Predict-and-Optimise through Time at Water Recycling Treatment Plants

Vincent Barbosa Vaz

Supervisors: James Bailey, Christopher Leckie (University of Melbourne and Peter Stuckey (Monash University)
Industry mentor: David Bergmann (South East Water)

Organisations are making complex decisions every day. Traditional approaches consist of a two-stage process: a learning function learns from past data and provides forecasts; these predictions are then fed into an optimiser and delivers optimal policies. While this is true that perfect predictions will lead to optimal decisions, in reality, predictions are not perfect and rather inaccurate. We show that better predictions alone do not necessarily lead to better decisions, but rather investigate the benefits of deep integration of machine learning and optimisation largely untested on time-series data.

Context

South East Water has a significant amount of Pressure Sewer Systems (**PSS**) installed in the Peninsula which feeds into the Boneo Water Recycling Plant (**WRP**). Currently, all the volumes at the residential level are released at the same time. It represents a considerable amount of sewage conveyed on the network and to handle for the plant, resulting in stress on the treatment processes and increased capital costs of upsized pipe and pump networks. Volumes can be retained in pressure sewer tanks at the residential level and selectively released in a way that can optimise the flows to provide network capacity increases of the current network, and improve operations of the downstream treatment plant.

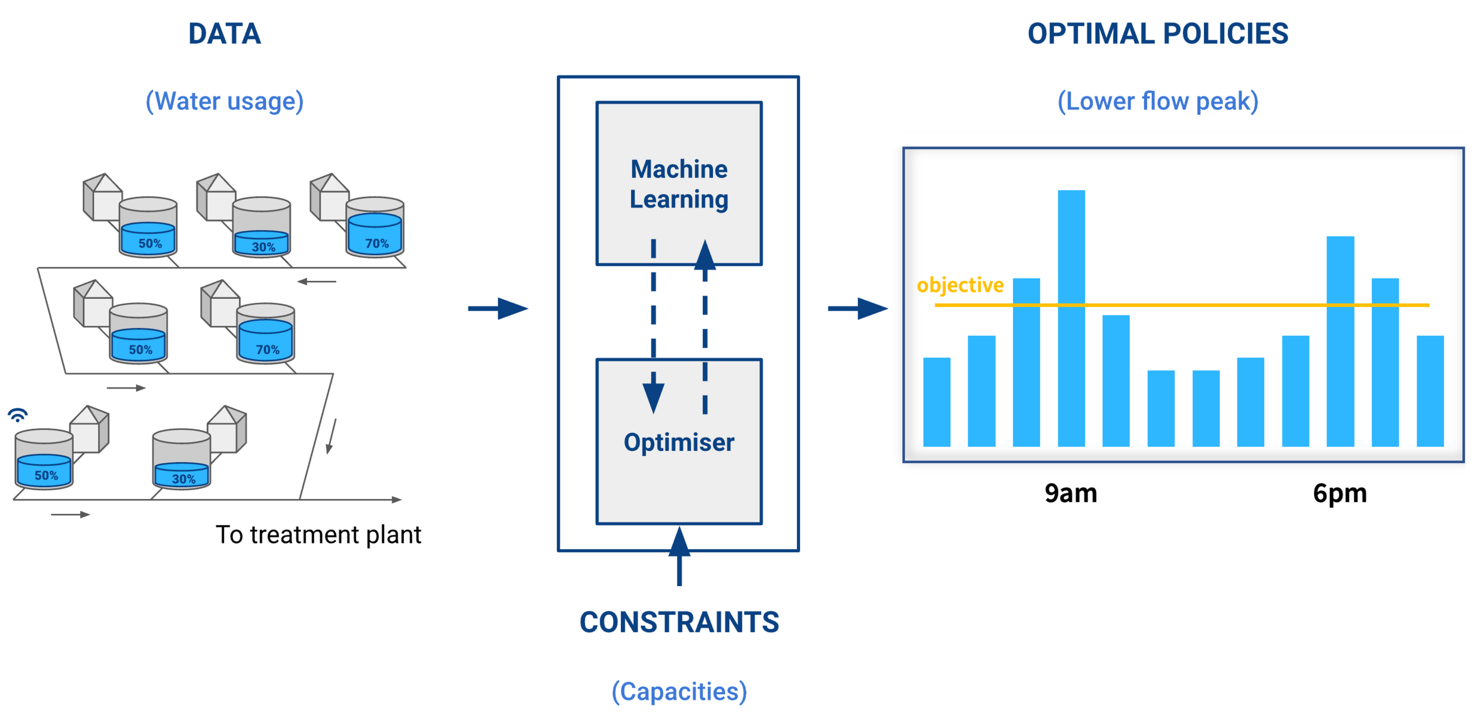

Figure 1: Pressure sewer network (left) and water usage (right) depicting a morning and an evening peak, with objective

Methodology

In a real scenario, information is partial at the time of solving (future inflows are unknown) and decisions have to be made on incomplete and or inaccurate data. Rather, new information arrives and must be incorporated into the problem, also called as **online optimisation**. We build an online optimisation system by generating offline problem instances with uncertainty on the data using **historical sampling**. The optimisation problem is implemented using the MiniZinc framework allowing for fast experimentations across different solvers (Gurobi, Gecode). We provide two formulation for the Constraint Programming (**CP**) model. An off-the-shelf model by directly specifying the constraints and a formulation based on the temporal knapsack problem that reduces the complexity of the problem by vectorising part of the calculations out of the CP problem.

