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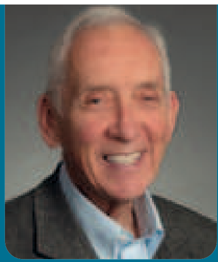
# ARTIFICIAL INTELLIGENCE IN WATER MANAGEMENT AND HYDRO-ENVIRONMENT PROBLEMS

## EDITORIAL BY DRAGAN SAVIĆ & ANGELOS FINDIKAKIS

Last year IAHR published a white paper[1] on the ways that water planning and management can benefit from advances in artificial intelligence (AI) and machine learning (ML). As discussed in this paper, the AI and ML applications in water management and hydro-environment engineering and research have been increasing rapidly during the last few years. In the present issue of Hydrolink, the first of two focusing on AI, four articles describe the use of AI and ML methods in the operation and management of different types of water systems. AI methods and tools have been embraced by many water utilities which use them to support the planning, operation and maintenance of their distribution networks, improve customer service and predict water demand. These utilities often deal with large volumes of data, often referred to as "big data".

**Dragan Savić**
***Guest Editor***



**Angelos N. Findikakis**
***Hydrolink Editor***

The article by Cominola, Monks and Stewart in this issue discusses the application of Artificial Neural Networks (ANNs) on data from smart water meters to predict water demand and increase operational efficiency in water supply systems. In addition, the article points out that advance data analytics in combination with high-resolution smart meter data can increase customer engagement, proactively handle customer complaints and credit management, and provide innovative customer products and services. The vision for the future is that utilities serving different sectors, such as water, electricity, gas, and telecommunications, will be able to identify and exploit synergies in order to share big data and use AI techniques to reduce operating costs and improve service.

The use of AI in water distribution networks is also the subject of the article by Romano, Boatwright, Mounce, Nikoloudi and Kapelan, which describes a system that uses a combination of several self-learning AI techniques and statistical data analysis tools to detect events such as pipe bursts and leaks, as well as equipment and other failures in the network. The system learns from historical events to improve the detection of future events. This system, which was developed for United Utilities in northwest England, significantly improved the ability to deal with such events.

The use of AI and ML for the management of sewers is described in the article by Myrans, Zheng and Kapelan. Artificial Neural Networks and Decision Trees have been used to predict sewer collapse / blockage rates that are critical for proactive asset management of sewer systems. They used data from level, flow and water quality sensors, as well as from other sources, such as closed-circuit television (CCTV) inspection videos in combination with information on the sewer characteristics, environmental conditions and maintenance. ML methods have also been used to detect and predict blockages and to develop models that can predict threshold flow conditions that lead to self-cleansing conditions in sewers. The article presents an example of the use of cutting edge ML and computer vision techniques for the analysis and classification of tens of thousands of CCTV images of sewers of South West Water in the United Kingdom, aimed at identified broken, cracked, deformed or otherwise damaged parts of the sewer network.

AI methods have also been used in environmental problems, as illustrated in the article by Lee, Guo. Chan, Choi, Wang and Leung, which describes the development of a system for the real-time forecasting of harmful algal blooms. The system uses an ANN model that assimilates high-frequency data to predict sea surface temperature (and vertical density stratification) that controls the stability of the water column, one of the two conditions (the other being the level of nutrients) for the algal population to grow. The article also describes the development of a system for the classification of high-frequency microalgae image data that can be acquired in-situ through an imaging FlowCytobot, an automated, submersible equipment that can be continuously deployed underwater for months. The classification system employed a random forest algorithm with robust image processing and feature selection techniques and a pre-trained Convolution Neural Network.

Digitalisation is described as a major technology shock of the 21st century, which is affecting every aspect of our lives, from digital banking and retail to the entertainment industries. Water management and hydro-environmental engineering are no exception to that, but are perceived to lag behind other sectors in coming fully onboard the digitalization train. The articles in this issue of Hydrolink demonstrate clearly the potential of the digital technology applications for water management and hydro-environment engineering, which have already made their impact in practice. The breadth of applications, from water efficiency improvements via smart domestic water metering, through water and wastewater network anomaly detection, to algal bloom management, also demonstrate the level of maturity that has been attained in the development and application of hydroinformatics, a science field pioneered and championed by IAHR members. From the late 1980s and early 1990s, IAHR (together with IWA) was among the first professional organizations to recognize the potential and importance of this new field, by establishing an IAHR/IWA Joint Committee on Hydroinformatics, starting the Journal of Hydroinformatics (published by IWA) and supporting the organisation of a bi-annual conference on Hydroinformatics. Judging by the quality of the papers presented in this issue, the water sector will soon catch up with the sectors and industries that have gone further on the digital transformation curve.

