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Active learning of optimal controls for pump scheduling optimization

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Two approaches are possible in Pump Scheduling Optimization (PSO): *explicit* and *implicit control*. The first assumes that decision variables are pump statuses/speeds to be set up at prefixed time. Thus, the problem is to efficiently search among all the possible schedules (i.e., configurations of the decision variables) to optimize the objective function – typically minimization of the energy-related costs – while satisfying hydraulic feasibility. Since both the energy cost and the hydraulic feasibility are black-box, the problem is usually addressed through simulation-optimization, where every schedule is simulated on a "virtual twin" of the real-world water distribution network. A plethora of methods have been proposed such as meta-heuristics, evolutionary and nature-inspired algorithms. However, addressing PSO via explicit control can imply many decision variables for real-world water distribution networks, increasing with the number of pumps and time intervals for actuating the control, requiring a huge number of simulations to obtain a good schedule.

On the contrary, implicit control aims at controlling pump status/speeds depending on some control rules related, for instance, to pressure into the network: pump is activated if pressure (at specific locations) is lower than a minimum threshold, or it is deactivated if pressure exceeds a maximum threshold, otherwise, status/speed of the pump is not modified. These thresholds are the decision variables and their values – usually set heuristically – significantly affect the performance of the operations. Compared to explicit control, implicit control approaches allow to significantly reduce the number of decision variables, at the cost of making more complex the search space, due to the introduction of further constraints and conditions among decision variables. Another important advantage offered by implicit control is that the decision is not restricted to prefixed schedules, but it can be taken any time new data from SCADA arrive making them more suitable for on-line control.

The main contributions of this paper are to show that:

- thresholds-based rules for implicit control can be learned through an active learning approaches, analogously to the one used to implement Automated Machine Learning;
- the active learning framework is well-suited for the implicit control setting: the lower dimensionality of the search space, compared to explicit control, substantially improves

computational efficiency;

- hydraulic simulation model can be replaced by a Deep Neural Network (DNN): the working assumption, experimentally investigated, is that SCADA data can be used to train and accurate DNN predicting the relevant outputs (i.e., energy and hydraulic feasibility) avoiding costs for the design, development, validation and execution of a “virtual twin” of the real-world water distribution network.

The overall system has been tested on a real-world water distribution network.