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Review

Sweating the assets – The role of instrumentation, control and automation in urban water systems

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ABSTRACT

Instrumentation, control and automation (ICA) are currently applied throughout the urban water system at water treatment plants, in water distribution networks, in sewer networks, and at wastewater treatment plants. However, researchers and practitioners specialising in respective urban water sub-systems do not frequently interact, and in most cases to date the application of ICA has been achieved in silo. Here, we review start-of-the-art ICA throughout these sub-systems, and discuss the benefits achieved in terms of performance improvement, cost reduction, and more importantly, the enhanced capacity of the existing infrastructure to cope with increased service demand caused by population growth and continued urbanisation. We emphasise the importance of integrated control within each of the sub-systems, and also across the entire urban water system. System-wide ICA will have increasing importance with the growing complexity of the urban water environment in cities of the future.

Contents

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1. Introduction

1.1. Urban water grand challenges

Population growth, urbanisation and climate change are causing major impacts around the world. These megatrends present fundamental challenges to the water sector. Significant changes in water quantity and quality are occurring around the world (WMO, 2018; Lall et al., 2018; IPCC, 2018; Kunkel et al., 2018), and more changes are predicted for decades to come.

OECD (2012) predicted that, without any new policies, water demand globally will increase by 55% over the years 2012–2050. The main increases in water requirement will be in emerging economies and developing countries. The rise in demand for manufacturing, electricity production and domestic use are predicted to increase by 400%, 140% and 130%, respectively. The demand for water for irrigation is also expected to increase substantially. FAO (2018) projects that feeding a world population of 9 billion people in 2050 would require raising overall food production by some 60% over the years 2018–2050. Production in developing countries would need to almost double. In the face of these competing needs, water scarcity already affects more than 40% people in the world, a proportion predicted to reach around 65% by 2050 FAO (2018). Consequently, there will be increasing competition for freshwater in the near future. There is an urgent need for more water sources, and for improved efficiency of water use. It also must be acknowledged that around 80% of population growth will take place in urban areas, which will create a Herculean challenge for urban water management.

In addition to population growth and urbanisation, urban water services also face the challenges caused by climate change, including temperature rise, changed precipitation patterns and extreme weather conditions. Current water infrastructure is typically designed based on historical climate and environmental conditions. How to operate such infrastructure in the wake of ongoing climate change is a critical question requiring complex answers. Similarly, how new infrastructure should be designed and operated requires a new way of thinking. The new design and operational strategies must account for changing climate conditions in order to reduce future risks to urban water management.

Typically, to overcome a lack of water supply we look for water sources which are often less accessible, e.g. remotely sourced or from deep groundwater, with substantially increased costs and environmental impact. It is becoming clear that future cities must apply integrated solutions, and manage the whole urban water cycle. Future water services will require the integrated use of multiple water sources such as surface waters, recycled water, stormwater and seawater. There is also a trend towards a hybrid structure involving water production and wastewater treatment at both centralised and decentralised scales (Jones and Olsson, 2017). Fit-for-purpose water production will also become more important, as different water uses do not necessarily require the same water quality. These strategies add another level of complexity to the already complex urban water system.

1.2. ICA in urban water systems

An urban water system consists of several sub-systems, including catchments for water collection and storage, water treatment plants, water distribution systems, domestic and industrial water consumption, wastewater collection and treatment systems, stormwater collection and retention/treatment systems, and receiving waters. The recycling of wastewater and harvesting of stormwater at multiple scales are recent augmentations to urban water systems.

Instrumentation, control and automation (ICA) is currently widespread in water and wastewater treatment plants. ICA attracted the attention of the water and wastewater industry in the early 1970s because many operators recognised that while treatment plants were designed for average loads, the true load varies significantly over time (Olsson et al., 1973; Olsson, 2012). Therefore, to date the primary function of ICA has been to keep treatment systems running efficiently, achieving the desired performance at an affordable cost, in the presence of large fluctuations in loading (Olsson et al., 2005).

In recent years, there has been a greater emphasis on the use of ICA to improve the capacity of existing systems to cope with increased loading caused by population increase and urban growth. In this case, the use of ICA defers the need for infrastructure upgrade, which typically requires substantial capital investment. Such opportunities are available because conventional planning for increased drinking water demand and wastewater services involved designing the treatment plants to handle a sufficiently large volume. As a result, existing infrastructure has additional capacity to cope with higher average loads, provided that there are proper methods to deal with the peak loads. In this context, ICA can help attenuate the load, temporarily shift the operational targets, and temporarily or even permanently reduce the load.

Notably, most of the control systems used today focus on individual units in a sub-system, at most, covering several process units in a sub-system. Integrated control of multiple sub-systems is still rare, with the exception of combined sewer overflow control for the benefit of receiving water quality (Benedetti et al., 2013). Widening the perspective from individual processes to sub-systems and then to the entire urban system is necessary considering the increasing complexity of urban water systems. Rodriguez-Roda et al. (2002) contributed to this school of thought over a decade ago. This transition requires systems thinking, where the multitude of couplings between processes and individual controllers are considered (Beck, 2005). All systems and components in the urban water cycle - from the water source to the receiving water - are parts of a whole system.

ICA is considered an enabling technology for integrated urban water management. The rapid development of sensors, instruments, and communication systems enables real-time data collection from a wide range of process units across the entire urban water system, while more powerful computers and advanced data analytics support system-level optimisation, achieving global rather than local optimum (Olsson, 2012). However, system-wide ICA is still in the early stages of development.

In this paper, we review the current state of ICA application in various components of the urban water system, with a particular focus on the roles of ICA in increasing the capacity of existing infrastructure to cope with future needs, i.e. in sweating the assets. We also identify and discuss new opportunities for ICA, including IoT (Internet of Things), in the context of integrated urban water management.

2. Control architecture and methodology, and hierarchy in an urban water system

Control systems consist of four key components: the process, the measurement, the decision-making, and the implementation. Fig. 1 presents a conceptual view of a simple feedback- and a simple feedforward control system.

Feedback control (Fig. 1 upper) is a powerful concept. It can stabilise unstable systems and improve the reliability of poorly performing components. The controller senses the operative state of a system, compares it against a desired response, computes corrective actions (sometimes based on a model of the system's response to external inputs), and actuates the system to effect the desired change. This basic *feedback loop* of sensing, computation, and actuation is the central concept in control, and this conceptual view is applicable to any processes.

Alternatively, *feedforward* compensation (Fig. 1 lower) is where we measure the disturbances, and take anticipatory actions to compensate or cancel out the effects of the disturbance. An example of feedforward control is measuring a concentration or a flow rate deviation upstream of a wastewater treatment plant, and then correcting the plant operation to eliminate the consequence of the deviation. However, models are needed to determine how much compensation is required.

Feedforward control is normally used for a fast anticipatory response, while feedback control takes care of model inaccuracies in the compensation as well as unmeasured disturbances.

In an urban water system, the aforementioned basic control concepts can be applied at multiple levels, namely:

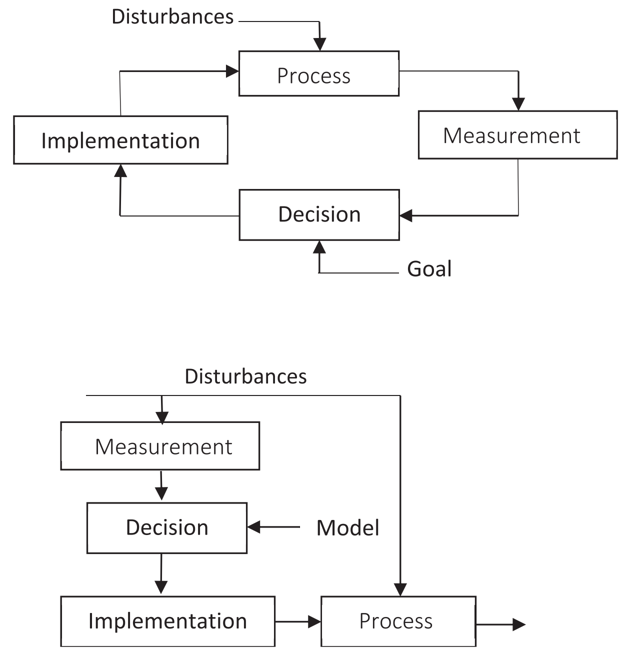

Fig. 1. The concept of feedback (upper) and feedforward (lower) control.

- *Equipment level*: This involves controlling the actuators, including pumps, compressors, valves, and motors. Control at this level is not unique for water operations, and is applied in all process industries. However, at this level the operation is limited in many water systems. Often the designer does diligent work in static design but leaves too little flexibility to manipulate the system to handle significant disturbances. Kukudis (1973) stated at the first ICA conference arranged by IAWPRC (predecessor of IWA), "Even if we had the most sophisticated, automated plant in existence, it still would not be able to operate at maximum efficiency, because the designs of wastewater treatment plants are based on uniform combined sewer flow without consideration for periodic intensity due to storm flow or periodic lows during dry weather spells or hours of least demand. So, much of the time the flow into the plant is either above or below the maximum efficiency level."
- *Unit process level*: Once the basic operations are functioning, attention can be paid to the various unit processes. Usually controllers at this level are relatively simple, i.e. based on one sensor, and influencing one actuator. The primary focus is to satisfy effluent quality requirements. Once regulatory constraints are satisfied, operations can be optimised with respect to resource utilisation, such as energy and chemicals.
- *Sub-system level*: In order to better utilise resources, it is necessary to apply sub-system-wide perspective. There are sequential couplings between various process units within a sub-system. This means that actions taken at a process unit will often affect downstream units. In the case of a wastewater treatment plant, recirculation also occurs between process units, e.g. between secondary settlers and bioreactors, which further complicates unit-level control. Therefore, it is necessary to apply a plant wide perspective, and to implement integrated control of multiple process units to achieve plant-wide optimisation.
- *Entire urban water system level*: The goal to operate the complete water cycle as one system under one organisation is not new (Beck, 1976). One good example for integrated control of

multiple sub-systems is the connectivity of a sewer system and a wastewater treatment plant (WWTP), with water quality in the receiving water body as the control objective. In such a case, the influent flow to the WWTP is no longer an uncontrollable disturbance but an internal variable of the combined system. Measurements and control in the sewer will obviously have a profound impact on the operation of the WWTP. The final test of the accomplishment of integrated sewer and WWTP control is the receiving water quality. Feedback from measurements of the receiving water quality should guide operation of the upstream sub-systems. A natural consequence of integration is that each sub-system cannot be optimised individually. Instead, there must be compromises in the operation of each sub-system in order to achieve the best for the whole system (Schütze et al., 1999; Olsson and Newell, 1999, Ch. 20). This is not an easy task and involves a lot of non-technical issues related to governance and individual operator responsibility: "Why should I run my unit process at a sub-optimal level in order to help the other parts of the system? I do not want to be blamed for low performance!"

The principles of feedback and feedforward control are applicable all the way up to high-level strategic decisions. The framework is always the same, whereas the measurements, the analyses, and the decisions are different. Hence, it is vital to understand this way of thinking in order for utilities to become smarter, more robust, resilient, efficient, effective and most importantly, more sustainable (Ingildsen and Olsson, 2016).

To maximise the capacity of urban water systems it will be important to systematically address challenges and opportunities of control, such as:

- Translating the general goal of protecting the urban and natural environment into operational goals of urban water system control;
- Meeting the need for information with sensors. Sensors will provide a huge amount of online information about operations, from real-time basic equipment function to sophisticated water quality analysis on a slower timescale;
- Utilising the rich spectrum of analytical methods and computing tools to analyse raw data for interpretation into reliable and useful information that can form the basis for decisions;
- Developing sufficient control authority. Control methods can handle all possible operational challenges that appear in water supply and wastewater treatment systems. Can the controllability be increased by installing more actuators?
- Developing flexible actuator hardware that translates decisions into real actions in the urban water system; and
- Building an information management system with connectivity to sensors, control computers, actuators, and people.

It is important to acknowledge the role of people in the control systems outlined previously, particularly at upper levels, forming human-in-the-loop (HITL) control systems. In this case, the machine system serves to collect and transmit data, provide early warning and analyse the data to provide information to operators/managers, who make the operational/management decisions to be implemented through the control system. The feedback and feedforward principles are still the underpinning methodology. With the rapid development of machine learning and artificial intelligence, humans may eventually be replaced by machines in this complex decision-making process. This will be further discussed in Section 6. In any case, systems thinking is the key to integrated urban water management (Beck, 2005).

The tasks described are a challenge for control and systems engineers, and due to the truly cross-disciplinary nature, will also influence urban planners, architects, civil, electrical, chemical and mechanical engineers as well as non-technical specialists in human and social systems. It should be noted that "water" has been recognised as a crucial topic for electrical engineers (by IEEE, the Institute of Electrical and Electronics Engineers) and for mechanical engineers (by ASME, The American Society of Mechanical Engineers). Water is certainly a topic not only for water professionals. However, we water professionals must reach out and try to understand what we can expect from other specialists in order to solve the water system challenges.

3. ICA in water supply systems

Water supply systems are large and complex, requiring significant economic investment for construction, maintenance and operation. Therefore, in the last few decades many researchers have focused on the optimisation of these systems, including minimising energy requirements, early detection and localization of leaks, and meeting customer demand at minimum cost. The optimisation of Water Distribution Systems (WDS) have become even more important recently, as increasing water demand and dwindling available sources due to climate change cause additional stress on WDS. It is imperative to find the best solutions able to meet service requirements with the minimum economic and environmental impact.

The following sections highlight the benefits and possibilities in application of ICA to manage water supply systems, in particular, for water treatment processes, for the design and operation of WDS, for the detection of leaks, and for customer water demand management.

3.1. ICA in drinking-water treatment plants

In recent decades, most drinking-water treatment plants (DWTPs) have been automated for consistent operation. The use of automated operation increases objectivity and alleviates the problem of variable and contradictory heuristics between operating personnel (Olsson et al., 2003). However, for the first automation projects, the goal was to operate the DWTPs in the same manner as human operators. Therefore, the configurations consisted of a heuristic control strategy based on historical, operator experience.

There is currently a shift in the operation of DWTPs from experience-based to knowledge-based, driven by the actual state of the plant. The use of feedforward and feedback control in various units in DWTPs enhances the water quality as well as reduces the operational costs.

For example, van Schagen et al. (2010) developed a design method for the control of DWTPs, which focuses on disturbance identification, and using control to take known disturbances into account. Using this design method, chemical usage was reduced by 15% in the softening treatment step, thereby also reducing the maintenance effort. The previously existing control was deduced from steady-state calculations, but when taking into account dynamic disturbances such as changing water temperature, the steady-state optimum was not achieved. The new design method focuses on disturbance rejection keeping the process condition close to optimum.

Coagulation followed by separation is one of the most important treatment processes for drinking water treatment. Worldwide, several million tons of metal salts (Al– or Fe–based coagulants) are used annually for water and wastewater treatment, costing multiple billions of US dollars pa (Ratnaweera and Fettig, 2015). The online control of coagulant dosing in water treatment has been extensively studied, as reviewed in Dentel (1991), Ratnaweera (2014), and Ratnaweera and Fettig (2015). Feedforward control with chemical dosing rate determined based on the measurements of feedwater flow rate, and feed water quality (e.g. turbidity, pH, conductivity and temperature) in some cases, is the most commonly used approach. This is typically done by establishing an empirical relationship between the dosing rate and the flowrate and feedwater quality parameters based on operational or experimental data. The relationship is subsequently used to calculate the dosing rates on-line, based on real-time measurements of water quantity and quality parameters. The feedforward controllers are in some cases augmented by feedback loops with controlled variables being water quality parameters of the coagulant-dosed water or finished water (e.g. streaming current, pH, turbidity, and size, shape and strength of flocs formed after coagulation). Full-scale demonstration of a feedforward + feedback algorithm delivered better water qualities compared with the feedforward-only controller, although chemical consumption was not reduced (Liu and Ratnaweera, 2016). It was showed, however, savings in chemical consumption of 3.7–15.5% could have been achieved if the control objective was only to avoid over-dosage rather than to also simultaneously improve water quality.

Coagulant dosing control in ultrafiltration (UF), which is often used prior to reverse osmosis for solids and organic matter removal, has also been studied recently, with the aim of reducing the UF membrane fouling. Gao et al. (2017) presented a dosing controller that relied on real-time tracking of cycle-to-cycle UF resistance after each backwashing (the so-called PB resistance). The controller increased or decreased the coagulant dose depending on improvements in the cycle-to-cycle change in UF PB resistance. The controller was implemented and field demonstrated on a pilot seawater desalination plant (18,000 GPD), and shown to achieve lower PB resistance with reduced chemical dosing.

Chew et al. (2018) developed controllers to automatically adjust the filtration and backwashing time of a dead-end UF to enhance its efficiency. An artificial neural network (ANN) predictive model was used to estimate specific cake resistance using transmembrane pressure and turbidity data. The model prediction was subsequently utilized by two ANN controllers to control filtration and backwash durations. The water loss due to backwash was significantly reduced compared with a case with constant filtration and backwash durations, due to increased filtration time.

In addition to achieving improved water quality and reduced operational costs, ICA has been used to level the production demand for DWTPs. In a survey conducted in the Netherlands in 2011, involving all ten Dutch water supply companies, it was found that 57% of the total production flow was controlled by model predictive flow control. The other 43% of production flow was controlled by level-based flow control (Table 1). To compare the performance of level-based- with model-based production control, Bakker et al. (2013) switched off model-based production control at five treatment plants for one week, and compared plant performance with- and without model-based control. In the level-based control loop, the production flow set-point was directly related to the level in the reservoir. The production flow set-point increases/decreases with the water level in the reservoir (Fig. 2). A model predictive flow control algorithm consists of a short-term water demand forecasting algorithm and a control algorithm. For the production flow control, the forecasting horizon is typically 24–48 h (Bakker et al., 2003). The control algorithm calculates the production flow set-point that matches the forecasted demand, on the condition that the level in the reservoir stays between a chosen upper and lower limit. With this method, the water production was stabilised at approximately 2,000 m^3/day throughout the day (Fig. 2), as opposed to varying between ~1,000 and ~4000 m^3/day without the forecasting facility. This implies that with advanced model predictive control to attenuate the variation, the treatment plant has the capacity to meet a much higher average water demand caused by, for example, population growth.