[1] Savić, D. 2019: "Artificial Intelligence: How can water planning and management benefit from it?", an IAHR white paper,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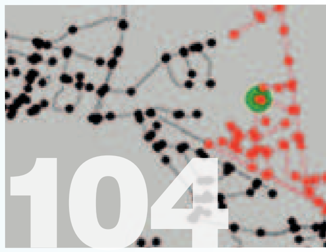
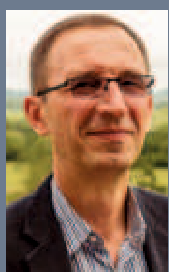
## Artificial Intelligence





## Guest Editor

Dragan Savić is Chief Executive Officer at KWR Water Research Institute based in the Netherlands. He is also Professor of Hydroinformatics at the University of Exeter in the UK and Distinguished International Professor at the National University of Malaysia.

Professor Savić is an international expert in smart water systems with over 35 years of experience working in engineering, academia and research consultancy. His work has resulted in patentable innovation and spinout companies. In addition to innovation and leadership skills, he is known for believing in bridging science to practice in the wider water sector and utilities in general.

He is a long-term member and supporter of IAHR, having served as the Editor-in-Chief of the IAHR/IWA Journal of Hydroinformatics and the Chair of the IAHR Technical Committee on Hydroinformatics.

# MACHINE LEARNING APPLICATIONS IN SEWER SYSTEMS

BY JOSH MYRANS, FEIFEI ZHEN AND ZORAN KAPELAN

**Given the growing scarcity of clean freshwater sources, the water industry as a whole has largely focused on the sustainable distribution and security of potable water. However, the less glamorous task of wastewater management is a constant pressure for all, requiring an equally significant investment into research and development. As if to further highlight this problem, the average age of sewer pipes in the UK is rapidly increasing, with many pipes still in service long past their intended lifespan. This article explores the advances in machine learning which are helping to better manage wastewater (or sewer) networks.**

Since a wastewater network is often expected to collect sewers from all different water users in a particular urban region, its spatial scale as well as the structure complexity has typically substantially increased over the past few decades as a result of population growth and quick urbanization. These physical changes combined with system ageing result in a number of issues during the sewer network management or operation. Typical issues include (i) pipe blockages (e.g., sand sediments) that can directly affect flow capacity of the sewer pipes, causing manhole overflows and odour problems, (ii) illicit inflows (e.g., toxic discharges from local factories, rainwater, and groundwater) that may induce functional failures of wastewater treatment plants (WWTPs) and consequently result in significant contamination of the receiving water body, and (iii) leaks of the sewers that can directly induce serious contamination to the surrounding water environments. To solve these problems, deploying sensors in the sewer networks can be promising, aimed to detect or warn such events in an efficient manner.

Currently, sensors are often only placed at the end of a sewer system, monitoring treatment processes and discharges into the local environment. However, this is slowly changing with the introduction of low-cost robust sensors, providing the network visibility required to inform and improve pipe maintenance and rehabilitation. This constant stream of data can provide many insights into the status of a network, although many of these are hard to spot with only human eyes. Fortunately, machine learning thrives in the age of data, capable of interpreting patterns in vast quantities of data that no human being could ever hope to identify. These data driven techniques have been well demonstrated in many other professional sectors including telecommunications, gas/oil and finance, where inordinate quantities of data are produced every day.

Working with cutting edge AI technology provides the wastewater industry with a wealth of opportunities for more efficient means of practice. The strengths of machine learning include the ability to rapidly process and highlight trends and patterns in enormous volumes of data. From this skillset we can achieve the automation of tasks that would be extremely time consuming and tedious for a trained professional, real time analysis of sensor data and effective management of complex interrelated systems. This article will discuss a number of successful applications of machine learning within the wastewater sector, providing a number of examples, including one with more in-depth information.

## Machine Learning in sewer Management

Artificial Intelligence (AI) and Machine Learning (ML) in particular are playing an increasing role in the management of sewer systems, ranging from improved operation and maintenance of these systems to their long-term planning and asset management. Most of AI based solutions are built around smart processing of some data and extracting the useful information from it[5]. The data often comes from various sensors installed in these systems (e.g. level, flow and water quality sensors) but frequently from other sources too (e.g. inspection CCTV videos, digital maps, asset data, etc.). The current situation in most water and sewer utilities is often described as DRIP – Data Reach Information Poor. AI/ML enables to solve this problem by extracting useful information from large amounts of data and using it for improved management of sewer systems.


