Making water smart

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Editorial: Making water smart

Wherever we measure we gather data, wherever we have data we have information, and wherever we have information we have potential knowledge. However, we cannot assume that this knowledge is useful just by ensuring that we measure. The continual growth of data volume, velocity and variety has necessitated the development of tools that can assure its veracity to meet the criteria defined by its ultimate use. Where these tools provide computational functionality that are outside the abilities of a human operator, are non-routine and handle data large or complex in characteristics, we can define them as 'smart'. This and analogous terminology, such as 'intelligent' or 'cyber physical', has become ubiquitous within the data science community and has been embraced by manufacturing and processing industries as the 4th Industrial Revolution (Industry 4.0). The water industry is no exception to this and perspectives for Smart Water were neatly presented in two recent IWA whitepapers on Digital Water (IWA 2019; van Thienen & Savic 2020), as part of their ongoing Digital Water Programme. This very much looks at the present and the future of smart technology and intelligent management and use of data across the water sector. For over thirty years, pockets of academics and practitioners have attempted to 'smarten' water processes, building on modelling and control foundations, most notably within the Industrial Control and Automation (ICA) community. While some traction has been made (Olsson 2006), general acceptance and integration of methods by industry has been sporadic and limited due to an array of reasons. Nevertheless, we believe that the ideas and approaches for smartening water systems are being embraced wholesale and data analysis and utilisation is being elevated from the mundane to the critical, sitting alongside process and control engineering in the armoury of skills required by practitioners in the water industry to meet present and future challenges facing the sector with preparedness and resilience.

In this special issue of *Water Science and Technology*, 11 papers were selected that contribute to a broad discussion and demonstration of state-of-the-art for integration of digitalisation and water management processes. Therrien *et al.* (2020) provide an excellent introduction to the concepts embraced in this issue, highlighting the necessary steps required to extract applicable intelligence from raw data in water resource recovery systems. Sit *et al.* (2020) undertake a more focused review of contemporary deep learning techniques, which considers not only the process and challenges but governance and ethical management of data as a resource.

Icke *et al.* (2020) developed and tested an Artificial Intelligence approach at the Integrated Validation Plant of Singapore's National Water Agency. With a self-learning feedforward algorithm that uses load prediction and machine learning for nutrient removal control, they achieved up to 15% reduction of aeration compared with conventional feedback control. They also applied quantile regression neural network modelling for anomaly detection to deliver data-driven operational support for process operators.

Eerikäinen *et al.* (2020) present results from a series of interviews with stakeholders working in ICA of wastewater systems. The findings of the study echo some of the historical reasons identified as barriers for the uptake of machine learning and, more broadly, data analytics and data-driven models in the sector. However, given advances in technology and the quantifiable measure of their performance, the general feedback from practitioners is one of optimism.

Antzoulatos *et al.* (2020) propose a unified framework called SMART-WATER for the efficient management of the water supply network. This urban water management platform is based on Internet of Things (IoT) solutions for remote telemetry and control of water consumption in combination with machine learning techniques. Consumers and water utilities obtained feedback on water usage, providing an enhanced awareness of water consumption.

The dimension reduction technique Principal Component Analysis (PCA) is slightly older than the activated sludge process, being developed by the eminent statistician Karl Pearson in 1901. The adoption of multivariate statistics, which includes PCA, by industry in the 1970s was a significant milestone towards the use of data-driven approaches, and eventually machine learning, for application in monitoring water processing facilities, especially wastewater treatment. Kazemi *et al.* (2020) present a novel, adaptive monitoring approach called Incremental PCA that is able to track and detect true process faults (as opposed to disturbances), even when those faults are small in comparison to the signal.

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Using long-term datasets, Jones *et al.* (2020) identify benefits of using real-time sensors in small community water systems, where limited compliance monitoring can miss elevated nitrate concentrations, and large community water systems that need decision-support tools to initiate nitrate management strategies.

Carriço *et al.* (2020) provide an overview of the information systems used by Portuguese water utilities to collect, store and manage data and propose a possible solution for data integration from different information systems to facilitate assessment. An initial platform has been presented; however, the authors provide the caveat that scalability problems are a risk, depending on the chosen technology.

Cardenes *et al.* (2020) demonstrate how a hybrid linear and multi-objective optimisation approach can be used to identify key energy consumption elements in a water supply system, and evaluate the amount of investment needed to achieve significant operational gains at those points in the supply network. As an illustration, an application to the water supply system for the city of London show that up to 18% savings in daily energy consumption are achievable but the optimal results are sensitive to the financial value placed on greenhouse gas emissions.

An data-driven model for prediction of biomethane shortfall and optimisation of Combined Heat and Power (CHP) requirements from anaerobic digestion is presented by Laing *et al.* (2020). Using one year of historical plant data, operational performance was significantly improved resulting in an 11% increase in financial return. The authors highlight that replacing the retrospective optimisation approach used here by a forecasting method would give scope for employing the model for short- to mid-term operational planning.

Finally, Offiong *et al.* (2020) demonstrate the use of a recurrent artificial neural network approach to predict solar powered water taps in sub-Saharan Africa. The use of such a technique not only delivers prediction and classification of tap failures, but has an immeasurable public health benefit for remote communities relying on the taps as a source of clean water.

This final paper highlights where we should value the use of Smart Water technologies most. They do not reside solely in the domain of data analysts or process engineers, for the purpose of reducing operating costs and maximising performance, but can be utilised to deliver transformative and simple solutions for those that need it most. Smart Water will contribute to delivering global solutions that address the greatest water challenges.

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