In addition to production capacity increase, Bakker et al. (2013) also showed that the model predictive control led to better water quality and higher energy efficiency:

- Production variation was 3–8 times lower,
- Turbidity values were 12–28% lower,
- Particle volume values were 12–42% lower,
- Overall energy consumption was 1.0–5.3% lower,
- Overall energy costs were 1.7–7.4% lower.

The increased use of soft sensors in water treatment is worth highlighting. Soft sensors are computer models that calculate estimates of variables that are difficult to measure directly. The estimates are based on other variables that can be more easily and/or more frequently measured. van Schagen et al. (2008), Rietveld et al. (2010), Wuister et al. (2012) and Worm et al. (2013) showed that quality improvements can be achieved by monitoring treatment processes using soft sensors. For example, the direct measurement of water quality for process optimisation is difficult. Changes in water quality often test the accuracy of the measurement device. However, water quality can be estimated using physical parameters, such as pressure, flow and valve position, simple chemical parameters, such as redox and conductivity, and accurate models.

The mathematical models that can be used vary from white-box models to grey-box models. If white-box models are available, the modelling effort for application in a new treatment plant is minimal. The white-box model can then be used to determine measurement accuracy directly, without model calibration. Applying

Table 1
Application of model predictive control (MPC) for production flow control in 2011 at water supply companies in the Netherlands, based on interviews conducted in summer 2012 (Bakker et al., 2013).

Company	Total production [million m^3 pa]	MPC controlled production [million m^3 pa]	Fraction
Brabant Water	167	27	16%
Dunea	69	69	100%
Evides	176	176	100%
Oasen	46	43	93%
PWN	100	95	95%
Vitens	329	68	21%
Waternet	65	65	100%
WBG	42	20	48%
WMD	28	0	0%
WML	72	62	86%
Total	1,094	625	57%

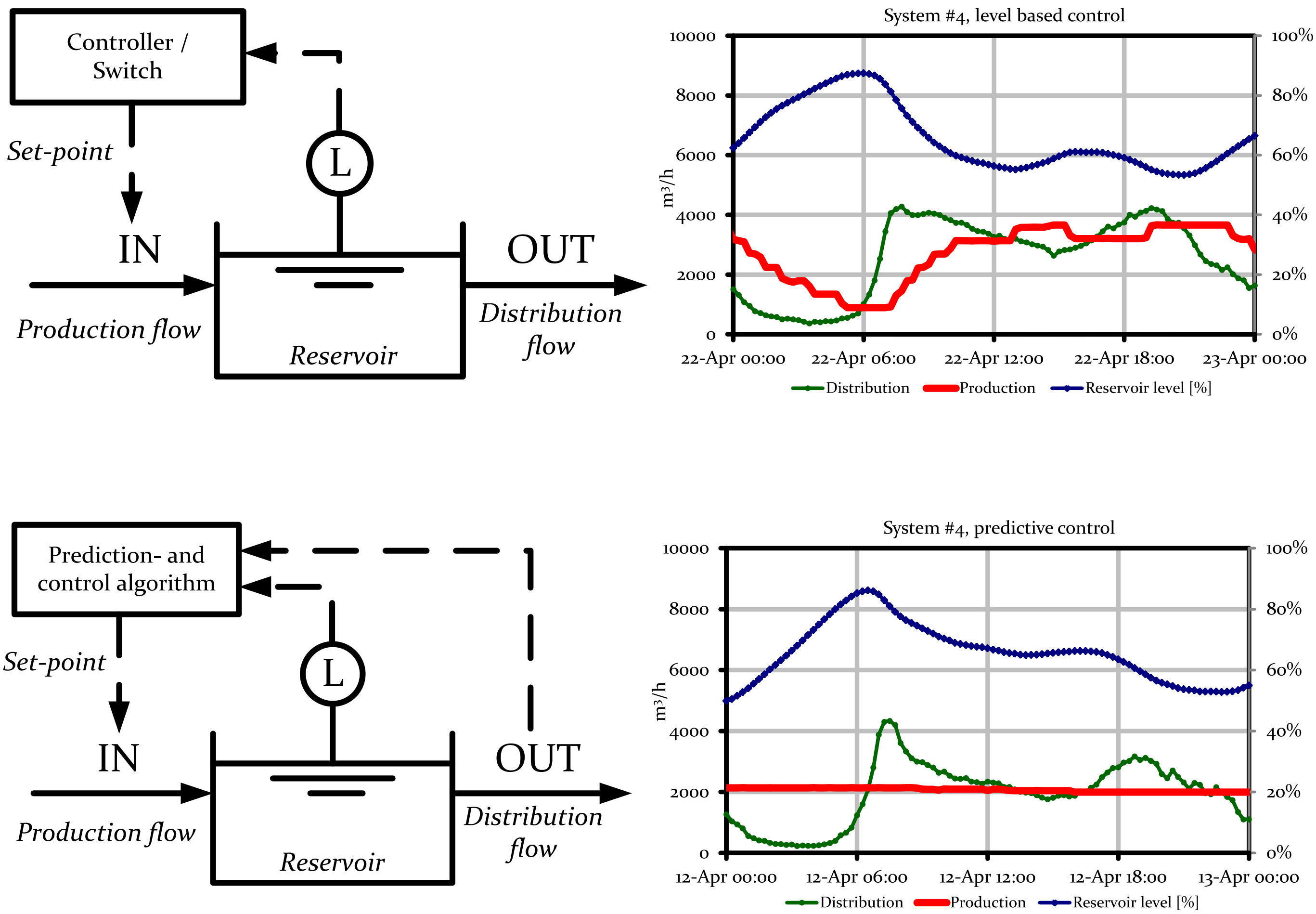

Fig. 2. Upper: Principles of level-based flow control, and trends of production flow, distribution flow, and level in the drinking water reservoir on a typical day. Lower: Principles of model predictive flow control, and trends of production flow, distribution flow, and level in the drinking water reservoir on a typical day (Bakker et al., 2013).

grey-box models makes it possible to acquire more information from the plant data, even without knowing the exact processes that are taking place. Moreover, less modelling effort is required, in comparison to back-box modelling, before the model can be applied to real process data. However, black-box models are partly data-driven, and application is more plant-specific than using a white-box model.

3.2. Water distribution system optimisation

Water distribution systems (WDS) comprise a set of pipes, pumps, valves and tanks arranged together to deliver water of suitable quality from the water source (or sources) to the final users. WDS are designed to guarantee a satisfactory level of service for a set of normal and abnormal operating conditions.

A typical operational challenge is the optimisation of pump operations, which consists of finding a set of controls that minimises pumping costs, while also meeting the system requirements. The pump optimisation problem has been well studied in the literature using different formulations. These include, for example, minimisation of cost (López-Ibáñez et al., 2008), minimisation of cost and number of pump switches (Savić et al., 1997), and minimisation of cost and greenhouse gas emissions (Stokes et al., 2015). Various optimisation algorithms have been used, including linear programming (Jowitt and Germanopoulos, 1992), non-linear programming (Rastogi, 1989), dynamic programming (Zessler and Shamir, 1989), Genetic Algorithm (Savić et al., 1997), and Ant Colony Optimization algorithm (López-Ibáñez et al., 2008).

The optimisation of WDS operation can potentially result in large savings. The Electric Power Research Institute (EPRI, 2002) estimated that electricity costs for treatment and distribution are approximately 80% of the cost of municipal water processing and distribution. This energy accounts for about 4% of the U.S power generation. In California, 19% of the state's electricity is used to satisfy the energy requirements of water-related uses (California Energy Commission, 2005). It should be noted, however, the majority of this energy is used by the customer for heating water, and statistics from various countries show that more than 90% of water-related energy use is in the home (DOE, 2001; Reffold et al., 2008; Kenway et al., 2011; Olsson, 2015).

Despite extensive research on water-related energy consumption and costs, the application of energy- and cost-saving measures is still limited because often only a 24-h operational period is optimised. Given the variability in water demand, applying the optimal pump regime developed for a specific period may result in failures or in sub-optimal operation for other demand conditions. To overcome these issues, research is moving towards near-real-time control of pump operations, where ICA is fundamental. Salomons et al. (2007) were the first in outlining the 3-step process: 1) a tool e.g. an Artificial Neural Network, to predict the daily demands is required, 2) the WDS hydraulic model with the forecasted demands is optimised, and 3) the optimal pump regime is implemented. Measurement of the system characteristics, e.g. pressures and tank levels, are used to verify the predicted network behaviour, and to initialise the next period of the optimisation. Supervisory Control and Data Acquisition (SCADA) facilities are required for monitoring the network, sending the data to the control centre, and remotely implementing the optimal pump regime.

Using recorded data, Salomons et al. (2007) estimated an annual saving of 25% in energy costs for the Haifa-A case study in Israel. Using the same methodology, Martinez et al. (2007) showed that costs could be reduced by 18% for WDS operation in Valencia (Spain). Cost-savings within a similar range were also predicted for a medium-sized water transmission system in Seoul (South Korea) (Jung et al., 2015). In order to save computational time and efficiently determine the optimal pump regime, Odan et al. (2014) replaced the WDS hydraulic model with a meta-model based on an artificial neural network algorithm. Savings of approximately 16% were predicted in applying this methodology to a WDS in Brazil.

Implementation of optimised real-time control of pump operations was described by Ganidi and Holden (2014). After a first phase in which the optimisation model was tested off-line, a semi-automated version was incorporated into the operational routine. The telemetry data were uploaded automatically, and the pump schedule was generated in an automated way, however, implementation of the pump schedule remained a manual process. During this second phase, 97.1% of all pump schedules were successful, while 1.7% needed to be optimised again. The remaining 1.2% failures were related to IT and telemetry issues. The conservative estimate of the savings carried out during the off-line phase of the project was a 3.4% reduction in costs, which corresponded to 217,000 £/year and 787 MWh/year, equivalent to a reduction of 428 ton$CO_{2\text{-eq}}$/year in greenhouse gas emissions.

Ganidi and Holden (2014) demonstrated that real-time control could be successfully applied to full-scale WDS. However, for the correct operation of the system, the authors highlighted the importance of the quality and quantity of the measurements, and that a shorter scheduling period (3 h instead of 12 h) decreased the failure rate. Thus, to improve the reliability of ICA, practical applications require faster optimisation algorithms.

Other aspects of WDS can also benefit from ICA. At a basic level, instrumentation can be used to quantify parameters such as pressure and flow, which can help monitor the system. While off-line data (data that is collected and analysed at a later time) is still beneficial for WDS management, analysing real-time data can shorten the detection times of anomalies (such as water leakages, component malfunctioning and water thefts), and reduce water and energy wastage, and associated costs (Stoianov et al., 2007; Armon et al., 2011; Mounce et al., 2010).

Measurements, and therefore instrumentation, are necessary to calibrate a WDS hydraulic model (e.g. Salomons et al., 2007; Broad et al., 2010; Gibbs et al., 2010), which can then be used to simulate the consequences of changes in the layout or operation of the network components. The only full-scale example known to the authors where measurements from WDS sensors are automatically used to calibrate the hydraulic model is the Wireless Water Sentinel in Singapore (Allen et al., 2011). This system allows modifications to the network to be automatically incorporated into the model so that engineers can assess the performance of the WDS in real time. Ideally, this could also be used to automatically modify the normal operation of the system in order to improve the service to the users. Well-calibrated hydraulic models and good data are important in the expansion of existing WDS, where the design of the new part should take into account the existing parts in order to minimise the whole of life costs.

The minimisation of capital and operational costs has been investigated previously (e.g. Farmani et al., 2006; Wu et al., 2010a), but it is less commonly reported for complex case studies. SA EEA (South Australian Engineering Excellence Awards, 2010) brought to light an application of ICA to deliver water from a desalination plant to the metropolitan area of Adelaide (South Australia). In this case, the contribution of ICA to the WDS design was limited to model calibration. However, depending on the characteristics of the network, it may have been possible to avoid the capital cost of system augmentation by controlling valves and pumps in real time. This option, although interesting, is difficult to explore because of the uncertainty of water demand, the numerous requirements associated with WDS, and the uniqueness of each case.

3.3. Leakage detection in water distribution systems

Leak management in WDS is a significant problem worldwide. Water utilities lose a considerable amount of treated water due to leaks, particularly in ageing water infrastructure. For example, the Energy and Water Department of the World Bank estimated that the total global annual cost of leakage to utility companies was approximately US$14 billion, comprising 48 billion m^3 of wasted, treated water, with a third of this occurring in developing nations (Kingdom et al., 2006). In Western Australia it is estimated that 30 billion litres (8.4% of all water supplied) was lost to pipeline leakage in 2012–13 (OAG, 2014). Australia's National Performance Report on Urban Water Utilities for 2012–13 reports median real losses of 79 L/c/d (litres/connection/day) with outliers as high as 416 L/c/d for some utilities (NWC, 2014). In the United States, an estimated 7,000 km of pipe requires replacement each year at a cost of US$2.7 billion, while water losses (estimated to be 10%) are valued at US$4.3 billion per year (Whittle et al., 2013).

The challenge of leak mitigation requires a water entity to predict the size and location of leaks in a WDS given measurements such as flows at certain locations, pipe materials and age, or acoustic measurements. Leak quantification is one part of the broader task of managing water losses in distribution networks by assessing, detecting and controlling losses (Puust et al., 2010). The main challenge of leak detection is to obtain reliable evidence on the size and location of leaks at a reasonable cost for equipment and effort. Leak detection methods fall into three categories, based on the data source: 1) data obtained outside the distribution network, 2) data from sensors brought into the network at certain times, and 3) data from a permanent network of sensors. Methods for the first two categories are well-established (Fanner, 2007; Farley and Trow, 2005; Farley, 2010; Puust et al., 2010; Mutikanga et al., 2013). The third category is a novel approach for water distribution systems, made possible by new sensor technologies at lower cost and improved telemetry (Shiddiqi et al., 2018). Decisions on the approach of choice for leakage reduction are ultimately cost-driven, although informed by governance regulations (NWC, 2014; Fanner, 2007). Water utilities need to establish strategies that balance the cost of water with the cost of leak reduction for their own, unique circumstances.

Several low cost approaches exist for leak management. Managing water pressure throughout the network is a commonly used proactive method. Because leakage volume is positively related to network pressure, maintaining network pressure as low as possible while still satisfying customer demand is a cost effective strategy for leak reduction (Puust et al., 2010; Fanner, 2007). Another low cost strategy is purely reactive, i.e. water utilities respond to- and repair leaks when they are reported by the public or staff (Fanner, 2007). Minimising the response time for repairing these reported leaks reduces water losses. Condition-based maintenance methods use historical data to find correlations between pipe failure rates and factors such as pipe material, climate and soil parameters. This information can be used to prioritise pipe replacements before leaks occur (Pratt, 2011).

Step-testing is a top-down method used since the 1980s for leak detection. It subdivides a network by closing valves during minimum night flow to create district metered areas (DMAs). Flow meters are then used to measure the water balance within a district, and this indicates the size of leaks in a locality (Farley, 2010). To pinpoint the position of the leak, acoustic logging, ultrasonic sensing, ground motion sensors or ground penetrating radar can be used (Puust et al., 2010). Leak noise correlation uses two microphones in contact with a pipe or valve stem on either side of the leak. It can detect a leak position to within 1 m, and is most effective for clean, small diameter, metal pipes in high water pressure areas (Puust et al., 2010), but not suitable for plastic pipes.

A network of permanent sensors can be used to monitor pipeline distribution systems continuously in order to detect anomalies such as leaks (Shiddiqi et al., 2018). Recent developments of new types of sensors with lower costs and better telemetry are making this approach more reliable and cost effective. Examples of new sensor technologies include ultrasonic and electromagnetic flow meters, and flow meters that can be inserted directly into a pipe (Farley, 2010).

Sensor network leak detection uses a combination of sensed field measurements from the network, hydraulic models, and machine learning algorithms. Leak detection can be posed as an inverse problem: system characteristics such as flows in pipes, pipe length, network topology and pipe diameters are known, while leak size and location are unknown (Pudar and Liggett, 1992). Solving a system of non-linear hydraulic modelling equations for the unknowns enables leak predictions to be made. Sensor networks provide current flow information for predicting leaks. In an early study, De Silva et al. (2011) used a machine learning algorithm to train a support vector machine as the classifier for leak size and location, based on pressure measurements in the network. However, they reported low accuracy for their classifier. The EPANET hydraulic model has been combined with a rule-learning algorithm to generate human-readable prediction rules for quantifying leaks (Cardell-Oliver et al., 2015). Leak signatures can be used to optimise the placement of a limited number of sensors (Shiddiqi et al., 2017). These methods allow for measurement uncertainty and can optimise the number and placement of flow sensors, allowing trade-offs to be made between prediction accuracy and network cost. Wu et al. (2010b) used a genetic algorithm to determine the hydraulic model that gives the best explanation of leak position and size to account for known pressure and flow values in a pipeline network. Possible areas of water loss were narrowed down under low flow rate conditions, but the model could not identify the size of leaks or their precise location.

Only a few studies have reported industry trials of leak detection methods. The WaterWiSe project in Singapore has tested real-time monitoring of a WDS using a wireless sensor network and a suite of decision-making algorithms (Whittle et al., 2013). With a focus on minimising cost, the system can detect and locate burst leaks, and monitor hydraulic parameters. Burst detection is performed using transient pressure signals triangulated from relative time-difference-of-arrival measurements from network sensors. The Intelligent Water Network of Victoria (Australia) reported practical field trials of several sensor technologies. The trials showed that flow sensors and acoustic sensors are more effective than pressure sensors for identifying small leaks (Teo, 2012).

Leak detection using permanent sensor networks is a promising approach, but there are many open research problems. Research is needed to address the multi-objective problem of trade-offs between leak detection accuracy and the type and placement of sensors. Emphasis should be placed on establishing design principles for new infrastructure to facilitate leak detection, as is now common for DMAs (Farley, 2010). Practical demonstrations of novel, sensing technologies and techniques, as reported by Teo (2012) and Whittle et al. (2013), are needed in order for industry to adopt new leak detection methods.

3.4. Smart metering for customer water demand management

Water conservation targets, such as a 15% demand reduction by 2030 (Water Corporation of Western Australia, 2009), are common in the water industry. Achieving these targets requires a detailed understanding of the patterns of water use that affect demand. Smart metering is a key emerging technology for discovering usage patterns that are needed for customer demand management. Data for this task is provided by smart meters that record end-user consumption automatically each hour (or more often) and report it daily. Data mining methods are then applied for analysis of this data. Data mining can be used to answer four types of questions: 1) Explore, e.g. What patterns of water use occur for a given population?, 2) Explain, e.g. How is water used during summer months? When does highest water use occur?, 3) Predict, e.g. Based on past history, how much water will a certain individual use next week, at what times?, and 4) Plan, e.g. How do current trends in water use inform future infrastructure planning? Several commonly used computer-based methods that can transform data into useful information are reviewed in Corominas et al. (2018).