**Dr Josh Myrans** is a Data Scientist at the University of Exeter partnered with the UK water company: South West Water. He graduated from the University of Exeter in 2014 with a BSc in computer Science and Mathematics, before continuing to complete his PhD in Water Informatics Engineering in 2018 (also at Exeter University). Josh has been working within South West Water as a KTP associate since November 2018, where he continues to develop his postgraduate research for practical application within the water industry.

**Professor Feifei Zheng**, a PhD from the University of Adelaide, Australia. He is now a Professor in Zhejiang University, China, with research focus on design and operation of water infrastructures, hydroinformatics, as well as decision support systems for various water systems. He has led 12 research and consulting projects from national natural science foundation of China and various water utilities, and has published more than 50 journal papers in his research area.

**Professor Zoran Kapelan** is a Professor at the Delft University of Technology in the Netherlands where he is leading a research group on urban water infrastructure. He also holds a part-time professorial position at the University of Exeter in the UK. He is an IWA Fellow with 30 years of research and consulting experience in water engineering. His research interests cover a wide range of challenges related to water and wastewater infrastructure including development of various machine learning based technologies. Prof Kapelan pioneered the award winning burst/leak detection technology that is now used companywide in one of the largest UK water utilities resulting in large savings via reduced operational costs. He has published over 150 peer-reviewed journal papers.

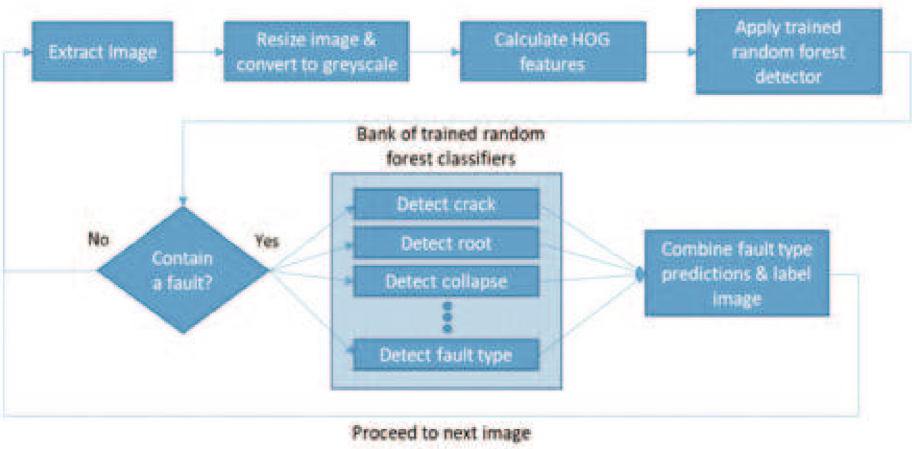



**Figure 1. Flowchart depicting the process of applying automated labelling to raw images.**

Some of the examples of ML methods developed for sewer systems include:

- ML for predicting sewer collapse/blockage rates and the remaining asset life.
  ML methods such as Artificial Neural Networks and Decision Trees have been used to predict sewer collapse / blockage rates that are critical for proactive asset management of sewer systems [1]. Most of these methods work by establishing a link between the above variables and potential explanatory factors such as sewer characteristics (e.g. pipe material, diameter, slope, condition), the environment (e.g. soil type, weather) and other factors (e.g. maintenance level). This data is used by the AI method to effectively learn under what combination of conditions sewer blockages or collapses occur.
- Early warning systems for blockages and other events in sewer systems. ML methods such as advanced Artificial Neural Networks and Fuzzy Theory have been combined with fault detection and isolation methods such as Statistical Process Control to detect or even predict blockages in sewer systems by raising alarms in near real-time [10]. Detection is typically done in the case of more instantaneous blockage events whereas prediction is usually more accurate for the gradually forming blockages (e.g. due to siltation or fat/oil/grease build up).
- Flood risk assessment and forecasting. The Cellular Automata based methodology has been used to predict the extent of flooding in the urban environment [6]. When compared to more conventional methods, these and similar ML-based methods tend to be computationally much faster yet accurate enough which enables their application over much larger geographical areas and/or in flood forecasting in the near real-time context.
- Augmented Reality (AR) for improved visualisation and inspection of sewer system assets. AR methods that combine Virtual Reality with conventional video feeds have been used to enable improved visualisation of sewers and other underground assets. This may involve presentation of other data of interest (e.g. asset characteristics, current or predicted water level at the location, etc.). These methods provide great help to technicians doing work in the field.
- Sewer self-cleansing. ML methods such as Random Forests have been used to develop models that can predict threshold flow conditions that lead to self-cleansing conditions in sewers [8]. This, in turn, can be used for the (re)design of these systems that ensures more effective sediment transport in sewer systems.
- Real-time (online) modelling of sewer system. Data is crucial to enable the applications of various ML methods. Unfortunately, in many cases system state observations (e.g., i.e. flows, water depth and other state variables) are scarce. Sensor data can be used to enable the estimation of sewer system state at different locations in the system, especially where sensors are not present. For example, a research group from Zhejiang University in China has successfully utilized the water supply data in a novel way to drive the real-time simulation of the wastewater network [11]. The key feature of this modelling approach is the novel use of smart demand metering sensors from the water supply systems to enable more accurate state estimation of sewer systems. This, in turn, enables to develop real-time sewer models in a more cost-effective manner.
- Real-time sewer sensor data validation. Bayesian type methods have been combined with Neural Networks and Interval Mathematics to validate sensor data on flows, depths, electro-conductivity) in near real-time [2].

