ADVANCED MODEL - A DIGITAL INNOVATION FOR WATER QUALITY PREDICTION AND DYNAMIC OPTIMISATION OF WATER TREATMENT

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KEYWORDS,
Treatment optimisation, Extreme events, Process Model,

EXECUTIVE SUMMARY
Sydney's drinking water supply was repeatedly challenged in recent years by multiple extreme weather events. Two novel models were developed and applied - the raw water quality prediction model, and the process optimisation prediction model for water treatment. The spatial-temporal model based on weather forecasts can predict raw water quality five days in advance. The Process Model based on multiple linear regression of online data of the plant can predict the optimisation of water treatment parameters. The two advanced models provided sustainable operational solutions for water quality events influenced by climate change and accelerated the digitalisation of water operations.

INTRODUCTION

Sydney's water catchments have experienced several extreme weather events since 2019. There was a significant drought in 2018-19 when most of the water storage went below 50% of its capacity, then a devastating bushfire in the largest catchment in late 2019, followed by an intense drought-breaking rain in early 2020. Between 2020 and 2024, the water catchments experienced five major rain events when most of the dams overflowed. These extreme events resulted in significant degradation of source water qualities, and treatment processes were challenged by dynamic changes in raw water quality. In most instances, it was not possible to predict the impact on source water quality by extreme events in the catchment, nor the impact on the treatment process. It was a challenge to optimise the treatment while there was a rapid variability in raw water quality at the inlet of the plant. Therefore, a raw water quality prediction model and a dynamic optimisation model were thought to be developed. The objective was to apply advanced data analytics methods to build predictive models of water catchments. The two Water Filtration Plants (WFP) supply catchments in NSW, namely Macarthur and Nepean were investigated to build a raw water quality model. The WFP process model known as Sydney Water's Instantaneous Filtration Technology (SWIFT) was developed using real-time data from the water filtration plant's Supervisory Control and Data Acquisition (SCADA). While the SWIFT model has many functions as shown in Figure 3, this paper only focuses on the prediction of chemical optimisation and plant performance and model-driven automated optimisation by plant operators.

HIGHLIGHTS

- First known data-driven raw water prediction for five days in advance
- Spatial and temporal modelling integrating weather forecast
- Novel Process Model predicting treatment optimisation online in SCADA
- Optimised Sydney's five WFPs dynamically and automatically using the Process Model
- A sustainable digital solution for water operations facing the extreme events

METHODOLOGY/ PROCESS

Given the water quality sampling locations within each catchment, a breakdown diagram was constructed which defines how water flows across the sampling locations (Figure 1). It depicts the upstream and downstream relationships among the sampling locations. The data model assumes that raw water quality at a target location is attributed to factors in three aspects as shown in Figure 2, namely weather information both historical and forecasted, upstream water quality, and historical water quality at the target location (Inlet of WFPs). Thus, a spatial-temporal machine learning approach was used for catchment-independent raw water quality modelling.

The water filtration process model (SWIFT) was developed using real-time online data from the WFPs SCADA. Multiple linear regression models were dynamically developed to correlate the optimum chemical dose, raw water qualities, and filter performance. The SWIFT model structure is shown in Figure 3. Among the many useful features, the automatic prediction of chemical doses based on raw water turbidity and true colour enabled the plant operators to optimise the plant dynamically to respond to dynamic changes in raw water quality.

RESULTS

Models for turbidity prediction in each catchment have been built using historical 1-day water quality, historical 5-day weather, and 1-day ahead weather forecast. To evaluate the model performance quantitatively, two metrics were considered - median absolute error (MAE) and median absolute percentage error (MAPE). MAE is a scale-dependent metric while MAPE is scale-independent. Additionally, MAE and MAPE are also calculated solely on the samples with the top 5% largest actual observed turbidity, which are deemed to represent extreme conditions and pose a great challenge for water utilities in operation. As presented in Figure 4, for example, the raw water quality prediction error is extremely low when considering all the samples with MAPE less than 5%. The prediction performance is also very good in extreme conditions, with MAPE around 10% across different catchments. It demonstrates the developed models can predict turbidity accurately in both normal and extreme conditions.

