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A Water Demand Forecast-informed Framework for Optimal Control of Urban Water Distribution Networks

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Water Distribution Networks (WDNs) are crucial for meeting current and future urban water demands. Knowledge of future water demand at different time scales is fundamental for optimal WDN design and operations. Various predictive models of water demand have been proposed in the literature, ranging from traditional time series analysis to cutting-edge machine learning and deep learning techniques. However, the task of forecasting urban water demand remains mostly decoupled from the design of the optimal control of the related WDN. Current performance assessment of demand predictive models focuses predominantly on forecast accuracy, overlooking their practical implications on WDN operations. Meanwhile, the existing research on WDN management often assumes either perfect knowledge of future water demands or employs empirical approximations and aggregate statistics to estimate future water needs. This study bridges this gap by scrutinizing the actual operational value of water demand forecasts in designing optimal operations of WDNs.

Here, we develop a forecast-informed optimal WDN control framework to evaluate the operational value of water demand forecasts for WDN operations. Our framework comprises two main modules. The first module computes water demand forecasts. We comparatively evaluate a suite of different forecasting models —including Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors, Multilayer Perceptron, Convolutional Neural Network, and Long Short-Term Memory (a network augmented with an attention mechanism) —across various forecast horizons (1/6/12 hours and 1/3/7/14 days ahead). The most accurate forecasts are integrated into the second module, an economic nonlinear Model Predictive Control (MPC) algorithm designed to optimize WDN operations. Within this module, an Artificial Neural Network (ANN) – based surrogate model encapsulates the hydraulics of the physical WDN, enhancing the optimization process while reducing complexity.

We demonstrate our forecast-informed optimal WDN control framework on a real WDN of a rural town with approximately 10,000 inhabitants. Water demand data collected in the Netherlands for a period of 10 years (2007-2017) at 5-minute resolution and corresponding meteorological data are used to train the water demand forecasting models. The MPC module computes the optimal

control sequence for 7 pumps and 1 valve in the WDN to minimize pump energy costs while meeting water demands and ensuring safety storage in 5 tanks. Initial findings reveal that the ANN-based surrogate model can accurately incorporate the WDN characteristics ($R^2 > 0.85$), facilitating its integration into the MPC for an efficient and simplified representation of a real-world WDN. Further, MPC fed by 24-hour ahead water demand forecasts achieves potential energy savings of approximately 18% compared to a benchmark rule-based control strategy. Our framework yields a versatile simulation-based optimization tool for evaluating the impact of demand forecasts on WDN management. Future research efforts will aim at refining and comparing deterministic and stochastic water demand forecasts within the MPC framework, under diverse operational objectives.