Customer demand has been studied using different types of water meter data: low-, medium- or high-resolution. Low-resolution data reports annual, quarterly or monthly water consumption, medium-resolution has a period of one or more hours, and high-resolution has a period of seconds or minutes. Low-resolution data has been used to correlate consumption with possible influencing factors including dwelling characteristics, socio-demographic attributes, attitudes and beliefs, and policy levers (Corral-Verdugo et al., 2002; Grafton et al., 2011; Fox et al., 2009; Syme et al., 2004; Jorgensen et al., 2009).

Medium-resolution data for large populations has only recently become widely available as water utilities deploy smart meters on a large scale (Cardell-Oliver, 2013; Cardell-Oliver et al., 2016). There are only a few studies of pattern discovery in medium-resolution data. Britton et al. (2008) use smart meter data to identify customer-side leaks, and to inform a customer intervention program. More generally, water-use signature patterns have been proposed to characterise leaks, ad hoc- and periodic usage patterns, and their significance for individuals and for large populations (Cardell-Oliver, 2013).

High-resolution data can be used to train a recognition system to identify human activities such as flushing a toilet, taking a shower, or running the dishwasher (Willis et al., 2013; Beal et al., 2011). Each of these activities is associated with a continuous subsequence of high-resolution meter readings. Human experts label examples of these activities as they occur in a training set of smart meter readings for each user. Machine learning algorithms are then used to create an automatic software program that recognizes the same classes of activities in unlabelled meter data. This training process is labour intensive, and so current techniques are not suitable for analysing large populations (Nguyen et al., 2013). Another drawback is that only activities that have been identified by the trainer are recognised; ‘unknown unknowns’ in the data remain hidden. For example, relatively rare activities such as garden-watering, can play a significant role in overall water use, but are challenging to recognize as activity sequences, particularly when activities overlap one another.

The business case for smart metering can be difficult to quantify, especially in the short term, since the current cost of smart meters is relatively high compared with the price of water and achievable demand reductions. Apart from these costs, recent industry studies have shown that effective customer engagement is critical for realising the benefits of smart metering (Atkinson and Medbury, 2013; Devitt, 2014). A significant economic benefit of reducing consumption can be the delay of capital infrastructure upgrades. Delays are beneficial because the cost of capital (interest, redemption and depreciation) is typically a high contributor to water utility business costs. For example, one study estimated that a reduction of 10% in peak daily demand in the dry season could extend the life of a current treatment plant by 4 years (Devitt, 2014). Other benefits of smart metering include lower occupational health and safety costs related to automated versus manual collection of data, and increased metering accuracy. Another important factor is to integrate smart metering insights into existing operations workflows to build trust and confidence for the end-users (Patabendige et al., 2018).

Automated pattern discovery in water-use offers many opportunities for improving customer demand management. Research is needed on approaches that support more nuanced, evidence-based decision-making for water conservation. For example, for large populations, automatic methods are needed that combine data from water meters with contextual information such as climate data and customer demographics. Pattern discovery at the population level is also an area that promises significant efficiency gains. For example, segmentation of users with inefficient consumption habits can be used to prioritize customer engagement campaigns. Smart metering is a key technology for achieving these goals.

4. ICA in wastewater systems

For many decades, ICA has been applied to wastewater systems consisting of sewer networks and WWTPs. Initially, control was limited to hydraulic processes, but since the latter part of the last century, control has been extended to biological and chemical treatment processes. Most of the conventional control systems are unit-process oriented with the aim to enhance treatment performance leading to improved effluent quality, and reduced energy and chemical consumption. However, there has been an increasing trend in recent years to design control systems that consider multiple units in the plant to achieve plant-wide control, and in some cases to control the entire wastewater system comprising sewers and treatment plants. The use of ICA for improving the capacity of wastewater systems to handle increased loading has also attracted considerable attention in the past decade.

The use of ICA for the operation and management of wastewater systems will increase in coming years due to ‘push and pull’ forces. ‘Pull’ forces include continued population growth and urbanisation leading to increased wastewater load, a continued increase in the complexity of wastewater treatment plant function and capability (e.g. WWTPs are now often called resource recovery facilities, WRF), and extreme weather conditions associated with climate change. Several technology ‘push’ forces will make ICA increasingly economical to implement. With concomitant computational and instrumentation improvements there is an interesting trend towards smart sensors with multiple detectors and transmission abilities, which can be placed anywhere in the process train. Actuators, mostly variable speed drives for pumps and compressors, make control much more flexible. Control theory and practice today can offer almost anything that the water operator would need.

4.1. ICA in wastewater treatment plants

The control of unit processes in a WWTP is relatively mature. Some examples of state-of-the-art unit-process control include:

- Dissolved oxygen (DO) control with a constant or a variable set-point as part of the aerator unit process operation. Variation in the DO set-point is typically guided by nitrogen removal performance monitored with nutrient sensors;
- Aeration phase-length control in alternating plants based on nutrients, DO, pH, or Oxidation-Reduction Potential (ORP) measurements;
- Nitrate recirculation control in a pre-denitrification plant based on nitrate and DO measurements in the aerobic and anoxic zones;
- External carbon dosage control based on nitrate measurement in the anoxic zone;
- SRT (solids retention time) control based on sludge inventory using turbidity data;
- Return activated sludge flow control based on (proportional to) the influent flow rate;
- Step feed control based on influent flow to limit sludge overloading of secondary clarifiers;
- Control of anaerobic processes aimed at stabilizing the process and maximizing the biogas production; and
- Chemical precipitation control based on local measurements of phosphate concentration.

It has been demonstrated that ICA can increase the capacity of biological nutrient removal plants by 10–30%. With further understanding and exploitation of the relationship between operational parameters and the microbial population dynamics and biochemical reactions, combined with increased maturity of advanced online sensors, the improvements offered by ICA will likely be greater than 30% within the next 10–20 years. Comprehensive reviews of these control systems can be found in Olsson et al. (2005, 2014) and Olsson (2008, 2012). A review of literature comparing different control structures for aeration is found in Åmand et al. (2013), and several lessons from full-scale implementations of aeration control are documented in Åmand et al. (2014). Ammonia-based control can lead to energy savings through limiting aeration, as well as reducing effluent ammonia peaks (Rieger et al., 2014).

Over the years, the function of a wastewater treatment plant has evolved from COD (Chemical Oxygen Demand) removal only, to COD and nutrients (nitrogen and phosphorus) removal, and further to resource (water, energy and nutrients) recovery. Consequently, the complexity of a wastewater treatment plant has increased substantially, with strong interactions among different process units. Such interactions represent both challenges and opportunities for ICA:

- Interaction between different parts of the treatment plant can cause unintentional disturbances. For example, a sudden release of nitrogen-rich sludge supernatant from an anaerobic digester back to the influent of the wastewater treatment plant will cause an unnecessary overload of the plant if it happens during the high load periods of the day. Fig. 3 shows how the oxygen uptake rate increases significantly as the supernatant is recycled within the plant. The controlled release of such streams during low-load periods will beneficially attenuate the disturbance.
- The interaction between different parts of the treatment plant can be positively exploited through integrated control or plant-wide control, to derive additional benefits. For example, the bioenergy recovery from waste activated sludge can be

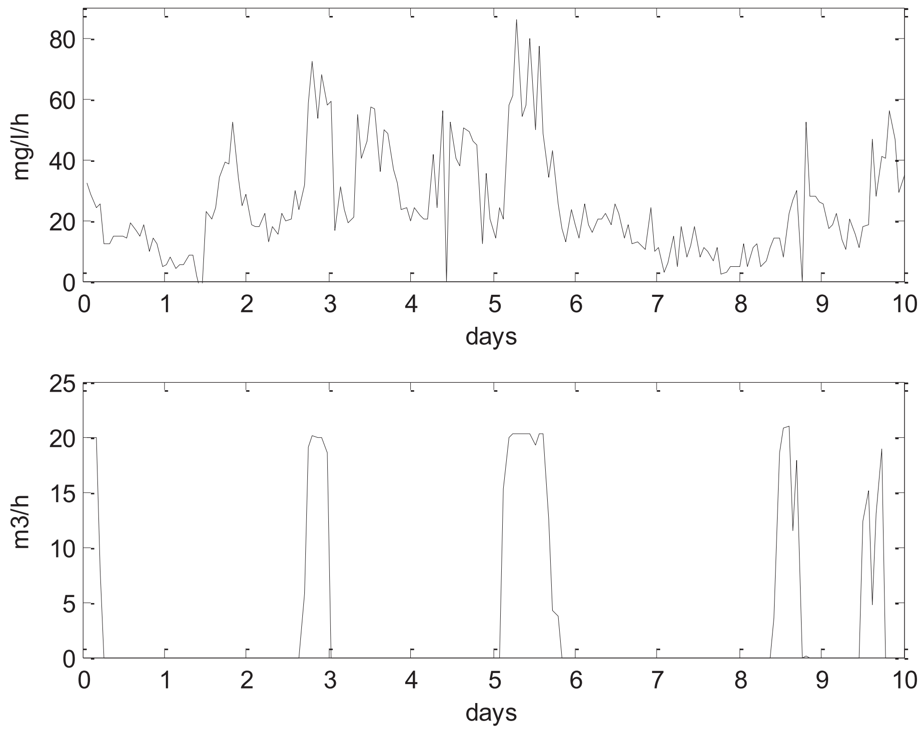

Fig. 3. The effect of supernatant recycling in a WWTP during a 10-day period. The lower graph shows the flow rate of the anaerobic sludge digestion liquor, which represents a few % of the total sewage flow but has a nitrogen content in the order of 1 g N/L. The upper graph shows the oxygen uptake rate in the aerobic reaction unit (data courtesy: M.K. Nielsen, Denmark).

enhanced by controlling the sludge age in the secondary treatment to a level just allowing full nitrification. This is because a relatively 'young' sludge is more biodegradable giving a higher yield for bioenergy recovery. This aim can be achieved through sludge retention time control (Olsson et al., 2005).

Integrated control will be a key focus of control design in the coming years. Such an approach is expected to not only deliver benefits in terms of treatment efficiency and costs, but also enhance the ability of a plant to cope with increased loading, thus deferring plant upgrades. One good example is the well-known aeration tank settling technology (Nielsen et al., 2000). During a storm event, the flow to a WWTP is expected to increase by several fold. This is the case even for separate sanitary sewers. The hydraulic capacity of a WWTP is typically limited by its secondary settler, as the solids loading to the settler during a high flow period can exceed its capacity. Nielsen et al. (2000) proposed to switch off aeration and mixing in the last part of the aerobic reactor, which feeds into the settler, a few hours prior to the arrival of the stormwater. The activated sludge settles in the reactor, reducing the solids loading to the settler and the amount of solids to be buffered in the settler. This significantly increases the hydraulic capacity of the plant, which is highly desirable for plants operated in an era of climate change and extreme weather conditions (Sharma et al., 2013).

The paradigm shift from wastewater treatment to resource recovery is also leading to the development of novel processes. In conventional WWTPs, energy contained in organic carbon is not recovered, rather, organic carbon is used to support denitrification or removed by aerobic processes that require much energy input. The A/B process, has recently been applied at full-scale with the aim to minimise aerobic oxidation of organic carbon, and to enhance bioenergy recovery. In this process, the organic carbon in wastewater is firstly absorbed or bio-assimilated by the activated sludge in the A stage. The energy-rich activated sludge is then passed on to the anaerobic digester for the production of methane as a renewable energy. As a large fraction of the organic carbon has been removed from the wastewater in the A stage, the B stage requires much less aeration (hence less energy consumption) in comparison to a conventional one-sludge system. As a result, the aeration requirement is reduced in the A/B process, and a larger fraction of organic carbon (compared to conventional activated sludge processes) is converted to biogas in an anaerobic digester. Supported by this technology, two municipal wastewater treatment plants in Austria (Strass and Wolfgangsee-Ischl treatment plants) are achieving energy self-sufficiency, and also feeding surplus electrical energy from the plant to grid (Nowak et al., 2011). However, the organic carbon used for energy production in the A/B process is no longer available for achieving a high level of nitrogen removal by conventional means. Consequently, nitrogen removal processes with a lower carbon demand such as the shortcut process (nitritation followed by denitritation) are needed. The ground-breaking discovery in the early 1990s of unique microorganisms which carry out anaerobic ammonium oxidation (Anammox), potentially provides an alternative, more attractive solution to the problem associated with the A/B process. Anammox bacteria have the unique metabolic ability to combine ammonium and nitrite to form nitrogen gas (Strous et al., 1999). Through a partnership between ammonia-oxidizing bacteria (AOB) and Anammox bacteria, completely autotrophic nitrogen removal via nitrite is possible. AOB consume a limited amount of oxygen to partially oxidise ammonia to nitrite, while Anammox bacteria convert residual ammonia and nitrite into nitrogen gas under anoxic conditions.

These novel process designs pose control challenges. Firstly, the A-stage should be operated such that a maximum amount of COD is absorbed/adsorbed/bio-assimilated, thus making more carbon available for bio-energy recovery. The manipulatable variables in an A-stage process are similar to those in a conventional activated sludge process, namely aeration, sludge wastage flow and sludge return flow (Miller et al., 2017). However, the control objectives are different. In a conventional activated sludge process, the effluent COD and TSS (total suspended solids) concentrations should be kept below their respective discharge limit. In comparison, there are no similar, strict limits for the A-stage effluent, although lower levels of COD and TSS in the A-stage effluent are desirable, when autotrophic nitrogen removal is employed in the B-stage. Another important goal is that the mineralized carbon i.e. converted to CO_2, in the A-stage should be minimised, to enable maximum bioenergy recovery. Miller et al. (2017) employed a cascade controller, with an airflow feedback loop being the slave controller, to control DO (dissolved oxygen) at pre-selected set-points. No obvious correlation between COD removal and DO was observed. In general, the impact of DO on the fate of organic carbon in the A-stage reactor is not fully understood at present, as COD removal in such a reactor involves multiple mechanisms including absorption/adsorption, bio-assimilation as cells or extracellular polymeric substances, and mineralization (Kinyua et al., 2017). DO level also affects sludge settleability and hence the effluent TSS and VSS (volatile suspended solids) levels. More research is required to fully understand these effects, before appropriate DO set-points can be identified. Miller et al. (2017) trialled two controllers for the manipulation of the waste activated sludge flow. One aimed to control SRT at a set-point by also considering sludge loss via the effluent. Different from a conventional activated sludge process, where TSS in secondary effluent can typically be neglected in SRT control, TSS in the A-stage effluent has a much higher concentration and thus a much higher impact on SRT. The SRT controller therefore required not only an MLSS (mixed liquor suspended solids) sensor in the bioreactor but also a TSS sensor to measure the effluent. This design failed as the controller was very sensitive to the accuracy of the sensors. The other controller aimed to keep the MLSS concentration in the A-stage bioreactor at a constant level, which was reported to be successful in the pilot plant study. However, the applicability of such a controller in practice is in question, as MLSS is sensitive to the influent flow and composition, which vary substantially in full-scale plants. It makes little sense to keep a constant MLSS level by increasing the wastage flow in a period when more COD is to be removed in a high-load period (possibly requiring more biomass), or vice versa. The control of returned activated sludge in an A-stage system is similar to that in a conventional system, i.e. to have it paced with influent (Miller et al., 2017), kept at a constant level, e.g. the average influent flow rate.

Even more challenging is the provision of suitable conditions in the AOB/Anammox reactor(s) such that AOB and Anammox bacteria develop in partnership while nitrite-oxidizing bacteria (NOB) are eliminated (Yuan et al., 2008). Online control of aeration is often necessary to out-select NOB through kinetic selection or through substrate competition with nitrite reducers (ordinary denitrifiers or anammox bacteria). For example, online control to maintain a constant ratio between the concentrations of DO and the total ammonia nitrogen (Bartrolí et al., 2010), or between the concentrations of NH_4^+ and $NO_2^- + NO_3^-$ (also termed AvN control, Regmi et al., 2014), was found to favour NOB out-selection. Online aeration control to suppress NOB based on pH (Lee et al., 2013; Yang et al., 2007; Gu et al., 2012) and OUR (oxygen uptake rate, Blackburne et al., 2008; Lemaire et al., 2008) has also been reported.

A further challenge that future ICA systems have to address is the mitigation of N_2O emissions from biological nitrogen removal plants. It is known that operational conditions such as DO, nitrite and inorganic carbon concentrations, pH, and biomass-specific nitrogen loading rate play critical roles (Law et al., 2012). Among these factors, DO control has been used to mitigate N_2O emissions. For example, based on simulation results (Ni et al., 2015), the South Australian Water Corporation (Australia) replaced the previously adopted 'intermittent aeration' strategy with a continuous aeration system with DO concentration controlled at ~0.5 mg O_2/L, and achieved a 30% reduction in N_2O emissions from a full-scale sequencing batch reactor (personal communication with Dr Ben van den Akker, SA Water). The integrated control of multiple operational parameters to minimise N_2O emissions in biological nitrogen removal, while deemed to be necessary, is yet to be developed and demonstrated.

4.2. Flow control in sewer systems

The primary function of a sewer system is to transport wastewater (and stormwater in the case of a combined sewer) away from the community to a wastewater treatment plant to protect both public health and the environment. Correspondingly, the two key objectives for sewer flow control are: 1) to prevent wastewater spill and flooding during its transport, and 2) to minimise the impact of wastewater on the receiving water. The latter, in particular, should involve the integrated control of sewers and WWTPs, with the quality of the receiving water as the ultimate goal (Fu et al., 2008; Dong et al., 2012).

4.2.1. Sewer flow monitoring and prediction

In contrast to a WWTP, a sewer is a distributed system. The two key requisites for sewer flow control are: sensors that can be widely deployed at key locations in the system, and accurate dynamic models that can predict flows across the network based on somewhat limited sensor data.