In the process model SWIFT, the one-minute time interval filter head loss and turbidity data from online instruments provided the backbone of filter performance analysis and modelling. As an example, Figure 5 shows the instantaneous data from online instruments of 5 filters at Nepean WFP during the 2022 rain event. Filter turbidity (red line) and head loss (blue line) were automatically analysed and modelled for change in turbidity and head loss during a filter operation cycle, filter runtime, and other key parameters when new data were uploaded into the model. Statistical regression equations for chemical doses were developed against raw water quality and filter performance in the SWIFT model using over 10 years of online SCADA data. These equations were used to predict chemical doses when raw water turbidity and true colour changed. Figure 6 shows an example of the SWIFT model prediction of optimum chemical doses for given raw water true colour and turbidity at Nepean WFP. The SWIFT model prediction enabled the operators to set the chemical doses very quickly and produce safe drinking water during raw water quality events. The SWIFT model also tracks the raw quality, filter performance, chemical dose, and cost (Table 1, Figure 7). Automated process and chemical dose optimisation significantly improved filter performance and saved operational costs.

CONCLUSION

The spatial-temporal machine learning approach for dynamic prediction of raw water quality using weather information helps the utility to select the best water source and can inform treatment optimisation in advance of an extreme weather event. The results indicate that the model can predict raw water quality at a higher level of confidence in both normal and extreme conditions. The water filtration Process Model, SWIFT, was applied and validated during recent extreme rain events at all five water filtration plants operated by Sydney Water. The SWIFT model optimsiation demonstrated that it is a very useful digital solution to dynamically optimise chemical dose and improve filter performance when raw water quality changes dynamically. The Process Model (SWIFT), due to automation in optimisation, significantly improved operational safety by reducing the number of operators needed for Jar tests and manual optimisation by trial and error during a raw water quality event. The two advanced models provided a sustainable operational solution for rapid water quality changes in extreme rain events, saved significant operational costs, and ensured a safe and clean drinking water supply despite catchment and treatment challenges. The models can be applied to any catchment and water treatment plants for decision-making in the source selection and dynamic optimisation of water treatment.

