LSTM-based policy model for minimising pump operational costs in water distribution systems

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Abstract: Water distribution systems (WDSs) are essential infrastructure systems for supplying water to residential, agricultural and industrial users. These extensive systems require substantial operational costs (i.e., pumping energy and pump maintenance costs) to function. Optimising pump operation to be more efficient and avoid frequent operational changes is an effective way for reducing pump operational costs.

Trigger level-based methods have been used for pumping decision-making but are limited in adapting to modern pump operations with variable and predictable demand and electricity prices. Artificial neural network (ANN)-based policy models have been developed using reinforcement learning to train ANNs that support decision-making in response to real-time operational conditions. However, due to the lack of temporal feature extraction capability, ANN-based policy models struggle to effectively incorporate forecast information, which can result in suboptimal decisions. This research aims to develop a policy model that incorporates forecasts of demand and electricity price to enable proactive pumping decisions that minimise pump operational costs.

In this study, a one-layer long short-term memory (LSTM) network has been used to develop the policy model. The LSTM is trained using the proximal policy optimisation (PPO) algorithm to maximise an objective function value subject to demand and pressure requirements. The objective function value consists of a reward related to pumping energy costs and a penalty for frequent operational changes (a surrogate indicator of maintenance costs), accumulated over the operational horizon. To comprehensively evaluate the performance of the proposed policy model, the models are trained under different forecast horizons (i.e., ranging from 4 to 40 hours with increments of 4 hours) and under varying operational conditions (i.e., summer and winter), using data from the Koondrook WDS in Victoria, Australia. The performance of the trained policy model is evaluated on a dataset independent of the training set, in terms of the objective function value.

The results show that under both summer and winter conditions, the LSTM-based policy model outperforms the ANN-based policy model in maximising the objective value, regardless of the length of the forecast horizon considered (Fig.1, where a deeper red colour indicates better performance). In addition, the LSTM-based policy model requires 16 hours of forecast data in summer and 8 hours in winter to achieve near optimal performance, yielding a 7.4% improvement in summer (energy cost reduced from \$448 to \$303 and the number of frequent operational changes from 142 to 67) and a 6.0% improvement in winter (energy cost reduced from \$332 to \$304 and operational changes from 187 to 62) compared with the ANN-based policy model. Extending the forecast horizon beyond these lengths does not lead to significant performance improvement, but it does increase computational cost. In summer, the LSTM-based policy model requires a longer forecast horizon to reach optimal performance compared to winter. This is attributed to the greater variability in water demand and electricity prices during summer. These findings highlight the value of incorporating forecast data in improving policy model performance, as well as the seasonal dependence of the optimal forecast horizon.

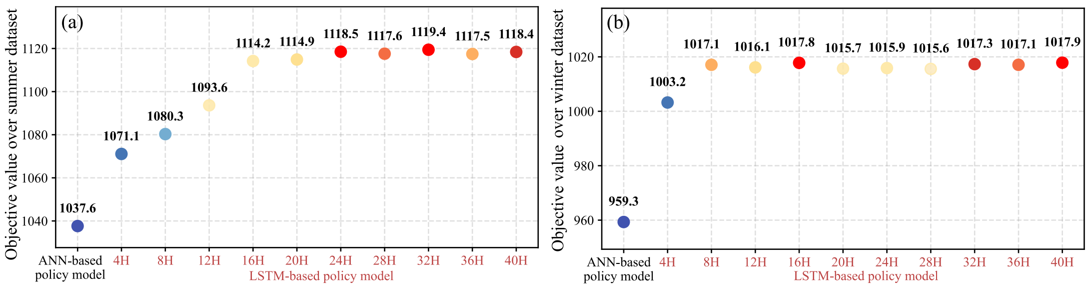

Fig. 1. (a) Model performance during summer; (b) Model performance during winter

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