Sensors for online measurement of water velocities, water levels and rain intensities are available, and have been widely deployed for sewer monitoring. It should be noted that flow measurement in sewers may not be as trivial as expected, as flow rates in sewers are typically low, leading to large relative errors when a sensor has a limited accuracy. Also, the location of a flow sensor is important, since the accuracy may depend on the position of the device (Mignot et al., 2012). Sewer sensors are currently being developed with IoT (Internet of Things) capacity with built-in wireless telecommunication abilities, for known reliability, low power-consumption and low-costs. This new development will enable the acquisition of much larger volumes of data from sewer networks. This aspect will be further discussed in Section 7.2.

In addition to physical sensors, software sensors have also been developed to estimate unmeasured parameters from other sensor signals. For example, Chen et al. (2014) estimated the sewage flow rate into a pumping station based on the ON/OFF timing of a pumping station. The method made use of the fact that, at an intermittently operated pumping station, the pump is turned on when the water level in the wet well reaches a pre-defined upper water level and turned off when a pre-defined lower water level is reached. As such, the average water flow entering the pumping station between the OFF time in the previous pump cycle and the ON time of the current cycle must be equal to the known wet-well volume between the upper and lower water levels. Based on a similar principle, the authors also developed an algorithm to estimate sewage flow entering a continuously operated pumping station. In this case, the algorithm requires continuous monitoring of the water level in the wet well (Chen et al., 2014).

In a slightly more complicated case, Ahm et al. (2016) calculated the volume of Combined Sewer Overflow (CSO) by estimating flow rates based on level measurements. The data-driven software sensor was developed by correlating the physical water levels and discharges. The authors achieved good accuracy when the estimates were compared with electromagnetic flow measurements.

Another software sensor concept was based on computational fluid dynamics (CFD) simulations of the physical layout of the CSO structures. This software sensor is an independent estimation and does not need any calibration to discharge measurements.

The real-time simulation of flows in a network requires prediction of the flows entering the network, based on real-time monitoring. Chen et al. (2014) developed a methodology for predicting future flows, a few hours ahead, using an ARMA (Auto Regressive Moving Average) model and multi-step iterative prediction. This methodology was validated with flow data collected from two pumping stations with different flow characteristics and different wet-well storage capacities. The proposed methodology was shown to be capable of predicting future flow rates with good accuracy under both dry and wet weather conditions. Li et al. (2019) extended the ARMA model into an ARMAX (Auto Regressive Moving Average with eXternal input) model with real-time rainfall data as an external input. The ARMAX model was shown to substantially reduce the prediction delays associated with the previously developed ARMA model (Li et al. (2019).).

For a given network, the flow profiles across the network can theoretically be predicted in real-time (Harremoës and Rauch, 1999), once all the external flows entering the network are known (measured and/or predicted). Indeed, dynamic models have increasingly been used for simulation of the hydraulics of sewer systems. Pollution transport in the sewer is often included in such simulations, as it is highly important for estimating the pollutant load to the treatment plant, or to the receiving water when CSOs occur. However, there is often a high level of uncertainty associated with such simulations particularly for large networks, for a number of reasons including inflow and infiltration that are often unaccounted for (see 4.2.2). It is necessary to perform additional physical measurements of hydraulic parameters e.g. velocity and levels within the network in order to verify model predictions. An important question here is how many flow rate and level measurements are required to get a confident picture of the hydraulics of the sewer system; the more measurements, the higher the confidence. However, there must be a balance between cost of measurements and accuracy of the estimated parameters or state variables of the system.

4.2.2. Estimating inflow and infiltration

One of the challenges for real-time prediction of wastewater flow through a network is the uncertainties associated with inflow and infiltration (I/I), which are often un- or inadequately accounted for during the prediction.

Inflow and Infiltration of unwanted water in the sewer system is not desirable since this will lead to a substantially higher hydraulic load to a WWTP (De Bénédittis and Bertrand-Krajewski, 2005; Ellis and Bertrand-Krajewski, 2010; Beheshti et al., 2015). In Australia, for example, it has been found that sewer I/I could raise sewage flow rate in a sanitary sewer to several times that of the dry weather (Chen et al., 2014; Li et al., 2019). Obviously, any reduction in the I/I will decrease the probability for CSO or an overload of the treatment plant. There are various methods to detect, localize and quantify I/I in sewer systems. Traditional methods to estimate the I/I are based on flow rate measurements, analysis of diurnal flow and load variation, and balancing of water inputs and outputs (Ellis and Bertrand-Krajewski, 2010). Flow rate methods are typically used off-line. The tracer test is another off-line method.

One qualitative online monitoring method is based on temperature measurements. Fibre-optic Distributed Temperature Sensing (DTS) can measure temperature with high resolution and frequency. This method has been widely used in other industries, for example to detect fractures in oil pipelines (Vosse et al., 2013; Schilperoort et al., 2013). Stormwater inflow can be detected as long as the temperature of this inflow differs from the in-sewer temperatures (Langeveld et al., 2012).

Online conductivity measurements have also been used to estimate rainfall-derived I/I when overflow happens at the same time (Zhang et al., 2018b). Usually it is difficult to distinguish between the two phenomena. Variations in the flow and water quality during dry weather conditions were analysed using Fast Fourier Transform, and a model was developed for estimating the rainfall-derived I/I based on conductivity data. The method has been successfully tested for light, medium and heavy rains.

4.2.3. Sewer flow control to prevent sewer spill and flooding

Sewer spill and local flooding should be avoided to protect public health. Often the first notification of a spill comes from a member of the public, hours and sometimes days after the first spill. The challenge is to find a way to predict the spill before it happens, so that appropriate actions can be taken in a timely manner.

Sewer spill can happen when sewer lines are blocked. A common pump problem in sewer operations is clogging caused by rags, pre-moistened wipes, and other consumer goods marketed as flushable. This causes sewage backups in the collection system. Indeed, the pump clog problem is increasingly caused by the use of ‘flushable’ wipes. One solution that has been applied is installing a special impeller that helps to counterbalance hydraulic forces and create a balanced, single flow path that passes problematic ‘flushables’. An early warning approach has also been used, where the online monitored flow rate is compared with the motor current, a standard method in many pumping applications. A rise in power consumption for a certain flow is reported as an early sign for clogging.

An early warning method for spills has also been developed by Nukon (http://www.nukon.com.au/). A model was developed using data from previous spills with the goal to find out if the model could detect a spill earlier than other methods. One indicator is the time between pump runs. A pump will start running when a wet well is filled. The time-to-fill was identified for on-peak, off-peak, weekends and weekdays under normal behaviour. The model identifies blockages by detecting abnormal time-to-fill behaviour. For example, if the fill time is unexpectedly long during peak times or the pump does not run, it is an indicator of abnormality or possible blockage. The model has been tested successfully and could detect historical blockages more than 12 h before they were reported by a customer.

High sewer flows during wet weather, when exceeding the hydraulic capacity of the sewer system, also cause spill and flooding. Hydraulic predictions as outlined in Sections 4.2.1 and 4.2.2 are needed to predict flows and the likelihood of spill and flooding, and to guide operation. The prediction often consists of coupled 1D drainage network- and 2D surface models to predict inundation depths in the surrounding area.

As emphasized by Savić (2017) the prediction horizon is crucial. The model must provide enough lead time for the flood prediction so that necessary actions can be taken. Model simplifications of large networks may have to be realised so that the computations can be finished in time. Savić (2017) describes two methods: fast overland flood modelling and data-driven (machine learning) sewer surcharge modelling. The overland flood modelling is realized by a 2D cellular automata model (Ghimire et al., 2013; Guidolin et al., 2016). This approach increases the computational speed by about an order of magnitude compared to traditional methods. The other approach is using machine learning, where the model is updated using an artificial neural network (ANN) model that uses computational data from several flood calculations via traditional models, which is combined with rainfall radar forecasts (Duncan et al., 2011, 2013). The model is then compared to real events. A similar approach is described by Rjeily et al. (2017). The flood risk is calculated by estimating the water depth variation within critical manholes. The ANN parameters describe how water depth variation in manholes is related to rainfall intensities.

It is crucial to find out how far the urban drainage system can be controlled, and then know how to act if it is not controllable. For example, a gravity sewer has much less controllability than a sewer supplied with pumps, as demonstrated in Christchurch, New Zealand after the major earthquake in 2011. Several pumps have been installed in the sewer system since to make it more controllable.

Climate change is causing an increase in extreme wet weather events. Kleidorfer et al. (2018) analysed a heavy rain event in Austria. The authors emphasize that the models may be calibrated for more common events like a 10-year rain event. However, data for extreme and rare events is seldom available, which makes flood prediction models unreliable, because the relationship between rainfall intensities and flooding is nonlinear.

Some actions may have to be taken outside the drainage system to reduce the flooding risk. One approach to deal with the sewer capacity problem is to store rainwater at source, which decreases the flow into the sewer (Butler and Parkinson, 1997). This also enables rainwater harvesting and use after treatment (see Section 5). It was realized early (Kollatsch, 1993) that the exclusion of stormwater from urban wastewater would be the most important measure to obtain more efficient drainage systems.

4.2.4. Integrated control of sewer networks and wastewater treatment plants

The sequential relationship between the sewer, the WWTP and the receiving water is obvious, and the need for control of flow in the sewers for the benefit of the downstream components was recognized early. For example, sewer control was applied in the early 1970s in Cleveland, USA (Kukudis, 1973). During dry periods, flow equalisation was employed. During storm periods the system was primarily designed to capture and treat the first 20 min of flow, i.e. the first flush. Any water which was bypassed out of necessity after the first period would have been heavily diluted.

A sewer flow control strategy, integrating sewers and wastewater treatment plants, seeks to prevent or reduce the detrimental direct discharge of wastewater into receiving water due to sewer overflow. An integrated control strategy can be used to equalize flows to the treatment plants, in particular, during wet weather when wastewater flow rates varying substantially.

The two, key requisites for successful implementation of integrated control are: accurate dynamic models for both systems, and reliable sensors. Following the advent of deterministic models of integrated drainage approximately two decades ago, integrated control was investigated by several groups, mostly in Europe (Nielsen et al., 1996; Bauwens et al., 1996; Pfister et al., 1998; Rauch and Harremoës, 1996a, 1996b; 1999; Schütze et al., 1999). Nearly all investigations focused on semi-virtual cases, utilizing simulation studies. While the implementation was demonstrated through computer modelling, the infrastructure studied was real, and these theoretical studies demonstrated the potential of integrated control, paving the way for practical implementation.

The early studies extensively researched stimulations based on models and control concepts (e.g. Weinreich et al., 1997; Pleau et al., 2001; Schütze et al., 2002, Zacharof et al., 2003; Erbe and Schütze (2005), Butler and Schütze, 2005; Vanrolleghem et al., 2005; Benedetti et al., 2008), case studies (e.g. Erbe et al., 2002; Seggelke et al., 2005), and novel optimisation methods (e.g. Brdys et al., 2008; Muschalla, 2008). An overview of these developments can be found in Schütze et al. (2004), Rauch et al. (2005), Olsson and Jeppsson (2006), Beeneken et al. (2013), and García et al. (2015). Among these, Olsson and Jeppsson (2006) emphasised the role of plant wide control and considering the inflow.

While various control structures and algorithms have been presented, it is difficult to compare the benefits of these methods, since the systems and the operating conditions are not identical. A similar dilemma was expressed in the early 1990s concerning wastewater treatment control. This led to the development of a benchmark system called the Benchmark Simulation Model (BSM) that has been extremely successful in testing and comparing control strategies for wastewater treatment systems (Gernaey et al., 2014). Based on a similar philosophy, a benchmark scheme for urban drainage systems ('Astlingen') has now been developed by working group, 'Integral Real Time Control' of the German Water Association (DWA) (Schütze et al., 2018).

Following development of the models, researchers together with operators developed the necessary technologies and experience for reliable online monitoring of sewer systems, which complemented the more established monitoring of the treatment plants. Online sensor development together with data quality control proved to be a significant step forward for implementation (Bertrand-Krajewski et al., 2003; Gruber et al., 2005; Rieger and Vanrolleghem, 2008; Métadier and Bertrand-Krajewski, 2012; Schilperoort et al., 2012; Vezzaro et al., 2013). Recent developments include the use of distributed sensing via fibre optics (Hoes et al., 2009), novel concepts for extracting information from sensors (Dürrenmatt et al., 2013), and the implementation of low-power consumption wireless telecommunication. In particular, the latter has potential for major innovation as it allows for spatially refined high-density information.

Integrated control is now being achieved in full-scale application, e.g. Eindhoven in The Netherlands (Weijers et al., 2012), Copenhagen in Denmark (Grum et al., 2011), Quebec, Canada (Fradet et al., 2011), and Wilhelmshaven in Germany (Seggelke et al., 2013), although the number of successful implementations is still limited (Benedetti et al., 2013).

A key barrier for wider implementation of integrated control is the fragmented urban water management framework. Sewers and wastewater treatment plants are typically managed by different departments or entities, which have different aims, procedures and cultures. Thus, the goals of sewer operation versus those of wastewater treatment are often contradictory. A major benefit of integrated control is mitigation of sewer overflows particularly during wet weather. While the prevention of sewer overflow brings direct environmental benefits, it causes hydraulic stress to the treatment plant, which may affect treatment performance. In contrast, while sewers can be used to equalise hydraulic load to the treatment plant, thus improving treatment performance and potentially reducing aeration costs (Aymerich et al., 2015), such an operation does not necessarily improve the sewer performance. In both cases, the benefit is only apparent when sewers and treatment plants together are seen as an integrated wastewater system with a unified goal, but unfortunately, this is uncommon because cross-discipline collaboration is not established easily. Another barrier to implementation is the absence of a standard solution. A 'one size fits all' approach is not feasible as each case is different, and requires a tailored approach to design due to the inherent complexity and need for reliability. Capacity building is also another challenge as training of operators in how to manage the integrated system is critical.

4.3. Chemical dosing control in sewers for corrosion and odour management

Sewer systems are critical infrastructure for modern urban societies. Today's underground sewer infrastructure is the result of enormous investment over the last 100 + years. In the USA, sewers represent an estimated asset value of one trillion (10^{12}) dollars equating to approximately 7% of the current gross domestic product (Brongers et al., 2002). However, globally, sewer infrastructure is under serious threat due to deterioration, with an estimated annual asset loss of around $14 billion in the USA alone (Brongers et al., 2002.).

Sulfide-induced concrete sewer corrosion costs billions of dollars annually and has been identified as a main cause of sewer deterioration (US Environmental Protection Agency, 1991). Under the anaerobic conditions typical in sewage, sulfate-reducing bacteria convert sulfate (SO_4^{2-}) in sewage to hydrogen sulfide (H_2S). Due to its low solubility in the wastewater, hydrogen sulfide is emitted from sewage into the air-space of gravity sewer sections, sewage pumping stations, and inlet structures of wastewater treatment plants. On concrete surfaces exposed to air, gaseous sulfide is oxidised forming highly-corrosive sulfuric acid. Water utilities around the world have focused on the removal of sulfide after its formation, incurring mitigation costs comparable to the value of asset losses.

There are currently several methods to control this sulfide-induced problem, with chemical dosing being the most widely used. According to a recent survey conducted among the major water utilities in Australia (Ganigué et al., 2011), the commonly used chemicals for sulfide control in sewers include oxygen and nitrate which both oxidise sulfide, iron salts to precipitate sulfide, and magnesium hydroxide to elevate pH thereby decreasing hydrogen sulfide transfer from the liquid to the gas phase.

The way chemical dosing is conducted has not only a major influence on the effectiveness of the chemical on sulfide control, but also significant implications for operational cost. Controlling chemical dosing in rising main sewers (Ganigué et al., 2011) is very challenging due to the plug-flow behaviour of a sewer system. According to the same industry survey (Ganigué et al., 2011), flow-paced or profiled dosing strategies are used at the majority of dosing sites. These strategies, which are commonly based on empirical guidelines developed through experience (de Haas et al., 2008), can lead to over- or under-dosage as sewers have a distinct dynamic behaviour, with large variations in sewage flow and characteristics occurring throughout the day, week and year. Additionally, rainwater inflow and infiltration may dilute sewage, and decrease its hydraulic retention time within the pipe, dramatically reducing the amount of chemical required for suitable sulfide control.

Online control of chemical dosing of magnesium hydroxide to a rising main was studied recently by Ganigué et al. (2016) (Fig. 4). The controller consisted of three components; the first being a local feedback controller, which raises the sewage pH to the set-point, before it is pumped into the rising main pipe. The second component was a feedforward controller, which adds additional magnesium hydroxide to the sewage while it enters the pipe to neutralise the predicted acid production in sewage while it is being transported through the pipe. The third component was a feedback controller that makes further adjustment to the dosing rate based on the long-term average pH at the end of the pipe. In a two-month field study at a pumping station with a total average dry weather flow of 12 ML/d followed by a rising main with a total length of 5.29 km and a pipe diameter of 600 mm, the chemical consumption was reduced by 15%. At the same time, the pH variation at the end of the pipe was also reduced substantially. A similar method was applied to iron salts-dosing for sulfide control through precipitation (Ganigué et al., 2018). The controller was applied to a 10 km sewer main with diameters varying between 603 and 750 mm, and an average dry weather flow of 21 ML/d. The control system achieved 25% savings in chemical consumption, combined with better sulfide control performance (Ganigué et al., 2018.).

To support the design of the aforementioned controllers, Chen et al. (2014) developed a methodology for real-time future flow prediction in sewers based on ARMA models and multi-step iterative prediction. The validation of the model and a later developed ARMAX model, with real-time rainfall data as an external input, using real sewer data have been described in Section 4.2.1. Online control of chemical dosing with real-time sewer flow prediction using these models was tested through simulation studies (Chen et al., 2014; Li et al., 2019), and yielded improved control performance and reduced costs.

Liu et al. (2013) extended the control design from a single pipe to a more complex system. By controlling the dosing and pump operations via hybrid automata control strategy, sulfide control was achieved across a network.