Note that the above examples present only a small sample of AI/ML methods and applications for improved management of sewer systems. The next section presents another, more detailed example of a successful ML-based solution for solving a real-world challenge in these systems.

## Automated sewer condition assessment using CCTV analysis

### Background

Currently the most common method of inspection for sewers is through the use of CCTV cameras, which traverse the network recording footage of the pipe interiors for analysis by trained technicians. These surveys are performed regularly and are vital to the effective maintenance of the network. However, most networks contain tens, if not hundreds of thousands of kilometres of sewer pipe, resulting in a constant stream of CCTV footage which must be manually reviewed. The labour-intensive nature of this task, makes it both time consuming and expensive. Furthermore, surveys are commonly mislabelled due to subjective fault codes and pure human error. With some cameras footage can instead be labelled as it is collected, making the process more efficient. However, the accompanying analysis is often even worse, with technicians now performing multiple jobs at once, working in the elements and often next to a busy road.

Fortunately, AI can begin to improve upon this vital practice, automating elements of the analysis procedure in real time, so as to take the pressure off of the surveyor. Not only should this improve the speed and efficiency of a survey's collection, but dramatically reduce the cost and improve the uniformity of analysis. Removing the pressure of annotation from the surveyors enables them to concentrate on capturing high quality footage, only requiring additional input for the annotation of the most obscure faults.

### AI-based methodology

To achieve automated fault detection and classification, a number of cutting edge machine learning and computer vision techniques are applied, namely random forests [3] and HOG (Histogram of Oriented Gradients) features [4]. In combination with a large dataset of labelled CCTV images these tools can first identify the presence of faults within an image, continuing to predict each individual fault type. This is done according to current industry standards, so as to produce a simplified report similar to that already used by the industry. Given the expedient and transportable nature of these techniques, the entire process can be performed in real time on site, in an office or on a server.

The procedure can effectively be broken down in to five stages: 'Frame Extraction & Pre-processing', 'Feature Extraction', 'Detection', 'Classification' and if applied to continuous footage 'Smoothing' [9]. The tasks associated with each stage are presented in the process diagram shown in Figure 1 require the collection of the image from the source video before re-sizing the image to match a uniform resolution and converting to greyscale. These two steps bring the data in line with the training set and eliminate unnecessary complexity from the image. This complexity is further reduced during the 'Feature Extraction' stage, where the image is reduced to a much smaller string of values representing its key components, this is done using HOG feature description. The next stage 'Detection' passes the feature descriptor to a single pre-trained random forest, which predicts the probability of the original frame containing a fault. If this is below a pre-determined threshold, the image is labelled as normal and the cycle restarts on a fresh image, otherwise a fault has been identified.

Once a frame is suspected to contain a fault the 'Classification' stage can occur, in which the feature descriptor is passed to a bank of random forests. Each of these random forests predicts the probability of the image containing a single fault type, i.e. that there is a single forest for cracks, a single forest for root intrusions etc. By combining and evaluating these predictions in a pairwise manner, a list of the most probable fault types can be identified for this image. Finally, if the image has been extracted from a continuous video source, additional information can be gained by comparing predictions to those of neighbouring frames. This is achieved during the 'Smoothing' stage, which applies a median filter among other techniques to process the entire sequence of predictions throughout a video. Amending predictions in this way massively reduces the impact of noise and eliminates many isolated misclassifications, producing a list of predictions much more in line with a surveyor's expectations.

