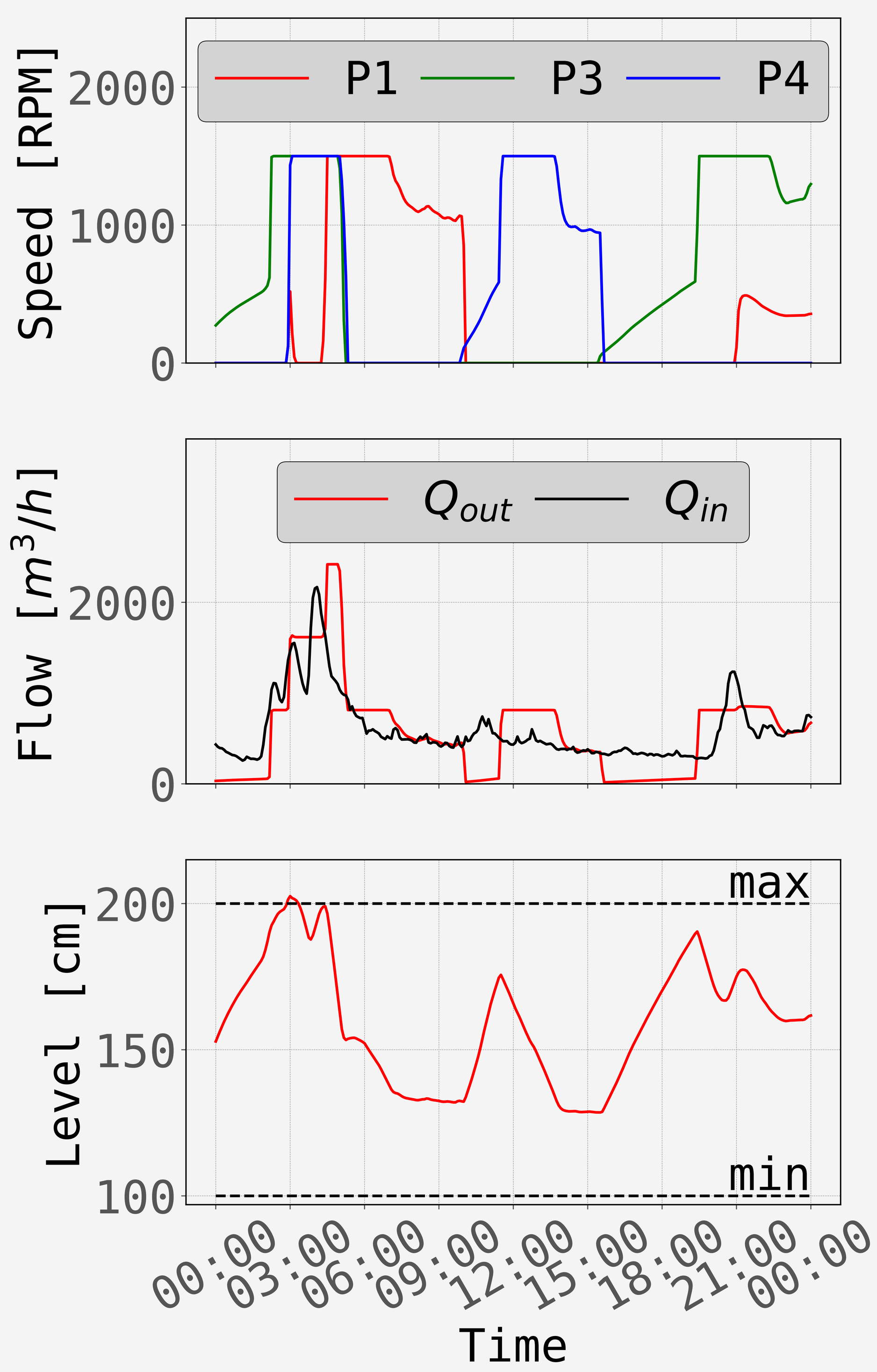

Figure 2: Controller performance under heavy rain event on 02. Aug. Note that, during peak load, P1 and P4 are automatically supplementing the enabled P3 to match the inflow.