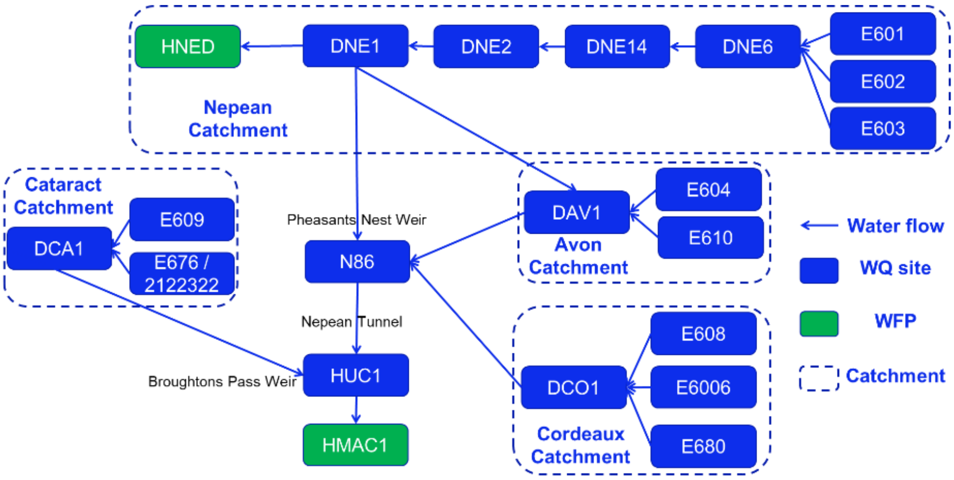

Figure 1: Macarthur and Nepean catchments breakdown

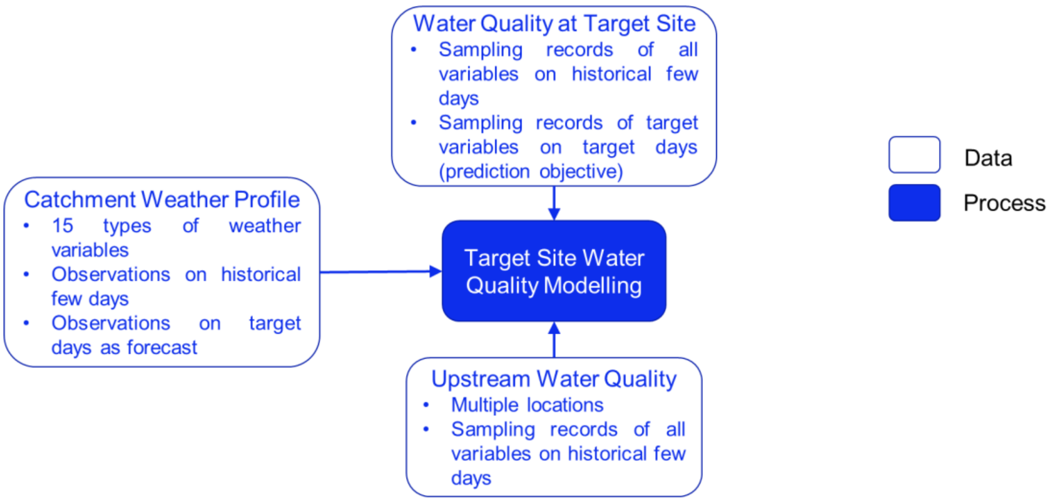

Figure 2: Catchment independent Raw Water Quality prediction modelling

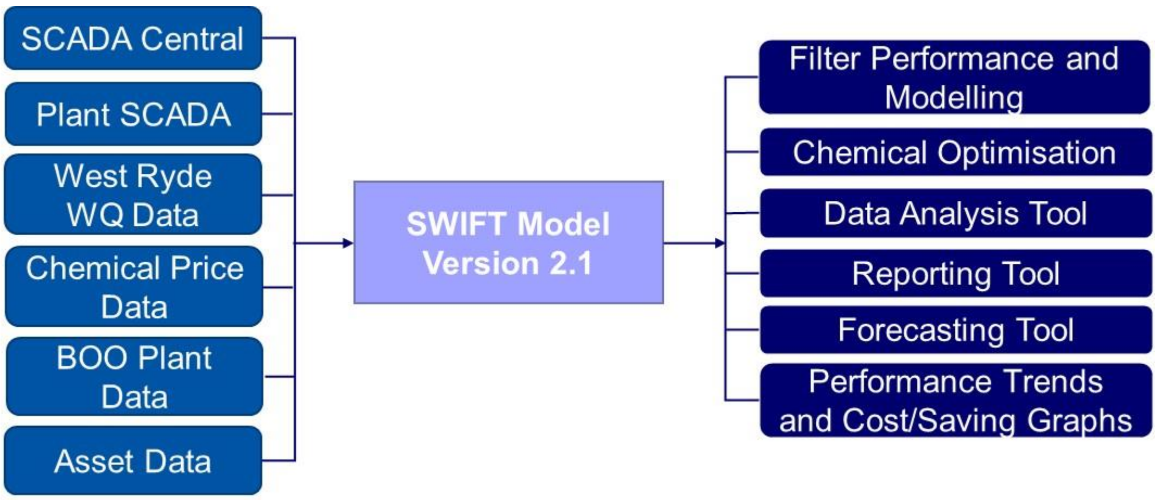

Figure 3: Process Model (SWIFT) structure

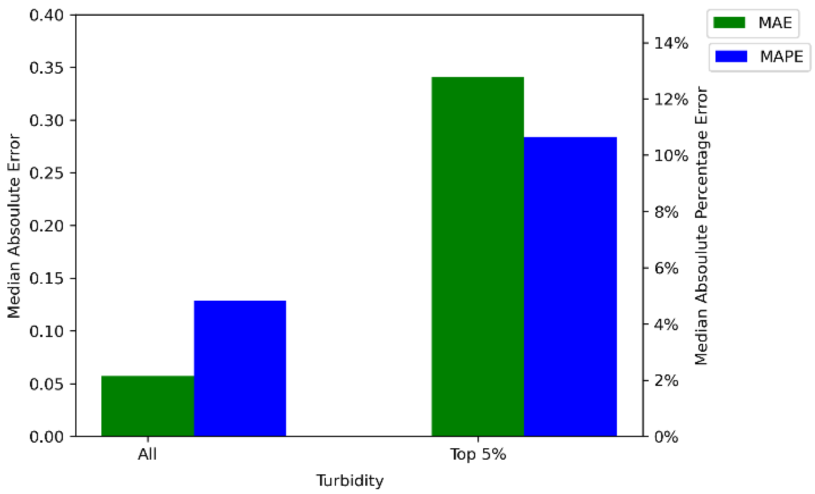

Figure 4: Performance on Raw Water Quality (turbidity) prediction at both normal and extreme conditions