Experimental results

The experimental results are based on a subset of the network (300 properties). The clairvoyant model corresponds to solving the problem in an offline fashion with exact values for the future inflows. For the online model, the data is sampled from a set of inflows from the past 2 weeks for a given tank. Both models generate a set of 24 decisions (empty or not) per tank for the next 24 hours. The decisions cannot be revised and we observe the output flow within the network.

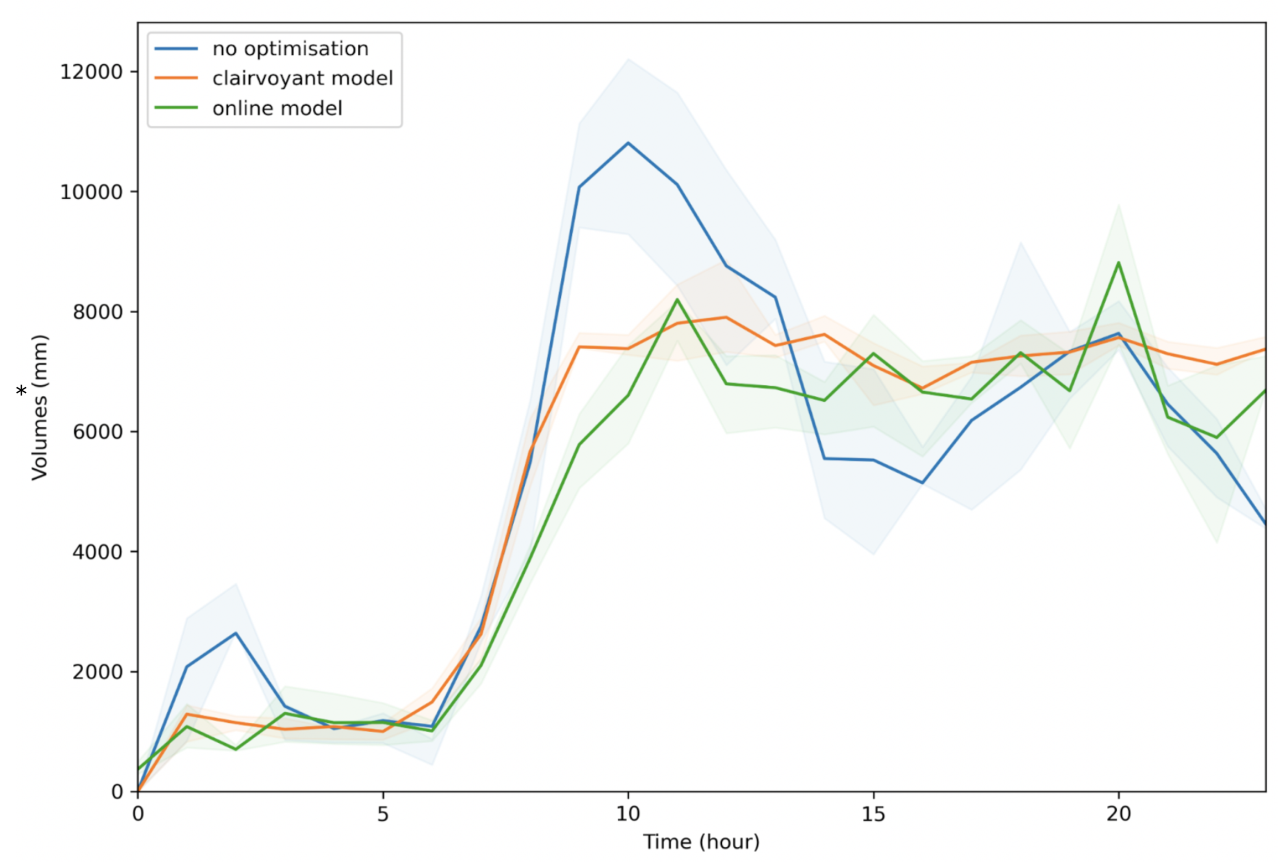

Figure 2: network output volumes (averaged over a period of 30 days) without optimisation (blue), using a model that has full knowledge of the future inflows (orange) and with estimated future inflows (green).
* The level of water (mm) within the tanks is used as a proxy for the actual volume

Conclusion and future work

The experimentations show that South East Water can greatly benefit from optimisation techniques to achieve their goal in reducing the morning peak and flatten the input flow at the treatment plant. Currently, the model generates a set of decisions for the next 24 hours. As we progress over time, new information about the network arrives and better decisions can be made. The online optimisation system can be extended to account for intermediate updates of the decisions (e.g. every hour) yielding to better overall results. We plan to conduct trials in 2023 to assess the benefits of our approach in a production scenario.

South East Water

FOR FURTHER INFORMATION

Vincent Barbosa Vaz
e vbarbosavaz@student.unimelb.edu.au
w www.optima.org.au

REFERENCES

E. Demirovic, P. Stuckey, J. Bailey, J. Chan, C. Leckie, K. Ramamohanarao, and T. Guns, "Predict+optimise with ranking objectives: Exhaustively learning linear functions" ; R. Bent and P. Van Hentenryck, "Online stochastic optimization without distributions."

ACKNOWLEDGEMENTS

This research was partially funded by the Australian Government through the Australian Research Council Industrial Transformation Training Centre in Optimisation Technologies, Integrated Methodologies, and Applications (OPTIMA), Project ID IC200100009.