4 Edge Implementation

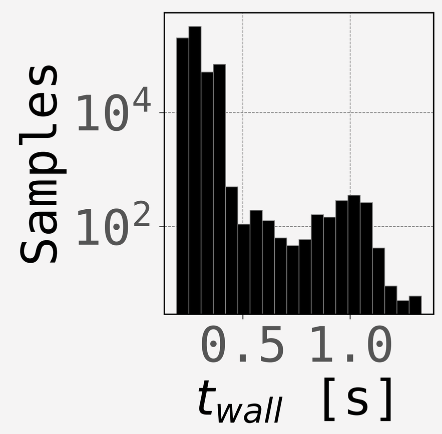

Figure 3: Proccessing time of controller over 655,164 samples. Note that the worst case time is $\bar{t}_{wall} = 1.33$ s

The **real-time** controller is implemented on a *RevPi Connect 4* and operates in closed-loop with collected real world data for the inflow disturbance, a sampling time $T_s = 5$ s, and a control horizon of $N = 24$ (2 min). Although the controller is written in Python, the optimization is solved in IPOPT written in C, hence **implementable** speeds are achieved (3).

5 Results

The developed control strategy **decreases energy consumption** by **16.7%** over a 38 day period in comparison to a conventional strategy (constrained pump speed $\omega_i \geq 750$ rpm). This is achieved by utilizing the tank volume in anticipation of the future inflow (4).

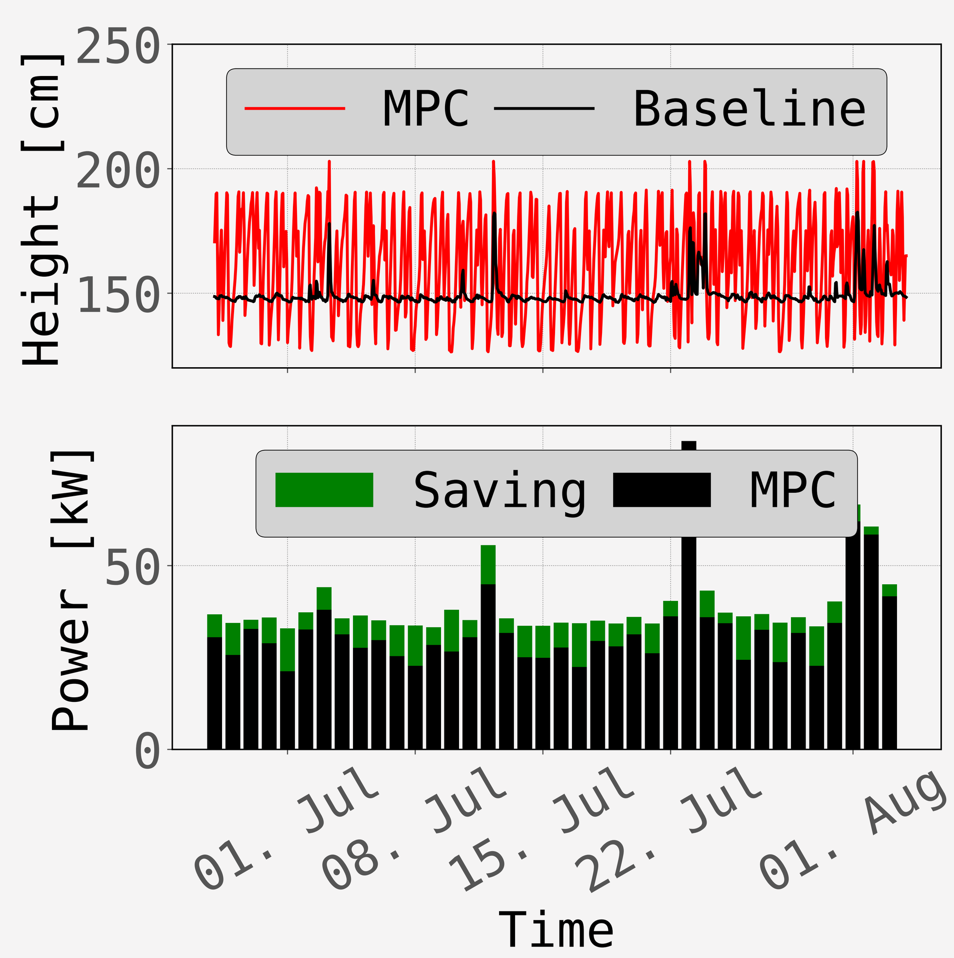

Figure 4: Comparison of controller strategies over one month. Note the consistently lower 24h-average power consumption of the MPC strategy.

[A] Andersson, Gillis, Horn, Rawlings, and Diehl, 'CasADi – A software framework for nonlinear optimization and optimal control', Math. Prog. Comp., vol. 11, no. 1, pp. 1–36, 2019.