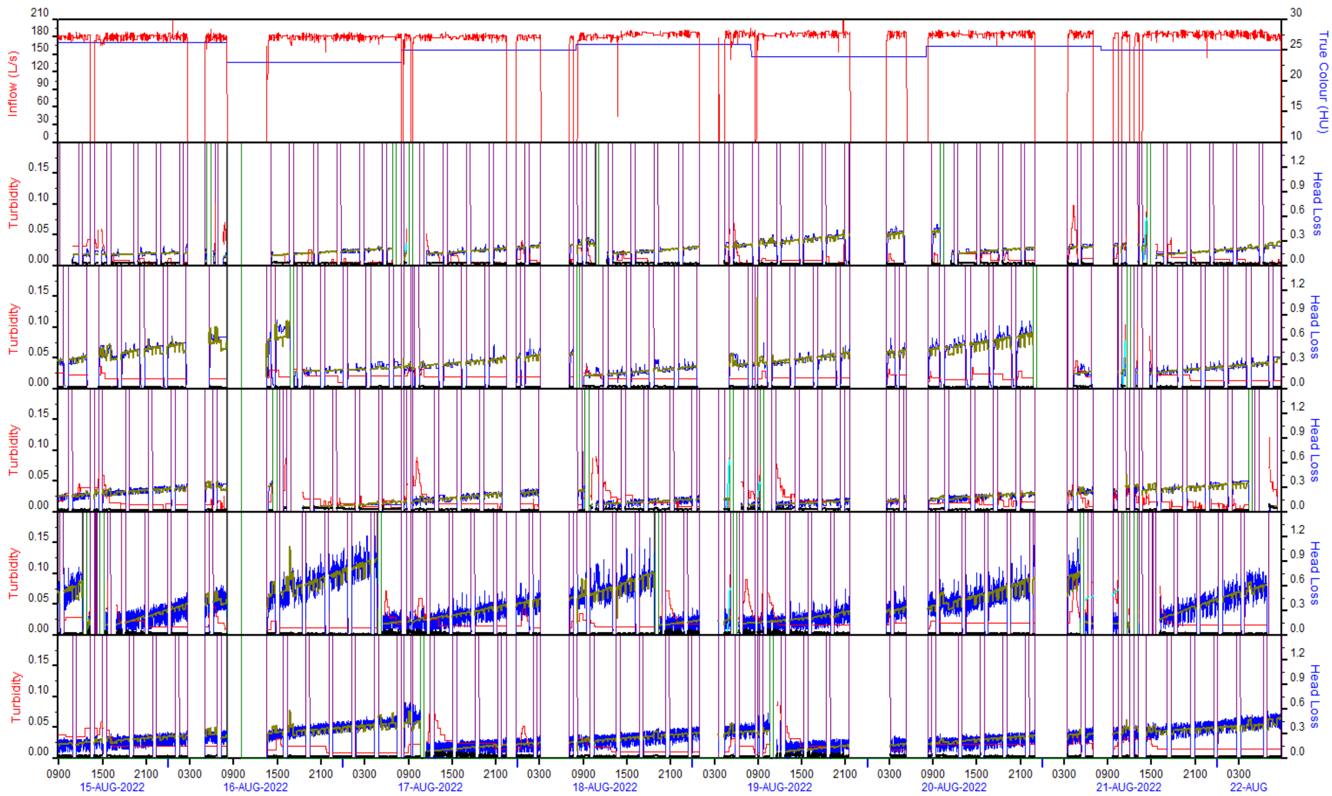

Figure 5: Process Model - one minute time interval data for filter outlet turbidity (red line) and head loss (blue line), modelled head loss (olive line), modelled change in turbidity (aqua line), filter or plant offline (between vertical purple lines), filter backwash (between vertical green lines)

