

Reinforcement Learning for Dynamic Pump Scheduling under Demand Uncertainty

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Keywords: Reinforcement Learning, Pump Scheduling, Demand Uncertainty

ABSTRACT

Reliable and cost-efficient scheduling of pumps is an important task in the daily operations of urban water distribution networks (WDNs). In this work, we address the pump scheduling problem using reinforcement learning (RL), which allows network controls to adapt to changes in demand in real-time after a data-driven training phase. Previous contributions have shown the general suitability of RL for control tasks in WDNs [1], [2]. However, most of them assume deterministically known demand patterns (cf. [1]) or consider uncertainty only for valve control (cf. [2]). As RL algorithms are designed for uncertain environments, we explore their potential for dynamic scheduling of the network's pumps under uncertain demand patterns. Our optimisation goal is to train a policy that complies with upper and lower pressure bounds at all nodes in the network while minimising the cost of pumping. To this end, we make use of the Soft Actor-Critic algorithm (SAC) [3]. SAC has specifically been developed to handle large and continuous action spaces in reinforcement learning problems, which makes it a good candidate for the pump scheduling task. Data for training and testing is collected using the EPANET simulator for two benchmark networks (Net1 and Anytown). For Net1, we consider the LeakDB [4] scenarios with uncertainties applied to pipe lengths, pipe diameters, roughness coefficients and demands. In all setups, the controller is trained without knowledge of the nodal demands. Instead, we make use of pressure and flow readings, measurements of pump operations and a time encoding. Our study shows promising results for a pump scheduler that can generalize the learned policy to unseen scenarios.

An example of the performance in terms of energy efficiency on a scenario from LeakDB is shown in Figure 1. We compare our approach to a baseline with an optimized constant pump speed. During the 7-day simulation, the RL-based controller is able to systematically exploit periods with low demands to save pumping energy. After an initial high-pressure event caused by an overfilled tank, the controller reliably complies with pressure constraints for all network nodes throughout the simulation. This result showcases the potential of Reinforcement Learning for the development of efficient, safe and dynamic pump schedulers.

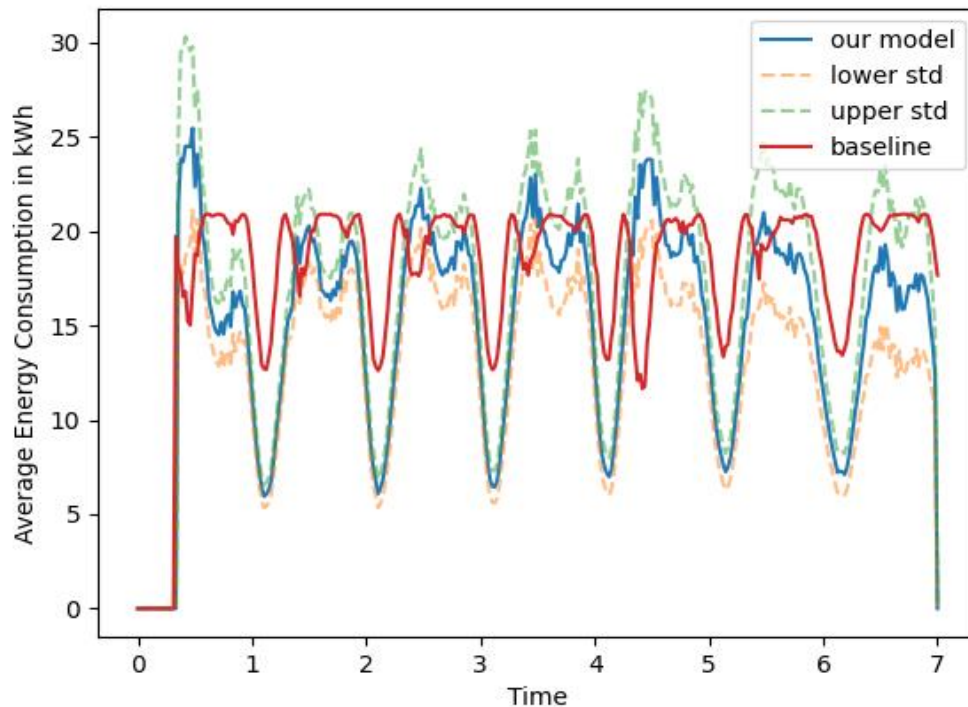


Figure 1: Comparison of the Reinforcement Learning controller to an optimised constant pump speed. Training was run 5 times. Mean performance is shown by the blue line while standard deviation is indicated by dashed lines. The scenario selected for the test (LeakDB [4] scenario 302) was not seen by the agent during training. After an initial overpressure phase due to the overfilled tank, pressure constraints can be met by both models. The RL-based model considerably reduces energy consumption.

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