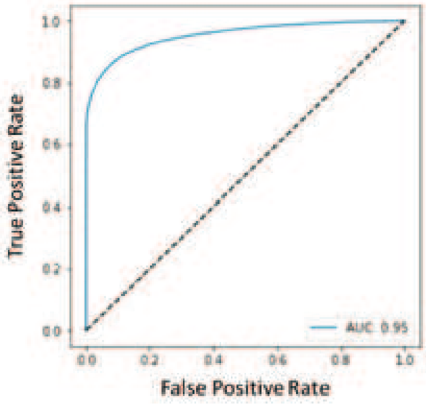



**Figure 2. Receiver operator characteristic curve, demonstrating the range of achievable true (TPR) and false (FPR) positive rates. The dashed line represents the TPR and FPR for a 50:50 guess. Finally, the AUC (area under curve) is a measure of the methods overall performance.**

It should be noted that all random forest classifiers will require training on a labelled dataset of images, processed using exactly the same 'Frame Extraction & Pre-processing' and 'Feature Extraction' stages as those intended for use on the video. This training sees each tree in a forest grown by randomly selecting features and splitting the training dataset according to their pre-assigned labels.

**Results**

This automated fault analysis has been performed in collaboration with the UK water company South West Water (SWW). This has granted access to a library of over 60,000 images, around half of which contained at least one labelled fault. In order to demonstrate the AI technology all these images are utilised via 25-fold cross validation [7]. This system ensures that training and testing datasets are not mixed, whilst making the most of the available data. Furthermore, the data has been arranged so as no images from the same pipe are present in both a training and testing fold.

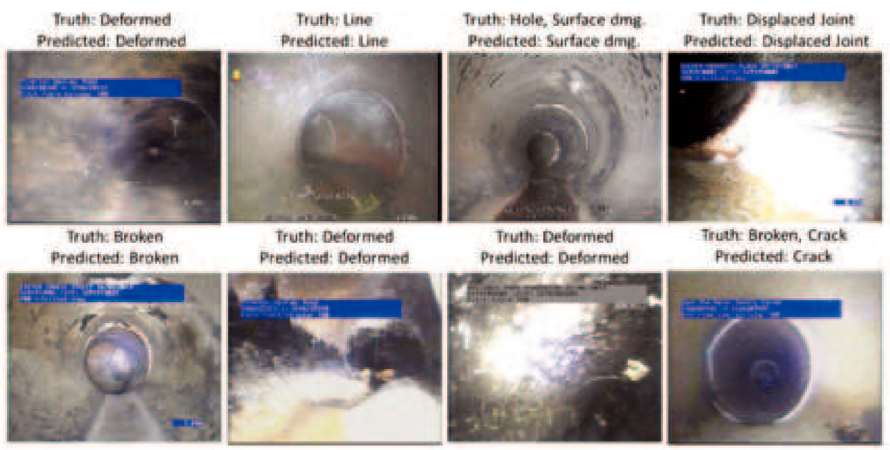
When the above approach was applied to the full dataset of labelled images an accuracy of 88% with a true positive rate (TPR) of 0.98 and a false positive rate of 0.24 was achieved. This means that the methodology correctly identified the status of the pipe 88% of the time, whether that be normal or faulty. Additionally, from the misidentifications, only 2% were missed defects and 24% were mislabelled normal pipe. By modifying the threshold on which an image is classified as faulty, the ratio between TPR and FPR can also be tweaked, as demonstrated by the receiver operating characteristic cure shown in Figure 2.

Applying the process of classification to detected faults, we must now acknowledge that a single image can contain multiple fault types. To do so, the methodology's results are evaluated using intersection over union (IoU), which measures the similarity of the predicted list of fault types with the true list of fault labels for a given image. This is a much more challenging task, assuming an image contains only a single fault, guesswork alone will only achieve an IoU of 6% (as we are using 18 different labels).

Although only a prototype, the methodology performs well, achieving an IoU of 35% and an accuracy on the primary fault of 70%. This performance is constantly improving, with the increased availability of high-quality labelled data. A handful of examples are shown below in Figure 3.