5. Control of stormwater systems

Flooding and environmental degradation due to polluted urban discharges are managed using a variety of structural and non-structural stormwater management options. In the 20th century,

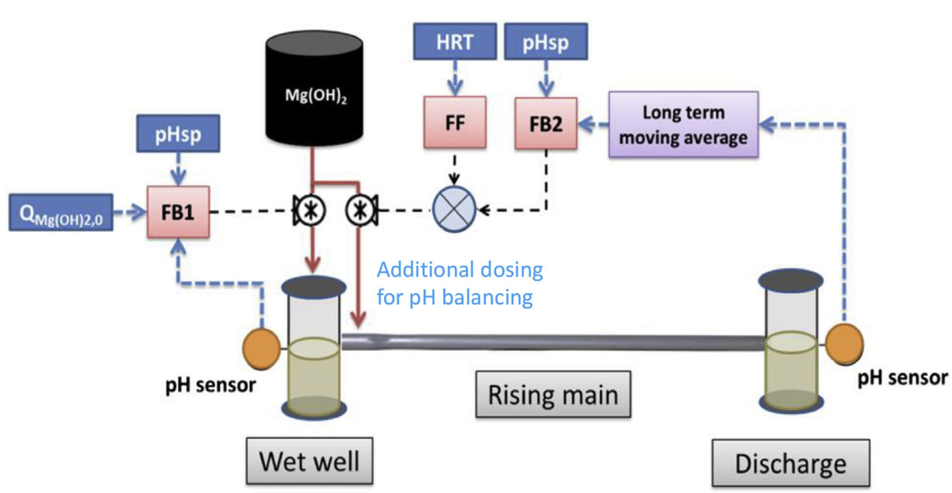

Fig. 4. An $Mg(OH)_2$ online dosing control scheme for sulfide control in sewers, involving both feedforward (FF) and feedback (FB) loops (adapted from Ganigué et al., 2016). pH_{sp} is the pH set-point, $Q_{Mg(OH)2,0}$ is the nominal $Mg(OH)_2$ dosing flow.

large stormwater drainage gutter/pipe/channel systems were introduced, alongside wet- and more often dry detention- and retention basins to manage pluvial flooding. Stormwater quality management is more recent (started in late 1980s), and is applied through Water Sensitive Urban Design systems, such as wetlands, ponds, swales and biofilters (also known as bioretention systems or rain gardens) (Wong et al., 2013). Over the past 10–15 years, rainwater and stormwater harvesting was introduced at an unprecedented scale in some regions that experienced prolonged droughts (Grant et al., 2012). For example, rainwater tanks are used at large scale in Australia for irrigation of urban gardens and toilet flushing (Ferguson et al., 2013). Over the past 50 years the complexity of stormwater management increased enormously because stormwater is regarded and managed as both a nuisance and a valuable water source.

Some stormwater structural measures can serve more than one purpose. Rainwater harvesting (RWH) systems, such as rainwater harvesting tanks (RWHT), are good examples of multifunctional systems; they can provide an alternate source of water while serving as detention/retention for roof runoff that would otherwise be discharged into the stormwater network leading to potential flooding and pollution. However, to achieve these often-competing multiple objectives, the RWH systems have to be controlled, often in real time. Control of RWH systems is a recent innovation, with only a few being demonstrated in practice. Control of RWHT can be via: 1) a passive system that slowly releases accumulated water between two rain events, and therefore ‘prepares’ the tank to detain runoff from the next event, or 2) an active system that uses real-time control to purge accumulated rainwater before a large storm event. The benefits of passive RWHT have been demonstrated by several desktop studies (e.g. Herrmann and Schmida, 1999; Melville-Shreeve et al., 2014; Bishop et al., 2013; Burns et al., 2012). Only a few passively controlled tanks have been installed and monitored in Australia (e.g. Burns et al., 2012), and in the USA (e.g. DeBusk et al., 2012).

It can be speculated that the efficiency of stormwater infrastructure could be much improved if active controls are included in the traditionally passive systems. A good example of an active RWHT system, installed in New Bern, North Carolina, USA, is presented in DeBusk et al. (2012). The system captures runoff from 290 m^2 of rooftop into five plastic tanks of 12,300 L in total. Water is extracted from the tanks using a pump for garden irrigation. The system is equipped with an RTC device (OptiRTC by Geosyntec https://www.optirtc.com) that automatically releases stored water based on real-time forecasted precipitation and current conditions within the RWH system. Using forecasted precipitation from the National Weather Service of the USA, the device triggers the RWH system to slowly release a given amount of water to ensure that the rainfall can be captured. Water is released before the critical storm events only if there is insufficient storage capacity within the tank to accommodate the forecasted precipitation. The maximum amount of water released by the system is equivalent to the volume of water associated with a 1-year, 1-h storm event, to meet the state water quality target. This system has been monitored but so far no data have been published in open literature. Another example of RTC rainwater tanks has been installed by South East Water in Melbourne, Australia. This ‘Talk Tank’, releases water based on forecast data, using a mobile phone app to manage i.e. monitor and purge, water volume in the tank.

Only in the past few years, have RTC systems been considered for management of stormwater discharge quality. A good example is an active stormwater tank installed as a part of drainage system in Quebec City in Canada, where the stormwater detention time is actively controlled to manage both the available storage volume for flood protection, and whenever possible, quality of realeased water (Muschalla et al., 2014; Gaborit et al., 2013). Recent laboratory-based work has also shown that efficiency of typical raingardens for stormwater treatment could be highly improved if an RTC system is included; the quality of treated water using an actively managed raingarden could improve to the point to enable safe stormwater harvesting for some non-potable uses (Shen, submitted).

In conclusion, the application of ICA technology in stormwater systems is in its infancy, although modelling studies are showing that there is great potential.

6. Why is ICA adoption progressing slowly in urban water management?

Load variations in a wastewater treatment system are considerable compared to most other process industries. The influent must be accepted and treated, regardless, and there is no returning it to the supplier. Water supply operations resemble electricity delivery, where the customer demand cannot be controlled under normal circumstances. The production at all times must adapt to the need. These are just some of the features of urban water systems calling for the use of ICA. However, the adoption of ICA in urban water management is far behind other process industries.

There are a number of reasons for the slow progress in application of ICA in urban water systems, not only technical, but also economic, regulatory and social.

6.1. Economic reasons

Profit motives: Urban water utilities are not as sensitive to capital and operational costs as other industries. Water utilities or private operators rightfully place serious focus on compliance. They are willing to employ safer but more expensive design and operational strategies to operate the systems comfortably within the boundaries rather than its more aggressive counterpart by taking up online control to operate the systems closer to the boundaries. While these companies are under pressure to cut costs for their services, customers have so far been willing to pay for the services.

‘Product’ price: The low ‘product’ price of water has certainly been playing a critical role in slow uptake of ICA. The price per m^3 of oil is 100–200 times higher than that of drinking water. Not surprisingly, a lot of methods and instruments have been developed for leakage detection and localization in oil pipelines (Swift et al., 2011; Vosse et al., 2013; Schilperoort et al., 2013). It is quite pleasing to observe that the value of water (both economic and social) is being increasingly recognised, which has led to the development and application of more advanced leakage detection and localisation methods in recent years (Section 3.3).

6.2. Technical reasons

Some technical aspects of water operations give control a lower priority.

Process dynamics: Most process units in urban water systems are inherently stable. This means that online control is not required for ensuring process stability. For example, except for anaerobic sludge digesters, virtually all units in an activated sludge wastewater treatment system can work stably without process control. Anaerobic sludge digesters will also operate stably if operated well below critical organic loading rates. However, it is increasingly recognised that connecting unit processes through recirculation creates internal disturbances, often causing operational problems. With increasing system complexity associated with these interactions, the human ability to predict and handle all the consequences of disturbances is becoming a limiting factor.

The 'one-end' control objective of product quality: Unlike most other process industries where products are required to have a well-defined composition, water and wastewater treatment plants are typically required to produce effluents with contaminant concentrations to be maintained below certain levels specified in regulations. Such one-end type of specifications can be met without process control, through conservative design and operational strategies such as over-aeration or over-dosing of chemicals, with concomitant costs. As discussed, the urban water sector is not overly sensitive to costs, and consequently, high effluent quality safety margins are often prioritised over operational costs. Take nitrogen and phosphorus removal as an example; the economic goal would mean that the total effluent nitrogen/phosphorus should be controlled *as close as possible* to the discharge limits (with reduced aeration and chemical costs) instead of keeping the concentration significantly *below* the limits. The former goal cannot be achieved without online control, but the latter can be through over-design and conservative operation. Unfortunately, a conservative attitude which outweighs the focus on costs prevents the use of advanced control, even when the economic benefits are demonstrated (Ingildsen, 2002, Ch. 11).

Online instrumentation: The reliability of advanced online sensors such as nutrient sensors for monitoring wastewater treatment systems is a current limitation to ICA application. Simpler sensors such as DO, pH, flow and level sensors have long been proven to be reliable and robust with required level of accuracy, and they can be used with minimum maintenance. Therefore, such sensors have been widely used in the control of urban water systems. In comparison, more complicated water quality sensors such as ammonium, nitrate, nitrite and phosphate sensors, which are critical for controlling biological nutrient removal and recovery processes, are far less reliable, and require more frequent maintenance. This has resulted in an inadequate level of confidence in these sensors, which has prevented wider application of the well-developed control algorithms required by these sensors.

Insufficient flexibility in design: The coupling of design and operation, in a control-integrated design, is seldom seen. Instead, ICA is often implemented as a complementary step in existing plants to improve efficiency or reduce costs. Inflexible design limits control potential and opportunities. For example, on/off instead of variable speed pumps or compressors are often used, and valves are often designed, for most favorable pressure drop rather than for control.

6.3. Regulatory reasons

The common practice, at least in European countries, is that laboratory measurements are the golden standard. Increasingly, plant managers favour online sensors, but face opposition from regulatory agencies which only accept results from manual sampling combined with laboratory analysis. The fact that both laboratory analysis and online sensors are prone to errors is often discussed but has not led to meaningful changes in practice. One key factor is the need for better information and education. There is a wide competence range among plant operation, and online sensors may be used for measurements outside the recommended range. This kind of misuse is often used as an argument against using sensors for operational oversight and compliance, with good reason. In an ongoing culture change, sensor manufacturers are improving their product information, and plant operators are being better educated and trained.

6.4. The human factor

The 'human factor' involved in successful operation is often neglected, though it can pose a greater challenge than the technology (Olsson and Newell, 1998). Incentives and motivations of the involved stakeholders — the public, federal agencies, provincial agencies, local political leadership, plant managers, operator-in-chief and operators — their interests, incentives, and pressures must be taken into account (Rieger and Olsson, 2012). For example, DO- and ammonia control is implemented in many activated sludge plants. However, quite often the operator changes the setpoints to increase the safety margins for effluent quality. The operator does not want to be blamed for not meeting the quality criteria but is seldom praised for saving electrical energy or chemicals. The following summarises some critical elements of the 'human factor':

Job protection: Automation of certain unit processes in wastewater treatment plants together with remote supervision has been applied since the early 1990s. Automation can lower personnel costs (Lumley et al., 1993), however, union resistance at many places has slowed progress towards automated operation.

Education: The need for education and training in design and operation was recognised early; John Andrews (1930–2011) noted in 1974 (Buhr et al., 1974), "A course in Process Dynamics and Control is commonly found in most chemical engineering curricula. We would be well advised to include a course in Dynamics and Control of Wastewater Treatment Systems in environmental engineering curricula." Still today, the need for training in dynamics, modelling and control is insufficient (Hug et al., 2009). Beck (2005) expresses a similar view, "All the major branches of engineering, except civil engineering (the traditional disciplinary host of environmental engineering), have integral elements of instruction and research addressing the operational performance of their products, i.e., process control." Recently, a truly significant contribution to better design has been the development of dynamic simulators, which assist designers to mimic possible plant behaviour under various load conditions (Ogurek et al., 2015).

Designer incentives: Treatment plant designers often have incentives to over-design the system. Designing high-capacity systems expands the safety margins, and ensures that regulatory requirements are met. In many cases there is a government subsidy for the investment (capital expenditure) in the system but not for operation, giving another reason for high-capacity design. Load variations create less impact in over-designed plants, thus decreasing the demand for control to attenuate disturbances.

7. Perspectives

7.1. Integrated control of urban water systems

Integrated control of sewer networks and wastewater treatment plants was discussed in Section 4.2.4. To date, efforts have been mainly limited to the control of hydraulics with the goal of protecting the receiving water quality. However, integrated control certainly has the potential to go beyond basic performance improvements during wet weather discharges. For example, Rebosura et al. (2018) showed that iron-dosing to sewers not only controls dissolved sulfide in sewage, thus reducing sewer corrosion and odour, but also removes dissolved phosphate in aerobic bioreactors, where FeS in sewage is oxidised regenerating iron ions for phosphate precipitation. In this case, the iron-dosing rate in sewers should be controlled not only for sulfide removal in sewers (Ganigué et al., 2018), but also for phosphate removal in the downstream wastewater treatment plant. Many other opportunities will be identified in the future. In particular, following recent advances in wastewater management progressing from pollutant removal to resource recovery, sewer systems could be used to provide tailored pre-treatment prior to arriving at a treatment plant for resource recovery. These integrated approaches could be site- and case specific.

Integrated control of urban water systems should also expand to include the water supply systems (water treatment and distribution network). The interconnections between water supply and wastewater systems are clearly recognisable as it is the same water that flows through both systems. Residual substances in drinking water can affect wastewater composition, as well as the chemical and biochemical reactions in sewers and WWTPs. For example, Pikaar et al. (2014) highlighted the major impact of sulfate in drinking water on sewer corrosion and odour, and called for the use of non-sulfate-containing coagulants in drinking water treatment. The study suggested that if a sulfate-containing coagulant is used, e.g. alum, its dosing rate should be controlled not only to reduce the operational costs for drinking water treatment but also to reduce impact on sewer corrosion. Chloride-containing coagulants, e.g. ferric chloride, are an alternative to sulfate-containing coagulants. However, while not having an effect on sewer corrosion, the presence of chloride in drinking water may cause corrosion of water supply pipes. Indeed, the cause of the Flint water crisis (Flint, Michigan, USA) was lead leaching from aging pipes due to a high-concentration of chloride (Hanna-Attisha et al., 2016). It was found that the chloride-to-sulfate ratio is a critical parameter affecting drinking water pipe corrosion (Nguyen et al., 2010; Edwards and Simoni, 2007). The role of ICA in ensuring this ratio is maintained within a safe range should be explored in the future.

Sun et al. (2015) identified a new possible connection between a drinking water treatment plant and sewers. Where a ferric-based coagulant is used for water treatment, the ferric-containing drinking water sludge can be discharged to sewer networks. Laboratory experiments showed that sulfide control in sewers could be achieved through re-use of iron in the drinking water sludge. Given the dynamics of sulfide production in sewers (Sharma et al., 2008, 2012), the online control of sludge-dosing would be essential for adequate sulfide control.

Future water services will be provided through the integration of multiple sources, such as catchment water, reuse water, stormwater, groundwater and seawater, at multiple scales through both centralised and decentralised services. Considerable opportunities will arise for the use of ICA to optimise overall water supply and system operation. One such opportunity is the optimised scheduling of alternative water source use, leading to attenuated peak demand for centralised systems. This could potentially defer the upgrading of both water production and distribution systems, and water treatment plants.

The use of decentralised wastewater treatment- and reuse systems is increasing in the urban water environment. One of the challenges faced is that small treatment plants are subject to extreme fluctuations in both inflow rates and wastewater composition. The flow rates can be intermittent, and wastewater composition can vary within minutes. Yet, these plants must consistently produce effluent of a quality which complies with environmental regulations. Without professional engineers or operators on site, ICA can play an important role in ensuring stable operation and consistent performance (Olsson et al., 2005; Olsson, 2013; Wilderer and Schreff, 2000). Another particular challenge for ICA application to a small, decentralised treatment plant is that monitoring has to be achieved through relatively simple, low-cost instruments such as flow, pH, level and pressure meters. This is because advanced, expensive sensors are not economically justifiable given the small scale. However, early warning systems are critically important for such systems, and telemetry is needed for remote monitoring and supervisory control.

The use of decentralised systems will also have a major impact on existing wastewater services, particularly on the sewer networks that collect and transport wastewater to centralised wastewater treatment facilities. The increased use of decentralised wastewater treatment and reuse systems will change both the flow and composition of wastewater discharged to sewer networks. In many cases, sludge produced by decentralised treatment systems will need to be disposed to existing sewer networks due to the lack of cost-effective, on-site sludge treatment and disposal opportunities. These changes in practice have significant implications for in-sewer sedimentation (potentially causing sewer blockage), and to the management of corrosion, odour and greenhouse gas emissions in sewer networks. To alleviate issues with sludge sedimentation in sewers, the potential role for ICA is to automatically control sludge discharge from decentralised systems in periods with high sewer flows. Increased aeration occurs in high-flow periods, and as such, the oxygen demand of the biologically-active wasted activated sludge discharged from decentralised wastewater treatment systems can be more easily met in-sewer, decreasing the likelihood of anaerobic conditions developing.

With the availability of stormwater harvesting, another opportunity for ICA application is the controlled use of stormwater for sewer flushing. Reduced wastewater flows and increased solids concentration in wastewater due to water conservation measures lead to increased solids sedimentation in sewer networks. At some locations, drinking water is being introduced into sewer networks to increase sewer flow, completely defeating the purpose of water conservation and water reuse. Here, stormwater is an attractive alternative to using drinking water. The timing and duration of sewer flushing will depend not only on what is required to erode the sediments but also the stormwater availability. While in-pipe sewer-flushing installations are common, the use of ICA to monitor and release stored stormwater for sewer flushing is uncommon but has great potential (e.g. Pisano et al., 2003).

Integrated urban water management could reach beyond water. The nexus of water and energy has been clearly identified (Olsson, 2015). Energy use in the urban water cycle should be analysed and considered from a total systems point of view. As such, ICA is expected to have a significant role in integrated urban water management, but opportunities are yet to be fully identified and explored. Future research is required to thoroughly and systematically address the challenges and exploit ICA opportunities (Olsson, 2013). The aforementioned examples show that opportunities for ICA application will be case specific, and that multiple benefits be achieved in an era of integrated urban water management.

7.2. Application of Internet of Things (IoT) to urban water systems

The Internet of Things (IoT), an emerging collection of technologies, is expected to have a major impact on the future of ICA in urban water systems. A search of “Internet of Things” on Web of Science (search topic, 11 July 2018), revealed that 249 IoT articles were published in 2010, and this increased to 7,104 articles in 2017, out of a total of 23,295 publications. This indicates IoT has developed very rapidly in the last decade and is creating value through widespread applications.

The definition of IoT is still evolving but it is commonly accepted that IoT comprises the connection of physical things to the internet enabling data exchange, based on low-cost sensors and low-power consuming wireless telecommunication. These features distinguish IoT sensors from traditional sensors and telemetry used for urban water systems, and enables their deployment to a much wider range of locations and at much higher densities. Consequently, the use of IoT sensors allows the collection of much larger volumes of data, possibly orders of magnitude larger compared to traditional sensors. Such large data sets enable machine learning or data-driven modelling, to provide support to online control or off-line decision making.