Table 1: Chemical savings in the last 5 years by applying process model SWIFT for optimisation

Plant	Nepean	Orchard Hills	Cascade	Warragamba	North Richmond
Ave. Daily production (ML/d)	12.0	65.0	12.0	3.7	20.0
Chemical Saving ($/Yr)	147,648	206,032	49,890	44,062	150,511

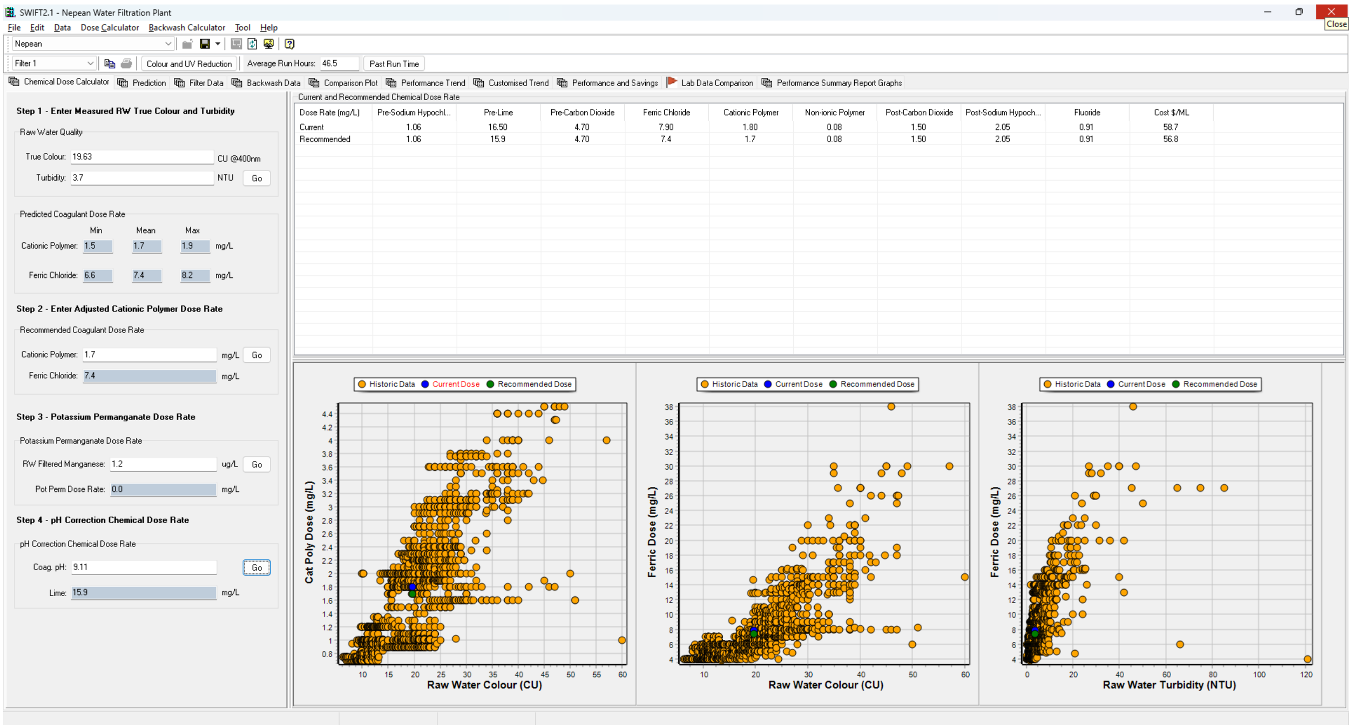

Figure 6: The Process Model (SWIFT) predicted chemical dose, for Nepean WFP as an example, for predicted raw water