It is also worth noting that these results are achieved using the labels assigned by the human observers which we know can be

**Figure 3. Example images and the classifications generated by the machine learning algorithm.**



inconsistent. A recent quality survey of 5% of the dataset found more than 30% of the labels to be incorrect, and 10% of them to be uninterpretable. Anecdotally this is good for the industry in general, however this does not bode well for the performance of data driven methodologies such as this.
This first step in the application of AI to the problem offers a great option for screening vast amounts of CCTV footage. It is much quicker than human analysis and can be performed outside of work hours in a massively parallel manner. Given its current role as a decision support tool, it can assist with operational efficiency, but continued development and increased data quality provide great prospects.

## Conclusion

This article addresses the use of Artificial Intelligence and machine learning in particular in the daily management of sewer systems. Several examples of such applications are provided including the technology for automated detection of faults in sewers.

This technology is a good example of how machine learning and AI can be influencing the wastewater sector. Current practices rely on the slow and expensive, human based coding of CCTV sewer surveys that is not always fully reliable. The machine learning based technology enables the automation of some of that process, accurately and more consistently identifying the presence of faults whilst providing a good estimate of potential fault types. Therefore, the AI-based solution has a great potential to help technicians do their job more effectively in the future whilst reducing related costs.

Based on the above and other examples presented in the paper it is clear that the future of AI and machine learning in the wastewater sector is bright and that the full potential of these methods is yet to be fully explored. ■

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# AI–BASED EVENT MANAGEMENT AT UNITED UTILITIES

BY MICHELE ROMANO, SHAUN BOATWRIGHT, STEVE MOUNCE, EIRINI NIKOLOUDI AND ZORAN KAPELAN

**Nowadays, water companies in the UK and worldwide face a significant challenge as they have ageing assets, have to deal with budget and resource constraints and, yet, they need to meet increasing customer expectations. To effectively respond to network events (e.g. pipe bursts/leaks, equipment failure, etc.), water companies must proactively manage the full life-cycle of events in the right priority and in a speedy manner. This will drive a higher efficiency in water network operations and result in much higher customer satisfaction. As digital technologies are penetrating every aspect of our society, the water sector is starting to leverage them to enable the move from reactive to proactive event management. This article presents three examples of the work that United Utilities has carried out in collaboration with two leading UK Universities to improve event management practices by using Artificial Intelligence (AI), Machine Learning (ML) and other advanced analytics techniques. These examples demonstrate not only the power of these technologies, but also that water companies can benefit from their adoption as they enable them to efficiently take a holistic, fully managed life-cycle of events approach.**

Within the UK and worldwide water industry, pipe bursts/leaks and other similar failure events are recognised as high priority issues. These events cause economic losses to the water companies, represent an environmental issue and have a negative impact on the water companies' operational performance, customer service and reputation. Water companies currently allocate a vast amount of resources to manage these events, but with limited success. The largest barriers to progress in the UK are the complexity of Water Distribution Systems (WDSs), ageing water supply infrastructure and unknown/unknowable condition of assets which make these events impossible to eliminate/avoid completely. In their day-to-day operations, water companies are tasked with operating their WDSs optimally to minimise costs and meet the required standards of service and, therefore, also managing contingency situations when events occur. In this scenario, an efficient event management process provides opportunities to improve the situation (e.g. by reducing the number/ duration of supply interruptions, conserving water and reducing the overall carbon footprint).

Event management in WDSs can be divided into three principal stages[1]: 1) event detection, 2) event location and 3) event response. The first two stages involve detecting and localising the event in the network and raising the relevant alarm. The third stage is associated with the decisions and actions required to reduce and, ultimately, eliminate the negative impact of the event on the water company and its customers.

In the last decade the importance of a proactive approach to event management, supported by near real-time assets monitoring, has become apparent as water companies in the UK have had to deal with tightening regulatory and budgetary constraints. Instrumentation, data gathering and communication technologies have also improved over the years and become less expensive to own and operate. As a result, a vast array of pressure and flow data originating from the many District Metered Areas (DMAs) that typically form a UK WDS is now frequently available and expected to quickly grow over time (especially data from pressure sensors, because of their lower cost and easier installation and maintenance when compared to flow sensors). The flow is nowadays typically measured at the DMA entry and exit points to allow the volume of water consumed in each DMA to be tracked over time and pressure is measured at a limited number of DMA critical monitoring points to ensure adequate pressure at the customers' taps.