A global trend in Smart Cities is the installation of sensors for surveillance of infrastructure, including urban water/wastewater systems. However, the application of IoT sensors to urban water management has been limited, relative to many other application areas. In spite of this, the value of IoT-enabled ICA (in comparison with traditional ICA) has been demonstrated in many case studies. For example, Abdelhafidh et al. (2017) used IoT sensors for pipelines (sensors, cameras and RFID tags) and water (flow, pressure, and pH) to enable real-time management of a 50-km long drinking water pipeline. Han et al. (2017) used IoT sensing data for fast detection of multiple simultaneous pipe failures by reducing the detection time by orders of magnitude, i.e. from hours/days to minutes. Smart water metering, which uses a digital electronic device that collects information on water use and sends it wirelessly to the water utility, is an example of innovative and effective IoT infrastructure for smart cities (Lloret et al., 2016). The real-time water demand data available to the utility and end-users enables an understanding of consumption habits, thereby supporting the development of strategies for improving network efficiency and contributing to water saving. IoT was also used with an artificial neural network model to understand human water use behaviour with different intervention procedures for improved and sustained hygiene practice (Fu and Wu, 2016). In addition, IoT was employed with SCADA for integrated drinking water production and distribution (Roy and Mukhopadhyay, 2016).

IoT has also found applications in urban drainage systems including wastewater and stormwater sewers. The first and most successful application is the management of combined sewer overflow (CSO). Different neural networks including the recently developed deep learning method, i.e. long short-term memory (LSTM) and gated recurrent unit (GRU) have been successfully applied to predict the CSO water levels based on real-time IoT sensors and rainfall (Zhang et al., 2018a).

Many commercial technologies have been trialled and implemented with success. The IBM Intelligent Operations Center dashboard, built upon 116 smart valve sensors, helped the city of South Bend (Indiana, USA) to reduce wet weather wastewater overflows by 23%, and almost entirely eliminated dry-weather incidents such as blocked sewers (Clancy, 2013). In Europe, Severn Trent Water deployed more than 4,000 IoT sensors over 94,000 km of sewers to monitor flow, and to prevent blockage and sewage overflow (Brakoniecki, 2017). The Metropolitan Sewer District of Greater Cincinnati (USA) developed a real-time monitoring-based 'smart sewer' that reduces overflow at a cost that is 20–40 times lower as compared with other commonly used methods, such as green stormwater controls and larger pipes (Gaskell, 2017). OneBox, a smart sewer wastewater level monitor designed and developed by iota Services (Australia), was adopted by Christchurch in the rebuild of the city after the 2011 earthquake (Dickers, 2016). Savings in capital cost was achieved through reduced peak flows and general flow management capabilities. It has been reported that many major water utilities in Australia are trialling or implementing IoT sensors for monitoring and managing wastewater levels, flow, temperature and even hydrogen sulfide (Hoey, 2017).

The current application of IoT in sewers is mostly limited to CSO or blockage reduction. However, corrosion and odour are two important aspects of sewer management providing many opportunities for the application of IoT technologies. IoT water quality monitoring in sewers could also provide wastewater data for improved operation of the downstream wastewater treatment plant (WWTP). The operation of a WWTP can be optimised using IoT and analytics too. IBM Research-Haifa undertook an IoT pilot to improve efficiency at a treatment plant in Lleida, Spain (Zadorojniy, 2016; Zadorojniy et al., 2017). The one-year trial was successful through updating process operations every 2 h, rather than adjusting on a seasonal basis. The consumption of electricity, use of chemicals for phosphorus removal, and the production of sludge dropped by 13.5%, 14% and 17%, respectively. The overall effluent quality and compliance with regulation were also improved. IoT coupled with cloud-based data analysis has proven useful for small wastewater treatment facilities in remote locations or small communities, such as the iMETland under development in Europe (Libelium, 2017).

IoT will likely become the backbone of next-generation ICA required for the success of integrated urban water management as a key attribute of Smart Cities. More IoT applications in urban water systems have become feasible because the cost and size of such devices continues to decrease, while their capability for measuring different parameters keeps increasing. Data gathered through IoT sensors can be used for many purposes through powerful big-data systems, e.g. Hadoop and Spark, two distributed systems on the market to manage large data volumes and varieties. There are many possibilities for application including, prediction of system status (flow, consumption, water level), reduction in overflows, detection of incidents, and characterisation of water end-user habits. The power of advanced artificial intelligence such as deep learning in advanced data analytics, real-time control and decision-making systems are yet to be fully realised.

8. Conclusions

Instrumentation, control and automation (ICA) are currently applied to various components of urban water systems with significant benefits reported. The primary application of ICA has focused on the control of various process units in water and wastewater treatment plants, leading to improved performance, reduced operational costs, and increased capacity of the plants. In addition, diverse applications of ICA include leakage detection and localisation in water distribution networks, and motivating consumer behavioural change through feedback mechanisms, leading to reduced water consumption.

Future research will focus on the integrated control of urban water systems. Through properly recognising the connections and interactions between various units in a treatment plant, and between sub-systems in an urban water system, ICA will play a significant role in more efficient use of existing urban water infrastructure, leading to system-wide optimisation.

ICA will enable us to better utilise existing assets and defer capital-intensive upgrades that would otherwise be necessary. IoT will contribute intrinsically to ICA applications, and shows great potential with advanced analytics to translate the big data gathered by IoT sensors into decision-making for operation, management and planning.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abdelhafidh, M., Fourati, M., Fourati, L.C., Abidi, A., 2017. In: IEEE/ACS 14th International Conference on Computer Systems and Applications. IEEE, New York, pp. 1184–1191.
Ahm, M., Thorndahl, S., Nielsen, J.E., Rasmussen, M.R., 2016. Estimation of combined sewer overflow discharge: a software sensor approach based on local water level measurements. Water Sci. Technol. 74 (11), 2683–2696.
Allen, M., Preis, A., Iqbal, M., Srirangarajan, S., Lim, H.B., Girod, L., Whittle, A.J., 2011. Real-time in-network distribution system monitoring to improve operational efficiency. Am. Water Work Assoc. AWWA 103 (7), 63–75. July 2011.
Åmand, L., Olsson, G., Carlsson, B., 2013. Aeration control – a review. Water Sci. Technol. 67 (1), 2374–2398.
Åmand, L., Laurell, C., Stark-Fujii, K., Thunberg, A., Carlsson, B., 2014. Lessons learnt from evaluating full-scale ammonium feedback control in three large wastewater treatment plants. Water Sci. Technol. 69 (7), 1573–1580.
Armon, A., Gutner, S., Rosenberg, A., Scolnicov, H., 2011. Algorithmic network monitoring for a modern water utility: a case study in Jerusalem. Water Sci. Technol. 63 (2), 233–239.
Atkinson, S., Medbury, K., 2013. Driving water efficiency improvements in large customers: linking customer engagement and high resolution water use data. In: AWA Water Efficiency Conference, Brighton Beach. Australian Water Association, Sydney. March 2013.
Aymerich, I., Rieger, L., Sobhani, R., Rosso, D., Corominas, Ll, 2015. The difference between energy consumption and energy cost: modelling energy tariff structures for water resource recovery facilities. Water Res. 81, 113–123.
Bakker, M., Van Schagen, K., Timmer, J., 2003. Flow control by prediction of water demand. J. Water Supply Res. Technol. - Aqua 52 (6), 417–424.
Bakker, M., Vreeburg, J.H.G., Palmen, L.J., Sperber, V., Bakker, G., Rietveld, L.C., 2013. Better water quality and higher energy efficiency by using model predictive flow control at water supply systems. J. Water Supply Res. Technol. - Aqua 62 (1), 1–13.
Bartrolí, A., Pérez, J., Carrera, J., 2010. Applying ratio control in a continuous granular reactor to achieve full nitritation under stable operating conditions. Environ. Sci. Technol. 44 (23), 8930–8935.
Bauwens, W., Vanrolleghem, P.A., Smeets, M., 1996. An evaluation of the efficiency of the combined sewer - wastewater treatment system under transient conditions. Water Sci. Technol. 33 (2), 199–208.
Beal, C.D., Stewart, R.A., Fielding, K., 2011. A novel mixed method smart metering approach to reconciling differences between perceived and actual residential end use water consumption. J. Clean. Prod. 60, 116–128. December 2011.
Beck, M.B., 1976. Dynamic modelling and control applications in water quality maintenance. Water Res. 10, 575–595.
Beck, M.B., 2005. Vulnerability of water quality in intensively developing urban watersheds. Environ. Model. Softw 20, 381–400.
Beeneken, T., Erbe, V., Messmer, A., Reder, C., Rohlfing, R., Scheer, M., Schütze, M., Schumacher, B., Weilandt, M., Weyand, M., 2013. Real time control (RTC) of urban drainage systems – a discussion of the additional efforts compared to conventionally operated systems. Urban Water J. 10 (5), 293–299.
Beheshti, M., Sagrov, S., Ugarelli, R., 2015. Infiltration/inflow assessment and detection in urban sewer system. Vann 01, 24–34 (Norway).
Benedetti, L., Bixio, D., Claeys, F., Vanrolleghem, P.A., 2008. Tools to support a model-based methodology for emission/immission and benefit/cost/risk analysis of wastewater systems that considers uncertainty. Environ. Model. Softw 23 (8), 1082–1091.
Benedetti, L., Langeveld, J., Comeau, A., Corominas, L., Daigger, G., Martin, C., Mikkelsen, P.S., Vezzaro, L., Weijers, S., Vanrolleghem, P.A., 2013. Modelling and monitoring of integrated urban wastewater systems: review on status and perspectives. Water Sci. Technol. 68 (6), 1203–1215.
Bertrand-Krajewski, J.-L., Bardin, J.P., Mourad, M., Béranger, Y., 2003. Accounting for sensor calibration, data validation, measurement and sampling uncertainties in monitoring urban drainage systems. Water Sci. Technol. 47 (2), 95–102.
Bishop, W., Law, S., Newton, J., Godfrey, M., 2013. Integrated water management opportunities for inner suburban areas. In: Proc. of WSUD 2013: 8th International Water Sensitive Urban Design Conference. Gold Coast, Australia, pp. 147–160.
Blackburne, R., Yuan, Z., Keller, J., 2008. Demonstration of nitrogen removal via nitrite in a sequencing batch reactor treating domestic wastewater. Water Res. 42 (8–9), 2166–2176.
Brakoniecki, D., 2017. IBM Solution Empowers Severn Trent with Big Data. Water & Wastewater International. https://www.waterworld.com/articles/wwi/2017/09/ibm-solution-empowers-severn-trent-with-big-data.html. (Accessed 13 December 2018).
Brdys, M.A., Grochowski, M., Gminski, T., Konarczak, K., Drewa, M., 2008. Hierarchical predictive control of integrated wastewater treatment systems. Contr. Eng. Pract. 16 (6), 751–767.
Britton, T.C., Cole, G., Stewart, R.A., Wiskar, D., 2008. Remote diagnosis of leakage in residential households. Water: J. Aust. Water Assoc. 35 (6), 56–60. September 2008.
Broad, D.R., Maier, H.R., Dandy, G.C., 2010. Optimal operation of complex water distribution systems using metamodels. J. Water Resour. Plan. Manag. 136 (4), 433–443.
Brongers, M.P.H., Virmani, P.Y., Payer, J.H., 2002. Drinking Water and Sewer Systems in Corrosion Costs and Preventative Strategies in the United States. United States Department of Transportation Federal Highway Administration Publication FHWA-RD-01-156, 2002.
Research needs for automation of wastewater treatment systems. In: Buhr, H.O., Andrews, J.F., Keinath, T.M. (Eds.), 1974. Workshop Proceedings. US EPA in cooperation with Clemson Univ., Clemson, S, Carolina, USA.
Burns, M.J., Fletcher, T.D., Duncan, H.P., Ladson, A.R., Walsh, C.J., 2012. The stormwater retention performance of rainwater tanks at the land-parcel scale. In: Wong, T.H.F., McCarthy, D.T. (Eds.), 7th International Conference on Water Sensitive Urban Design (Melbourne, Australia).
Butler, D., Parkinson, J., 1997. Towards sustainable urban drainage. Water Sci. Technol. 35 (9), 53–63.
Butler, D., Schütze, M., 2005. Integrating simulation models with a view to optimal control of urban wastewater systems. Environ. Model. Softw 20 (4), 415–426.
California Energy Commission, 2005. California's Water-Energy Relationship. Final Staff Report, CEC-700-2005-011-SF, November 2005.
Cardell-Oliver, R., 2013. Water use signature patterns for analyzing household consumption using medium resolution meter data. Water Resour. Res. 49, 8589–8599.
Cardell-Oliver, R., Scott, V., Chapman, T., Morgan, J., Simpson, A., 2015. Designing sensor networks for leak detection in water pipeline systems. In: 2015 IEEE 10th International Conference on Intelligent Sensors, Sensor Networks and Information Processing. ISSNIP 201, Singapore. https://doi.org/10.1109/ISSNIP.2015.7106909, 7/04/15.
Cardell-Oliver, R.M., Wang, J., Gigney, H., 2016. Smart meter analytics to pinpoint opportunities for reducing household water use. J. Water Resour. Plan. Manag. 142 (6), 04016007.
Chen, J., Ganigué, R., Liu, Y., Yuan, Z., 2014. Real-time multi-step prediction of sewer flow for online chemical dosing control. ASCE J. Environ. Eng. 140 (11), 04014037.1-04014037.9.
Chew, C.M., Aroua, M.K., Hussain, M.A., 2018. Advanced process control for ultrafiltration membrane water treatment system. J. Clean. Prod. 179, 63–80.
Clancy, H., 2013. IBM's Smart Tech Aids Water Management. https://www.greenbiz.com/blog/2013/07/10/ibm-smart-water-tech-m2m. (Accessed 17 December 2018).
Corominas, Ll, Garrido-Baserba, M., Villez, K., Olsson, G., Cortés, U., Poch, M., 2018. Transforming data into knowledge for improved wastewater treatment operation: a critical review of techniques. Environ. Model. Softw 106, 89–103.
Corral-Verdugo, V., Fras-Armenta, M., Prez-Urias, F., Ordua-Cabrera, V., Espinoza-Gallego, N., 2002. Residential water consumption, motivation for conserving water and the continuing tragedy of the commons. Environ. Manag. 30 (4), 527–535.
De Bénédittis, J., Bertrand-Krajewski, J.-L., 2005. Infiltration in sewer systems: comparison of measurement methods. Water Sci. Technol. 52 (3), 219–227.
de Haas, D.W., Sharma, K., Corrie, S., O'Halloran, K., Keller, J., Yuan, Z., 2008. Odour control by chemical dosing – a case study. Water 138–143. March 2008.
De Silva, D., Mashford, J., Burn, S., 2011. Computer Aided Leak Location and Sizing in Pipe Networks. Technical Report 17, second ed. Urban Water Security Research Alliance. April 2011.
DeBusk, K., Hunt, W., Quigley, M., Jeray, J., Bedig, A., 2012. Rainwater Harvesting: Integrating Water Conservation and Stormwater Management through Innovative Technologies, World Environmental and Water Resources Congress 2012: Crossing Boundaries. ASCE, 2012.
Dentel, S.K., 1991. Coagulation control in water treatment. Crit. Rev. Environ. Contr. 21, 41–135.
Devitt, J., 2014. Mackay regional Council water and waste services, it's not about meters or technology. In: QWater Conference, Gold Coast, Nov 2014.
Dickers, J., 2016. Smart Sewers: Revolutionising the Way Utilities Manage Wastewater Networks. https://utilitymagazine.com.au/smart-sewers-revolutionising-the-way-utilities-manage-wastewater-networks/. (Accessed 16 December 2018).
DOE, 2001. Water Heating. Office of Building Technology. Energy Efficiency and Renewable Energy (EERE), US Department of Energy. http://apps1.eere.energy.gov/buildings/publications/pdfs/building_america/26465.pdf. (Accessed 17 December 2018).
Dong, X., Zeng, S., Chen, J., Zhao, D., 2012. An integrated urban drainage system model for assessing renovation scheme. Water Sci. Technol. 65 (10), 1781–1788.
Duncan, A.P., Chen, A.S., Keedwell, E.C., Djordjevic, S., Savić, D., 2011. Urban flood prediction in real-time from weather radar and rainfall data using artificial neural networks. Weather Radar and Hydrology. April. In: Symposium Proceedings, Exeter, UK, vol. 351. IAHS Punblication, pp. 568–573, 2012.
Duncan, A., Chen, A.S., Keedwell, E., Djordjevic, S., Savić, D., 2013. RAPIDS: early warning system for urban flooding and water quality hazards. In: Machine Learning in Water Systems Symposium: Part of AISB Annual Conference,