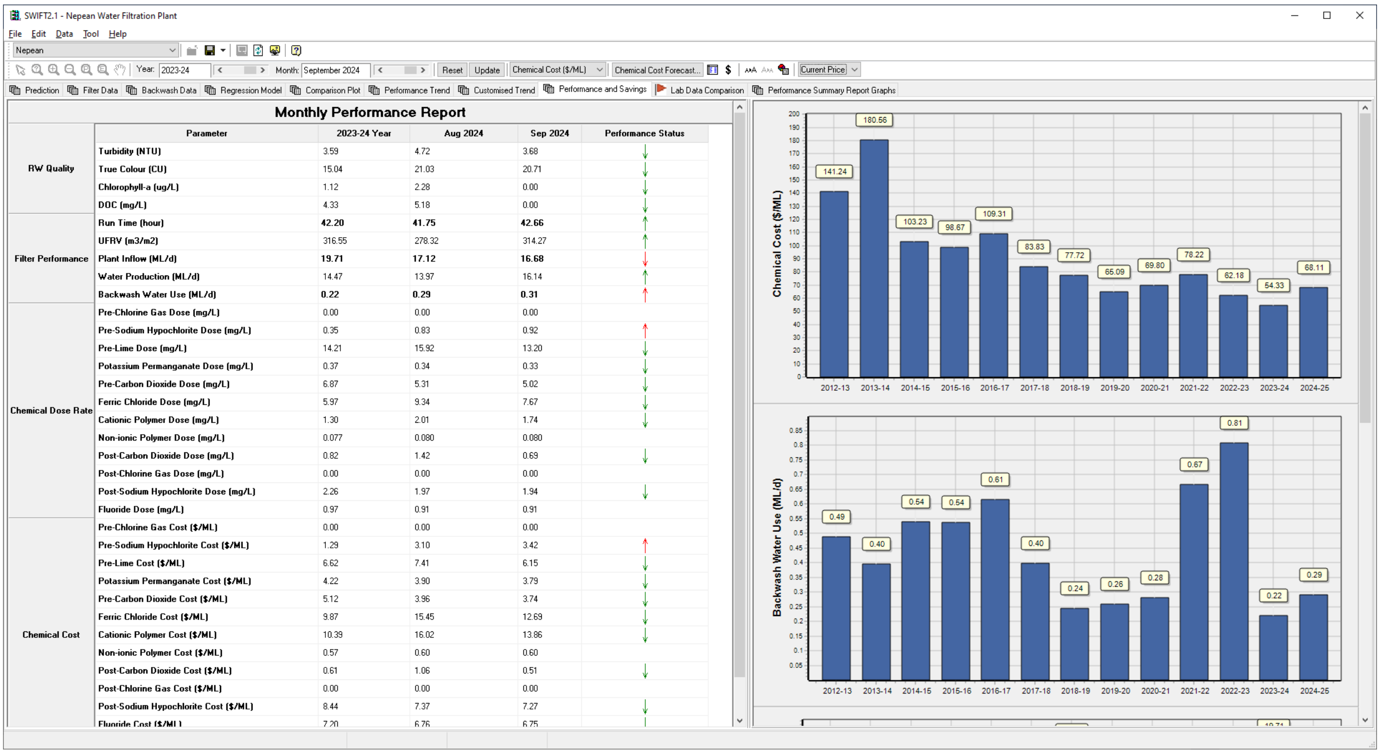

Figure 7: Water treatment tracking for performance and cost savings using Process Model (SWIFT), Nepean WFP as an example