The above monitored data can give insights into the operation and current/future status of WDSs (including pipe bursts/leaks and other similar events), especially when coupled with suitable data driven techniques. Advances in these techniques utilising advanced statistical tools, Machine Learning (ML) and Artificial Intelligence (AI) have led to the development of pioneering techniques that automatically manage and analyse increasing numbers of near real-time data streams aiming at enabling the detection[2-6], approximate location[7-9] and response[10,11] to pipe bursts/leaks and other similar network events. These techniques are very promising for alerting the water company personnel as soon as an event occurs, guide them to the problem area (i.e. for narrowing down the event search area within a DMA) and for supporting the control room operators in the identification of a suitable strategy to respond to those events in near real-time. This is mainly because they automate the mundane tasks involved in the data analysis process, provide more consistent analysis of the data and because they can efficiently deal with the vast amount of, and often imperfect, sensor data collected by modern supervisory control and data acquisition (SCADA) systems and extract information useful in making reliable operational decisions.

United Utilities has had a longstanding relationship with some of the, water systems engineering and hydroinformatics, leading UK Universities and in recent years has initiated a number of collaborative innovation projects with them. In some cases, these collaborations have taken advantage of programmes such as STREAM (the Industrial Doctoral Centre for the Water Sector - http://www.stream-idc.net) and WISE (Water Informatics: Science and Engineering Centre for Doctoral Training - http://wisecdt.org.uk) that are partially funded by the Engineering and Physical Sciences Research Council (EPSRC) and involve having a student based at United Utilities' headquarter pursuing an Engineering Doctorate (EngD) or Doctor of Philosophy (PhD) degree for industrially relevant research. These programmes are therefore also valuable as they enable the training of people capable of working at the interface of traditionally separate informatics, science and engineering disciplines and who understand both data science and the complexities of water challenges.

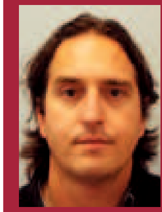
This article presents three complementary examples of the research work carried out in collaboration with the University of Exeter and the University of Sheffield to improve event management practices. Specifically, the first example focusses on event detection, the second example focusses on approximate event location and the third example focusses on post event response planning. These examples show how United Utilities is pursuing a fully managed life-cycle of events by taking a holistic approach to addressing the challenge of optimising the decision-making process of different teams in order to achieve the required level of service and the best utilisation of the assets at a minimum cost with an effective response time to all events. Indeed, a comprehensive, efficient and effective event management solution is key to such an optimisation challenge, which encompasses cross-organizational functions and works across different management levels.

**Event detection**

The first objective of a comprehensive event management solution is to provide near real-time, actionable event alerts such as, pipe bursts/leaks, pressure/flow anomalies, and sensor faults / telemetry problems. This enables water companies to become aware of all the events occurring in a timely fashion and better manage the situation, armed with valuable insights about these events (e.g. type, size, indication of their timing, etc.). This section briefly presents an AI-based system[4,5] that not only detects pipe bursts/leaks but also equipment and other failures in WDSs. This section additionally provides a couple of examples of the significant impact that this system has had on United Utilities' ability to deal with events in its WDS.

The detection system briefly presented here makes synergistic use of several self-learning AI techniques and statistical data analysis tools. In the detection system the automatic processing of pressure and flow data communicated by the DMA sensors in near real-time starts with using advanced techniques for ensuring that the data is cleansed and erroneous/missing data removed and/or infilled (e.g. wavelets are used for removing noise from the measured flow and especially pressure signals). The detection system then makes use of the pre-processed data to forecast the signal values in the near future using Artificial Neural Networks (ANNs). These values are then compared with incoming observations to collect different pieces of evidence about the failure event taking place. Statistical Process Control (SPC) techniques are also used for the analysis of the failure event -induced pressure/flow variations and gather additional pieces of evidence about the event occurring. The evidence collected this way is then processed using Bayesian Networks (BNs). BNs enable reasoning under uncertainty and simultaneously (synergistically) analysing multiple event occurrence evidence and multiple pressure/flow signals at the DMA level to estimate the likelihood of the event occurrence and raise corresponding detection alarms. The system also offers the capability to effectively learn from historical events to improve the detection of the future ones[5] (albeit it does not need information about historical events to start making reliable event detections when first applied to a DMA/WDS). It does not make use of a hydraulic or any other simulation model of the analysed WDS - i.e. it works solely by extracting useful information from sensor signals where bursts and other events leave their imprints (i.e. deviations from normal pressure and flows signals). This fact makes the detection system robust and scalable as it enables data to be processed in near real-time (i.e. within a 15 minute time window).