pp. 1–5.
Dürrenmatt, D.J., Del Giudice, D., Rieckermann, J., 2013. Dynamic time warping improves sewer flow monitoring. Water Res. 47 (11), 3803–3816.
Edwards, M., Simoni, T., 2007. Chloride-to-sulfate mass ratio and lead leaching to water. J. Am. Water Work. Assoc. 99 (7), 96–109.
Ellis, J.B., Bertrand-Krajewski, J.-L., 2010. Assessing Infiltration and Exfiltration on the Performance of Urban Sewer Systems (APUSS). IWA Publishing. ISBN: 184339149X. ISBN 13: 9781843391494.
EPRI, Electric Power Research Institute, 2002. Water and Sustainability, vol. 4. U. S. electricity consumption for water supply & treatment—The next half century, No. 1006787, Palo Alto, California.
Erbe, V., Schütze, M., 2005. An integrated modelling concept for immission-based management of sewer system, wastewater treatment plant and river. Water Sci. Technol. 52 (5), 95–103.
Erbe, V., Risholt, L.P., Schilling, W., Londong, J., 2002. Integrated modelling for analysis and optimisation of wastewater systems – the Odenthal case. Urban Water 4 (1), 63–71.
Fanner, P., 2007. Leakage Management Technologies. American Water Works Association (AWWA) Research Foundation, 2007.
FAO, 2018. 2050: Water Supplies to Dwindle in Parts of the World, Threatening Food Security and Livelihoods. Food and Agriculture Organization of the United Nations. http://www.fao.org/news. (Accessed 16 December 2018).
Farley, M., 2010. Are their alternatives to the DMA? Asian Water 10–16. December 2010.
Farley, M., Trow, S., 2005. Losses in Water Distribution Networks: a Practitioner's Guide to Assessment, Monitoring and Control. IWA Publishing, London.
Farmani, R., Walters, G., Savić, D., 2006. Evolutionary multi-objective optimization of the design and operation of water distribution network: total cost vs. reliability vs. water quality. J. Hydroinf. 08 (3), 165–179.
Ferguson, B.C., Brown, R.R., Frantzeskaki, N., De Haan, F.J., Deletic, A., 2013. The enabling social context for water system change: lessons from Melbourne. Water Res. 47 (20), 7300–7314.
Fox, C., McIntosh, B.S., Jeffrey, P., 2009. Classifying households for water demand forecasting using physical property characteristics. Land Use Pol. 26 (3), 558–568.
Fradet, O., Pleau, M., Marcoux, C., 2011. Reducing CSOs and giving the river back to the public: innovative combined sewer overflow control and riverbanks restoration of the St Charles River in Quebec City. Water Sci. Technol. 63 (2), 331–338.
Fu, Y., Wu, W.Y., 2016. Predicting household water use behaviour for improved hygiene practices in internet of things environment via dynamic behaviour intervention model. IET Netw. 5 (5), 143–151.
Fu, G., Butler, D., Khu, S.T., 2008. Multiple objective optimal control of integrated urban wastewater systems. Environ. Model. Softw 23 (2), 225–234.
Gaborit, E., Muschalla, D., Vallet, B., Vanrolleghem, P.A., Anctil, F., 2013. Improving the performance of stormwater detention basins by real-time control using rainfall forecasts. Urban Water J. 10, 230–246.
Ganidi, N., Holden, B., 2014. Real time control of water distribution systems using a multi criteria decision-support tool for optimal water network management - a case study. Proc. Eng. 89, 495–501.
Ganigué, R., Gutierrez, O., Rootsey, R., Yuan, Z., 2011. State of the art of chemical dosing for sulfide control in Australia. Water Res. 45 (19), 6564–6574.
Ganigué, R., Jiang, G., Sharma, K., Chen, J., Vuong, L., Yuan, Z., 2016. On-line control of magnesium hydroxide dosing for sulfide mitigation in sewers: algorithm development, simulation analysis and field validation. J. Environ. Eng. 142 (12), 04016069.
Ganigué, R., Jiang, G., Liu, Y., Sharma, K., Wang, Y., Gonzalez, J., Nguyen, T., Yuan, Z., 2018. Improved sulfide mitigation in sewers through on-line control of ferrous salt dosing. Water Res. 135, 302–310.
Gao, L.X., Gu, H., Rahardianto, A., Christofides, P.D., Cohen, Y., 2017. Self-adaptive cycle-to-cycle control of in-line coagulant dosing in ultrafiltration for pre-treatment of reverse osmosis feed water. Desalination 401, 22–31.
García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., Ocampo-Martinez, C., 2015. Modeling and real-time control of urban drainage systems: a review. Adv. Water Res. 85, 120–132.
Gaskell, A., 2017. Smart Cities and Smart Sewers. https://www.huffingtonpost.com/adi-gaskell/smart-cities-and-smart-se_b_14488630.html. (Accessed 17 December 2018).
Gernaey, K., Jeppsson, U., Vanrolleghem, P.A., Copp, J.B., 2014. Benchmarking of Control Strategies for Wastewater Treatment Plants. IWA Publishing. Scientific and Technical Report No. 23.
Ghimire, B., Chen, A.S., Guidolin, M., Keedwell, E.C., Djordjević, S., Savić, D.A., 2013. Formulation of a fast 2D urban pluvial flood model using a cellular automata approach. J. Hydroinf. 15 (3), 676–686.
Gibbs, M.S., Dandy, G.C., Maier, H.R., 2010. Calibration and optimization of the pumping and disinfection of a real water supply system. J. Water Resour. Plan. Manag. 136 (4), 493–501.
Grafton, R.Q., Ward, M.B., To, H., Kompas, T., 2011. Determinants of residential water consumption: evidence and analysis from a 10-country household survey. Water Resour. Res. 47, W08537.
Grant, S.B., Saphores, J.D., Feldman, D.L., Hamilton, A.J., Fletcher, T.D., Cook, P.L., Stewardson, M., Sanders, B.F., Levin, L.A., Ambrose, R.F., Deletic, A., Brown, R.R., Jiang, S.C., Rosso, D., Cooper, W.J., Marusic, I., 2012. Taking the "waste" out of "wastewater" for human security and ecosystem sustainability. Science 337 (6095), 681–686.
Gruber, G., Winkler, S., Pressl, A., 2005. Continuous monitoring in sewer networks an approach for quantification of pollution loads from CSOs into surface water bodies. Water Sci. Technol. 52 (12), 215–223.
Grum, M., Thornberg, D., Christensen, M.L., Shididi, S.A., Thirsing, C., 2011. Full-scale real time control demonstration project in Copenhagen's largest urban drainage catchments. In: Proceedings of the 12th International Conference on Urban Drainage, Porto Alegre, Portugal.
Gu, S., Wang, S., Yang, Q., Yang, P., Peng, Y., 2012. Start up partial nitrification at low temperature with a real-time control strategy based on blower frequency and pH. Bioresour. Technol. 112, 34–41.
Guidolin, M., Chen, A.S., Ghimire, B., Keedwell, E.C., Djordjević, S., Savić, D.A., 2016. A weighted cellular automata 2D inundation model for rapid flood analysis. Environ. Model. Softw 84, 378–394.
Han, Q., Nguyen, P., Eguchi, R.T., Hsu, K.L., Venkatasubramanian, N., 2017. In: Lee, K., Liu, L. (Eds.), IEEE 37th International Conference on Distributed Computing Systems. IEEE Computer Soc, Los Alamitos, pp. 2505–2506.
Hanna-Attisha, M., LaChance, J., Sadler, R.C., Schnepp, A.C., 2016. Elevated blood lead levels in children associated with the Flint drinking water crisis: a spatial analysis of risk and public health response. Am. J. Public Health 106, 283–290.
Harremoës, P., Rauch, W., 1999. Optimal design and real time control of the integrated urban run-off system. Hydrobiologia 410, 177–184.
Herrmann, T., Schmida, U., 1999. Rainwater utilisation in Germany: efficiency, dimensioning, hydraulic and environmental aspects. Urban Water 1 (4), 307–316.
Hoes, O.A.C., Schilperoort, R.P.S., Luxemburg, W.M.J., Clemens, F.H.L.R., van der Giesen, N.C., 2009. Locating illicit connections in storm water sewers using fibre-optic distributed temperature sensing. Water Res. 43 (20), 5187–5197.
Hoey, J., 2017. The next big thing. Curr. Aust. Water Assoc. Mag. 1 (7), 28–33.
Hug, T., Benedetti, L., Hall, E.R., Johnson, B.R., Morgenroth, E.F., Nopens, I., Rieger, L., Shaw, A.R., Vanrolleghem, P.A., 2009. Mathematical models in teaching and training: mismatch between education and requirements for jobs. Water Sci. Technol. 59 (4), 745–753.
Ingildsen, P., 2002. Realising Full-Scale Control in Wastewater Treatment Systems Using in Situ Nutrient Sensors. PhD thesis. Dept. of Ind. Electrical Engineering and Automation (IEA), Lund University, Sweden. Available at: www.iea.lth.se. (Accessed 5 January 2019).
Ingildsen, P., Olsson, G., 2016. Smart Water Utilities. IWA Publications, London.
IPCC, 2018. Global Warming of 1.5°C. Intergovernmental Panel on Climate Change. WMO, UNEP.
Jones, L., Olsson, G., 2017. Solar PV and wind energy providing water. Global Chall., Spec. Issue Water Energy 1 (5). Open access. http://onlinelibrary.wiley.com/doi/10.1002/gch2.201600022/full. (Accessed 17 December 2018).
Jorgensen, B., Graymore, M., O'Toole, K., 2009. Household water use behavior: an integrated model. J. Environ. Manag. 91 (1), 227–236.
Jowitt, P.W., Germanopoulos, G., 1992. Optimal pump scheduling in water-supply networks. J. Water Resour. Plan. Manag. 118 (4), 406–422.
Jung, D., Kang, D., Kang, M., Kim, B., 2015. Real-time pump scheduling for water transmission systems: case study. KSCE J. Civil Eng. 19 (7), 1–7.
Kenway, S., Lant, P., Priestly, A., Daniels, P., 2011. The connection between water and energy in cities: a review. Water Sci. Technol. 63 (9), 1983–1990.
Kingdom, B., Liemberger, R., Marin, P., 2006. The Challenge of Reducing Non-revenue (NRW) Water in Developing Countries. How the Private Sector Can Help: A Look at Performance-Based Service Contracting. Technical Report 8. Water Supply and Sanitation Sector Board discussion paper series. December 2006.
Kinyua, M.N., Elliott, M., Wett, B., Murthy, S., Chandran, K., Bott, C.B., 2017. The role of extracellular polymeric substances on carbon capture in a high rate activated sludge A-stage system. Chem. Eng. J. 322, 428–434.
Kleidorfer, M., Tscheikner-Gratl, F., Vonach, T., Rauch, W., 2018. What can we learn from a 500-year event? – experiences from urban drainage in Austria. Water Sci. Technol. 77 (8), 2146–2154.
Kollatsch, D-Th, 1993. Futuristic ideas to create a most efficient drainage system. In: Proc. 6th International Conf. on Urban Storm Drainage, Niagara Falls, Ontario, Canada, Sep. 12-17, 1993, pp. 1225–1230.
Kukudis, R., 1973. Problems involved in automating the wastewater treatment plant. Progress in Water Technology. In: Andrews, J.F., Briggs, R. (Eds.), Instrumentation, Control and Automation for Wastewater Treatment Systems, vol. 6. International Association on Water Pollution Research, London, 5-6.
Kunkel, K.E., Lewis, K.L.M., Maycock, T.K., Stewart, B.C. (Eds.), 2018. U.S. Global Change Research Program, Washington, DC, USA. https://doi.org/10.7930/NCA4.2018. CH3. https://nca2018.globalchange.gov/chapter/water. (Accessed 17 December 2018).
Lall, U., Johnson, T., Colohan, P., Aghakouchak, A., Brown, C., McCabe, G., Pulwarty, R., Sankarasubramanian, A., 2018. Water. In: Reidmiller, D.R., Avery, C.W., Easterling, D.R. (Eds.), Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, vol. II.
Langeveld, J.G., de Haan, C., Klootwijk, M., Schilperoort, R.P.S., 2012. Monitoring the performance of a storm water separating manifold with distributed temperature sensing. Water Sci. Technol. 66 (1), 145–150.
Law, Y., Ye, L., Pan, Y., Yuan, Z., 2012. Nitrous oxide emissions from wastewater treatment processes. Philosoph. Transact. Roy. Soc., B (Biology) 367, 1265–1277.
Lee, P.-H., Cotter, S.F., Reyes Prieri, S.C., Attalage, D., Sung, S., 2013. pH-gradient real-time aeration control for nitritation community selection in a non-porous hollow fiber membrane biofilm reactor (MBfR) with dilute wastewater. Chemosphere 90 (8), 2320–2325.

Lemaire, R., Marcelino, M., Yuan, Z., 2008. Achieving the nitrite pathway using aeration phase length control and step-feed in an SBR removing nutrients from abattoir wastewater. Biotechnol. Bioeng. 100 (6), 1228–1236.
Li, J., Sharma, K., Liu, Y., Jiang, G., Yuan, Z., 2019. Real-time prediction of rain-impacted sewage flow for on-line control of chemical dosing in sewers. Water Res. 149, 311–321.
Libelium, 2017. Smart Water Management for Wastewater Treatment in Isolated Communities. http://www.libelium.com/smart-water-management-for-wastewater-treatment-in-isolated-communities/. (Accessed 17 December 2018).
Liu, W., Ratnaweera, H., 2016. Improvement of multi-parameter-based feed-forward coagulant dosing control systems with feed-back functionalities. Water Sci. Technol. 74 (2), 491–499.
Liu, Y., Ganigue, R., Yuan, Z., 2013. Controlling chemical dosing for sulfide mitigation in sewer networks using a hybrid automata control strategy. Water Sci. Technol. 68 (12), 2584–2590.
Lloret, J., Tomas, J., Canovas, A., Parra, L., 2016. An integrated IoT architecture for smart metering. IEEE Commun. Mag. 54 (12), 50–57.
López-Ibáñez, M., Devi Prasad, T., Paechter, B., 2008. Ant colony optimization for optimal control of pumps in water distribution networks. J. Water Resour. Plan. Manag. 134 (4), 337–346.
Lumley, D.J., Sahlberg, K.Å., Haraldsson, J., 1993. Use of part-time unmanned operation at a large wastewater treatment plant. Water Sci. Technol. 28 (11–12), 29–36.
Martinez, F., Hernandez, V., Alonso, J.M., Rao, Z., Alvisi, A., 2007. Optimizing the operation of the Valencia water distribution network. J. Hydroinf. 9 (1), 65–78.
Melville-Shreeve, P., Ward, S., Butler, D., 2014. Developing a methodology for appraising rainwater harvesting with integrated source control using a case study from south-west England. In: 13th International Conference on Urban Drainage, Sarawak, Malaysia, 7–12 September, pp. 1–8.
Métadier, M., Bertrand-Krajewski, J.-L., 2012. The use of long-term on-line turbidity measurements for the calculation of urban stormwater pollutant concentrations, loads, pollutographs and intra-event fluxes. Water Res. 46 (20), 6836–6856.
Mignot, E., Bonakdari, H., Knothe, P., Lipeme Kouyi, G., Bessette, A., Rivière, N., Bertrand-Krajewski, J.-L., 2012. Experiments and 3D simulations of flow structures in junctions and their influence on location of flowmeters. Water Sci. Technol. 66 (6), 1325–1332.
Miller, M., Elliot, M., DeArmond, J., Kinyua, M.N., Wett, B., Murthy, S., Bott, C., 2017. Controlling the COD removal of an A-stage pilot study with instrumentation and automatic process control. Water Sci. Technol. 75, 2669–2679.
Mounce, S.R., Boxall, J.B., Machell, J., 2010. Development and verification of an online artificial intelligence system for detection of bursts and other abnormal flows. J. Water Resour. Plan. Manag. 136 (3), 309–318.
Muschalla, D., 2008. Optimization of integrated urban wastewater systems using multi-objective evolution strategies. Urban Water J. 5 (1), 59–67.
Muschalla, D., Vallet, B., Anctil, F., Lessard, P., Pelletier, G., Vanrolleghem, P.A., 2014. Ecohydraulic-driven real-time control of stormwater basins. J. Hydrol. 511, 82–91.
Mutikanga, H., Sharma, S., Vairavamoorthy, K., 2013. Methods and tools for managing losses in water distribution systems. J. Water Resour. Plan. Manag. 139 (2), 166–174.
Nguyen, C., Stone, K., Clark, B., Edwards, M., Gagnon, G., Knowles, A., 2010. Impact of Chloride: Sulfate Mass Ratio (CSMR) Changes on Lead Leaching in Potable Water. Water Research Foundation and USEPA, p. 159.
Nguyen, K., Zhang, H., Stewart, R.A., 2013. Development of an intelligent model to categorise residential water end use events. J. Hydro-Environ. Res. 7 (3), 182–201.
Ni, B.-J., Pan, Y., van den Akker, B., Ye, L., Yuan, Z., 2015. Full-scale modeling explaining large spatial variations of nitrous oxide fluxes in a step-feed plug-flow wastewater treatment reactor. Environ. Sci. Technol. 49 (15), 9176–9184.
Nielsen, M.K., Carstensen, J., Harremoes, P., 1996. Combined control of sewer and treatment plant during rainstorm. Water Sci. Technol. 34 (3), 181–187.
Nielsen, M.K., Bechmann, H., Henze, M., 2000. Modeling and test of aeration tank settling (ATS). Water Sci. Technol. 41 (9), 179–184.
Nowak, O., Keil, S., Fimml, C., 2011. Examples of energy self-sufficient municipal nutrient removal plants. Water Sci. Technol. 64 (1), 1–6.
NWC, 2014. National Performance Report 2012-13: Urban Water Utilities. National Water Commission, 2014. http://apo.org.au/system/files/39162/apo-nid39162-99906.pdf. (Accessed 18 December 2018).
OAG, 2014. Office of the Auditor General. Water corporation: Management of water pipes, Perth, Western Australia, 2014. https://audit.wa.gov.au/wp-content/uploads/2014/02/report2014_01-Water-Corporation-Management-of-Water-Pipes.pdf. (Accessed 18 December 2018).
Odan, F.K., Ribeiro Reis, L.F., Kapelan, Z., 2014. Use of metamodels in real-time operation of water distribution systems. Proc. Eng. 89, 449–456.
OECD, 2012. OECD Environmental Outlook to 2050: the Consequences of Inaction -. ISBN 978-92-64-122161 © OECD 2012. http://www.oecd.org/environment/. (Accessed 15 December 2018).
Ogurek, M., Alex, J., Rieger, L., Schraa, O., Schütze, M., 2015. A novel integrated approach for designing, testing and implementing WRRF process control solutions. In: Proceedings of the Water Environment Federation. WEFTEC, pp. 4087–4104, 2015.
Olsson, G., 2008. In: Henze, M., van Loosdrecht, M., Ekama, G., Brdjanovic, D. (Eds.), Process Control. Chapter in Biological Wastewater Treatment – Principles, Modelling and Design. UNESCO, IWA Publishing, London.
Olsson, G., 2012. ICA and me – a subjective review. Water Res. 46 (6), 1585–1624.
Olsson, G., 2013. The potential of control and monitoring (Chapter 12). In: Larsen, T.A., Udert, K.M., Lienert, J. (Eds.), Source Separation and Decentralization for Wastewater Management. IWA Publishing, London. ISBN – 9781843393481.
Olsson, G., 2015. Water and Energy: Threats and Opportunities, second ed. IWP Publishing. ISBN 9781780406930. 496pp.
Olsson, G., Jeppsson, U., 2006. Plant-wide control: dream, necessity or reality? Water Sci. Technol. 53 (3), 121–129.
Olsson, G., Newell, R.B., 1998. Talking of RAS - reviewing, assessing and speculating, final address at the 7th IAWQ symposium on ICA, brighton, UK, july, 1997. Water Sci. Technol. 37 (12), 397–401.
Olsson, G., Newell, R.B., 1999. Wastewater Treatment Systems. Modelling, Diagnosis and Control. IWA Publishing, London.
Olsson, G., Eklund, K., Dahlqvist, K.I., Ulmgren, L., 1973. Control Problems in Wastewater Treatment Plants. (Research Report TFRT-3064). Department of Automatic Control, Lund Institute of Technology, Sweden. Available at: http://portal.research.lu.se/portal/files/4620667/8726145.pdf. (Accessed 17 December 2018).
Olsson, G., Newell, B., Rosen, C., Ingildsen, P., 2003. Application of information technology to decision support in treatment plant operation. Water Sci. Technol. 47 (12), 35–42.
Olsson, G., Nielsen, M., Yuan, Z., Lynggaard-Jensen, A., Steyer, J.P., 2005. Instrumentation, Control and Automation in Wastewater Systems. IWA Publishing, London.
Olsson, G., Carlsson, B., Comas, J., Copp, J., Gernaey, K.V., Ingildsen, P., Jeppsson, U., Kim, C., Rieger, L., Rodríguez-Roda, I., Steyer, J.-P., Takács, I., Vanrolleghem, P.A., Vargas Casillas, A., Yuan, Z., Åmand, L., 2014. Instrumentation, control and automation in wastewater – from London 1973 to narbonne 2013. Water Sci. Technol. 69 (7), 1373–1385.
Patabendige, S., Cardell-Oliver, R., Wang, R., Liu, W., 2018. Detection and interpretation of anomalous water use for non-residential customers. Environ. Model. Softw 100, 291–301.
Pfister, A., Stein, A., Schlegel, S., Teichgräber, B., 1998. An integrated approach for improving the wastewater discharge and treatment systems. Water Sci. Technol. 37 (1), 341–346.
Pikaar, I., Sharma, K., Hu, S., Gernjak, W., Keller, J., Yuan, Z., 2014. Reducing sewer corrosion through integrated urban water management. Science 345, 812–814.
Pisano, W., O'Riordan, C., Ayotte, F., Barsanti, J., Carr, D., 2003. Automated sewer and drainage flushing systems in Cambridge, Massachusetts. J. Hydraul. Eng. 129 (4), 260–266.
Pleau, M., Pelletier, G., Coias, H., Lavaliee, P., Bonin, R., 2001. Global predictive real-time control of Quebec Urban Community's westerly sewer network. Water Sci. Technol. 43 (7), 123–130.
Pratt, C., 2011. Factors Influencing Pipe Failures in the WA Environment. Honours thesis. The University of Western Australia.
Pudar, R.S., Liggett, J.A., 1992. Leaks in pipe networks. J. Hydraul. Eng. 118 (7), 1031–1046.
Puust, R., Kapelan, Z., Savić, D.A., Koppel, T., 2010. A review of methods for leakage management in pipe networks. Urban Water J. 7 (1), 25–45.
Rastogi, A.K., 1989. Optimal pumping policy and groundwater balance for the Blue Lake aquifer, California, involving nonlinear groundwater hydraulics. J. Hydrol. 111, 177–194.
Ratnaweera, H., 2014. Coagulant dosing control—a review. In: Hahn, H.H., Hoffmann, E., Ødegaard, H. (Eds.), Chemical Water and Wastewater Treatment VIII. IWA Publishing, London, UK, pp. 10–18.
Ratnaweera, H., Fettig, J., 2015. State of the art of online monitoring and control of the coagulation process. Water 7, 6574.
Rauch, W., Harremoës, P., 1996a. The importance of the treatment plant performance during rain to acute water pollution. Water Sci. Technol. 34 (3–4), 1–8.
Rauch, W., Harremoës, P., 1996b. Minimizing acute river pollution from urban drainage systems by means of integrated real time control. In: Proceedings of the 1st International Conference on New/Emerging Concepts for Rivers (RIVERTECH'96), Chicago, USA.
Rauch, W., Harremoes, P., 1999. Genetic algorithms in real time control applied to minimize transient pollution from urban wastewater systems. Water Res. 33 (5), 1265–1277.
Rauch, W., Seggelke, K., Brown, R., Krebs, P., 2005. Integrated approaches in urban storm drainage: where do we stand? Environ. Manag. 35 (4), 396–409.
Rebosura, M.J.R., Salehin, S., Pikaar, I., Sun, X., Keller, J., Sharma, K., Yuan, Z., 2018. A comprehensive laboratory assessment of the effects of sewer-dosed iron salts on wastewater treatment processes. Water Res. 146, 109-107.
Reffold, E., Leighton, F., Choudhury, F., Rayner, P.S., 2008. Greenhouse Gas Emissions of Water Supply and Demand Management Options. Environment Agency UK. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/291728/scho0708bofv-e-e.pdf. (Accessed 18 December 2018).
Regmi, P., Miller, M.W., Holgate, B., Bunce, R., Park, H., Chandran, K., Wett, B., Murthy, S., Bott, C.B., 2014. Control of aeration, aerobic SRT and COD input for mainstream nitritation/denitritation. Water Res. 57, 162–171.
Rieger, L., Olsson, G., 2012. Why Many Control Systems Fail. Water Environment & Technology, Water Environment Federation, pp. 43–45. June 2012.
Rieger, L., Vanrolleghem, P.A., 2008. MonEAU: a platform for water quality monitoring networks. Water Sci. Technol. 57 (7), 1079–1086.

Rieger, L., Jones, R.M., Dold, P.L., Bott, C.B., 2014. Ammonia-based feedforward and feedback aeration control in activated sludge processes. Water Environ. Res. 86 (1), 63–73.

Rietveld, L.C., van der Helm, A.W.C., van Schagen, K.M., van der Aa, L.T.J., 2010. Good modelling practice in drinking water treatment, applied to Weesperkarspel plant of Waternet. Environ. Model. Softw 25, 661–669.

Rjeily, Y.A., Abbas, O., Sadek, M., Shahrour, I., Chehade, F.H., 2017. Flood forecasting within urban drainage systems using NARX neural network. Water Sci. Technol. 76 (9), 2401–2412.

Rodriguez-Roda, I., Sànchez-Marrè, M., Comas, J., Baeza, J., Colprim, J., Lafuente, J., Cortés, U., Poch, M., 2002. A hybrid supervisory system to support WWTP operation: implementation and validation. Water Sci. Technol. 45 (4–5), 289–297.

Roy, J.K., Mukhopadhyay, S.C., 2016. In: Mukhopadhyay, S.C. (Ed.), Next Generation Sensors and Systems. Springer International Publishing AG, Cham, pp. 257–287.

SA EEA, South Australian Engineering Excellence Awards, 2010. Delivering a Secure Water Supply to the Community: A Combined Optimisation and Multi-Criteria Analysis Approach, 2010. https://issuu.com/engineersaustralia/docs/engineering_excellence_awards_2010. (Accessed 21 January 2019).

Salomons, E., Goryashko, A., Shamir, U., Rao, Z., Alvisi, S., 2007. Optimizing the operation of the Haifa-A water distribution network. J. Hydroinf. 9 (1), 51–64.

Savić, D., 2017. A smart city without smart water is only a pipe dream! Keynote paper. In: International Association for Hydro-Environment Engineering and Research (IAHR) World Congress, Kuala Lumpur, Malaysia 2017.

Savić, D.A., Walters, G.A., Schwab, M., 1997. Multiobjective genetic algorithms for pump scheduling in water supply. Evolutionary Computing 1305, 227–236.

Schilperoort, R.P.S., Dirksen, J., Langeveld, J.G., Clemens, F.H.L.R., 2012. Assessing characteristic time and space scales of in-sewer processes by analysis of one year of continuous in-sewer monitoring data. Water Sci. Technol. 66 (8), 1614–1620.

Schilperoort, R., Hoppe, H., de Haan, C., Langeveld, J., 2013. Searching for storm water inflows in foul sewers using fibre-optic distributed temperature sensing. Water Sci. Technol. 68 (8), 1723–1730.

Schütze, M., Butler, D., Beck, M.B., 1999. Optimisation of control strategies for the urban wastewater system—an integrated approach. Water Sci. Technol. 39 (9), 209–216.

Schütze, M., Butler, D., Beck, M.B., Verworn, H.R., 2002. Criteria for assessment of the operational potential of the urban wastewater system. Water Sci. Technol. 45 (3), 141–148.

Schütze, M., Campisano, A., Colas, H., Schilling, W., Vanrolleghem, P.A., 2004. Real time control of urban wastewater systems—where do we stand today? J. Hydrol. 299 (3), 335–348.

Schütze, M., Lange, M., Pabst, M., Haas, U., 2018. Astlingen – a benchmark for real-control control (RTC). Water Sci. Technol. 2017 (2), 552–560.

Seggelke, K., Rosenwinkel, K.H., Vanrolleghem, P.A., Krebs, P., 2005. Integrated operation of sewer system and WWTP by simulation-based control of the WWTP inflow. Water Sci. Technol. 52 (5), 195–203.

Seggelke, K., Löwe, R., Beeneken, T., Fuchs, L., 2013. Implementation of an integrated real-time control system of sewer system and waste water treatment plant in the city of Wilhelmshaven. Urban Water J. 10 (5), 330–341.

Sharma, K.R., Yuan, Z., de Haas, D., Hamilton, G., Corrie, S., Keller, J., 2008. Dynamics and dynamic modelling of H_2S production in sewer systems. Water Res. 42 (10–11), 2527–2538.

Sharma, K.R., Corrie, S., Yuan, Z., 2012. Integrated modelling of sewer system and wastewater treatment plant for investigating the impacts of chemical dosing in sewers. Water Sci. Technol. 65 (8), 1399–1405.

Sharma, A.K., Guildal, T., Thomsen, H.A.R., Mikkelsen, P.S., Jacobsen, B.N., 2013. Aeration tank settling and real time control as a tool to improve the hydraulic capacity and treatment efficiency during wet weather: results from 7 years' full-scale operational data. Water Sci. Technol. 67 (10), 2169–2176.

Shen, P., 2019. Framework for Real Time Control and Operational Optimisation of Stormwater Biofilters. PhD thesis. Monash University, Australia.

Shiddiqi, A.M., Cardell-Oliver, R.M., Datta, A., 2017. Sensor placement strategy for locating leaks using lean graphs. In: Proceedings - 2017 3rd International Workshop on Cyber-Physical Systems for Smart Water Networks. CySWATER. https://doi.org/10.1145/3055366.3055372, 2017.

Shiddiqi, A.M., Cardell-Oliver, R.M., Datta, A., 2018. Sensing-based leak quantification techniques in water distribution systems. In: Tsakalides, P., Panousopoulou, A., Tsagkatakis, G., Montestruque, L. (Eds.), Smart Water Grids: A Cyber-Physical Systems Approach. CRC Press, Boca Raton, USA, pp. 129–147.

Stoianov, I., Nachman, L., Madden, S., 2007. In: PIPENET: A Wireless Sensor Network for Pipeline Monitoring. IPSN'07, April 25-27, Cambridge, Massachusetts, U.S.A., 2007.

Stokes, C.S., Simpson, A.R., Maier, H.R., 2015. A computational software tool for the minimization of costs and greenhouse gas emissions associated with water distribution systems. Environ. Model. Softw 69, 452–467.

Strous, M., Fuerst, J.A., Kramer, E.H.M., Logemann, S., Muyzer, G., Van De Pas-Schoonen, K.T., Webb, R., Kuenen, J.G., Jetten, M.S.M., 1999. Missing lithotroph identified as new planctomycete. Nature 400 (6743), 446–449.

Sun, J., Pikaar, I., Sharma, K.R., Keller, J., Yuan, Z., 2015. Feasibility of sulfide control in sewers by reuse of iron rich drinking water treatment sludge. Water Res. 71, 150–159.

Swift, A., Casey-Lefkowitz, S., Shope, E., 2011. Tar Sand Pipelines Safety Risks. A Joint Report by Natural Resources Defense Council, National Wildlife Federation, Pipeline Safety Trust. Sierra Club, 2011. www.nrdc.org/sites/default/files/tarsandssafetyrisks.pdf. (Accessed 5 January 2019).

Syme, G.J., Shao, Q., Po, M., Campbell, E., 2004. Predicting and understanding home garden water use. Landsc. Urban Plann. 68 (1), 121–128.

Teo, N., 2012. Intelligent Water Network Executive Report: Permanent Monitoring of Leakage. Yarra Valley Water, Australia.

U.S. Environmental Protection Agency, 1991. Technical Report: Hydrogen Sulfide Corrosion in Wastewater Collection and Treatment Systems. EPA publication, 430/09-91-010, Washington DC, 1991.

van Schagen, K.M., Rietveld, L.C., Babuška, R., 2008. Dynamic modelling for optimisation of pellet softening. J. Water Supply Res. Technol. - Aqua 57 (1), 45–56.

van Schagen, K., Rietveld, L.C., Veersma, A., Babuška, R., 2010. Control-design methodology for drinking-water treatment processes. Water Sci. Technol. Water Supply 10 (2), 121–127.

Vanrolleghem, P.A., Benedetti, L., Meirlaen, J., 2005. Modelling and real-time control of the integrated urban wastewater system. Environ. Model. Softw 20 (4), 427–442.

Vezzaro, L., Steen Mikkelsen, P., Deletic, A., McCarthy, D., 2013. Urban drainage models – simplifying uncertainty analysis for practitioners. Water Sci. Technol. 68 (10), 2136–2143.

Vosse, M., Schilpero ort, R., de Haan, C., Nienhuis, J., Tirion, M., Langeveld, J., 2013. Processing of DTS monitoring results: automated detection of illicit connections. Water Pract. Technol. 8 (3), 375–381. https://doi.org/10.2166/wpt.2013.037.

Water Corporation of Western Australia, 2009. Water Forever: towards Climate Resilience (Summary). https://www.watercorporation.com.au/-/media/files/residential/about-us/planning-for-the-future/water-forever-50-year-plan.pdf. (Accessed 18 December 2018).

Weijers, S.R., De Jonge, J., Van Zanten, O., Benedetti, L., Langeveld, J., Menkveld, H.W., Van Nieuwenhuijzen, A.F., 2012. KALLISTO: cost effective and integrated optimization of the urban wastewater system Eindhoven. Water Pract. Technol. 7 (2), 1–9.

Weinreich, G., Schilling, W., Birkely, A., Moland, T., 1997. Pollution based real time control strategies for combined sewer systems. Water Sci. Technol. 36 (8–9), 331–336.

Whittle, A.J., Allen, M., Preis, A., Iqbal, M., 2013. Sensor networks for monitoring and control of water distribution systems (Keynote Lecture). In: The 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure, Hong Kong, 9-11 December.

Wilderer, P.A., Schreff, D., 2000. Decentralized and centralized wastewater management: a challenge for technology developers. Water Sci. Technol. 41 (1), 1–8.

Willis, R.M., Stewart, R.A., Giurco, D.P., Talebpour, M.R., Mousavinejad, A., 2013. End use water consumption in households: impact of socio-demographic factors and efficient devices. J. Clean. Prod. 60, 107–115.

WMO, 2018. World Meteorological Organization. WMO Statement on the State of the Global Climate in 2017, ISBN 978-92-63-11212-5. WMO No. 1212.

Wong, T.H.F., Allen, R., Brown, R.R., Deletic, A., Gangadharan, L., Gernjak, W., Jakob, C., Johnstone, P., Reeder, M., Tapper, N., Vietz, G., Walsh, C.J., 2013. Blueprint 2013: stormwater management in a water sensitive city. In: Wong, T.H.F. (Ed.), Cooperative Research Centre for Water Sensitive Cities (CRCWSC). Monash University, ISBN 978-1-921912-02-3.

Worm, G.I.M., Wuister, J.J.G., van Schagen, K.M., Rietveld, L.C., 2013. Evaluation of control strategies for drinking water treatment plants using a process model. J. Water Supply Res. Technol. - Aqua 62 (4), 234–244.

Wu, W., Simpson, A.R., Maier, H.R., 2010a. Accounting for greenhouse gas emissions in multiobjective genetic algorithm optimization of water distribution systems. J. Water Resour. Plan. Manag. 136 (2), 146–155.

Wu, Z.Y., Sage, P., Turtle, D., 2010b. Pressure-dependent leak detection model and its application to a district water system. J. Water Resour. Plan. Manag. 136 (1), 116–128.

Wuister, J.J.G., Wuestman, R., Rietveld, L.C., Schoonenberg Kegel, F., Bakker, S., 2012. Plate aeration monitoring with soft sensors. In: IT & Water Conference Proceedings, Amsterdam, 2012.

Yang, Q., Peng, Y., Liu, X., Zeng, W., Mino, T., Satoh, H., 2007. Nitrogen removal via nitrite from municipal wastewater at low temperatures using real-time control to optimize nitrifying communities. Environ. Sci. Technol. 41 (23), 8159–8164.

Yuan, Z., Oehmen, A., Peng, Y., Ma, Y., Keller, J., 2008. Sludge population optimisation in biological wastewater treatment systems through on-line process control: a review. Rev. Environ. Sci. Biotechnol. 7 (3), 243–254.

Zacharof, A.I., Schütze, M., Butler, D., 2003. A methodology for assessing the operational potential of the urban wastewater system using integrated modelling. Water Sci. Technol. Water Supply 3 (1–2), 271–277.

Zadorojniy, A., 2016. How We Used IoT Data to Optimize Wastewater Treatment. https://www.ibm.com/blogs/research/2016/08/used-iot-data-optimize-wastewater-treatment/. (Accessed 17 December 2018).

Zadorojniy, A., Wasserkrug, S., Zeltyn, S., Lipets, V., 2017. IBM cognitive technology helps aqualia to reduce costs and save resources in wastewater treatment. Interfaces 47 (5), 411–424.

Zessler, U., Shamir, U., 1989. Optimal operation of water distribution systems. J. Water Resour. Plan. Manag. 155 (6), 735–752.

Zhang, D., Lindholm, G., Ratnaweera, H., 2018a. Use long short-term memory to enhance Internet of Things for combined sewer overflow monitoring. J. Hydrol. 556, 409–418.

Zhang, M., Liu, Y., Cheng, X., Zhu, D.Z., Shi, H., Yuan, Z., 2018b. Quantifying rainfall-derived inflow and infiltration in sanitary sewer systems based on conductivity monitoring. J. Hydrol. 558, 174–183.