Elements of the aforementioned detection system, developed initially as part of a research at the University of Exeter, have been built into United Utilities' new Event Recognition in the Water Network (ERWAN) system. The ERWAN system's development carried out in United Utilities also benefitted by the following additional technology enhancements: a) development of a new methodology to add the capability to handle alarms from cascading DMAs[12], b) development of a new methodology to add the capability to rank alarms (based on a risk framework that accounts for factors such as mains length, material, number of industrial and key customers in a particular area of the water network), and c) development of a new methodology to add the capability to determine the likely root cause of an event. These enhancements have provided United Utilities additional, helpful event management tools. The ERWAN system has been used operationally companywide since 2015. It processes data from over 7,500 pressure and flow sensors every 15 minutes and detects events such as pipe bursts and related leaks in

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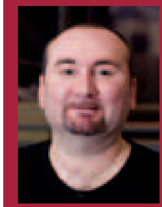
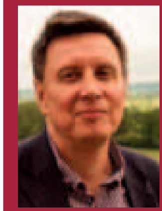
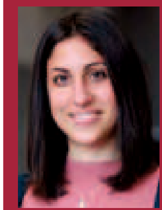


**Dr Steve Mounce** is a Visiting Research Fellow in Hydroinformatics at the University of Sheffield and the Director of Mounce HydroSmart Ltd. His PhD is in Computer Science and he has over twenty years of experience on research projects with over 100 academic publications. His research combines Artificial Intelligence and Water Engineering for such applications as leakage (including smart meter data mining), CSO analytics, water quality and burst event detection systems and fuzzy RTC.



**Professor Zoran Kapelan** is a Professor at the Delft University of Technology in the Netherlands where he is leading a research group on urban water infrastructure. He also holds a part-time professorial position at the University of Exeter in the UK. He is an IWA Fellow with 30 years of research and consulting experience in water engineering. His research interests cover a wide range of challenges related to water and wastewater infrastructure including development of various machine learning based technologies. Prof Kapelan pioneered the award winning burst/leak detection technology that is now used companywide in one of the largest UK water utilities resulting in large savings via reduced operational costs. He has published over 150 peer-reviewed journal papers.

**Shaun Boatwright** is an EngD candidate, based at the University of Sheffield and working with United Utilities, a large water company based in the UK, to develop a technique for localising leak/burst events in water distribution systems. He previously graduated with an MEng in Mechanical Engineering before working for a large engineering design consultancy on a number of potable water and wastewater projects for several UK water companies.



**Eirini Nikoloudi** is a WISE CDT student at the University of Exeter where she is pursuing a PhD degree. She obtained a MEng in Civil Engineering from National Technical University of Athens (NTUA) in 2015.

a timely and reliable manner - i.e. shortly after their occurrence and with high true and low false alarm rates.

Compared to previous company practice the ERWAN system has enabled United Utilities to detect pipe bursts and other failure events much more quickly. As an example, on the 31st of May 2016 there was a catastrophic failure of a 450 mm diameter main in the town of Formby which affected 10,600 properties. Using the ERWAN system the burst was identified more than three hours before the customers reported any disruption. This early event detection ensured planned responses were therefore deployed quicker. This also meant that customers were disrupted less as Alternative Supply Vehicles (ASVs – i.e. emergency tankers injecting water into the network) were deployed while the main was repaired. United Utilities estimates that this proactive response reduced interruptions to supply by 42%. Additionally, the ERWAN system has also demonstrated the potential to proactively prevent failures in some cases, e.g. via timely detection of faulty Pressure Reducing Valves (PRVs) often resulting in a follow-on pipe burst event(s). As an example of this situation, Figure 1 shows the ERWAN alert that was generated on the 9th of September 2019, indicating that the pressure had increased in a DMA. This alert prompted the Early Detection Team (EDT) to investigate the issue and immediately schedule a job for a minor PRV service as the automatically identified root cause suggested a fault of that asset. During that site visit, it was identified that the PRV had failed 'open'. Further work was then scheduled for a network resource to carry out a major service on the asset. Proactively identifying that issue with the PRV may have prevented a pipe burst in the relevant pressure-controlled DMAs (especially considering the observed significant pressure increase). The potential impact of such a failure would have been in excess of £900k in Customer supply Minutes Lost (CML) penalty cost alone, with the ASV fleet and resource utilisation costs and the disruption to the customers adding to that.

The use of the ERWAN system has resulted in major operational cost savings (due to the reduced number of pipe bursts/leaks needed to detect and repair) to date and contributed to United Utilities' CML, leakage and Customer Measure of Experience (C-Mex) performance (due to the avoidance or reduction in issues such as poor water pressure, no water, or poor water quality - therefore improving the service to over 7 million people and 200,000 business

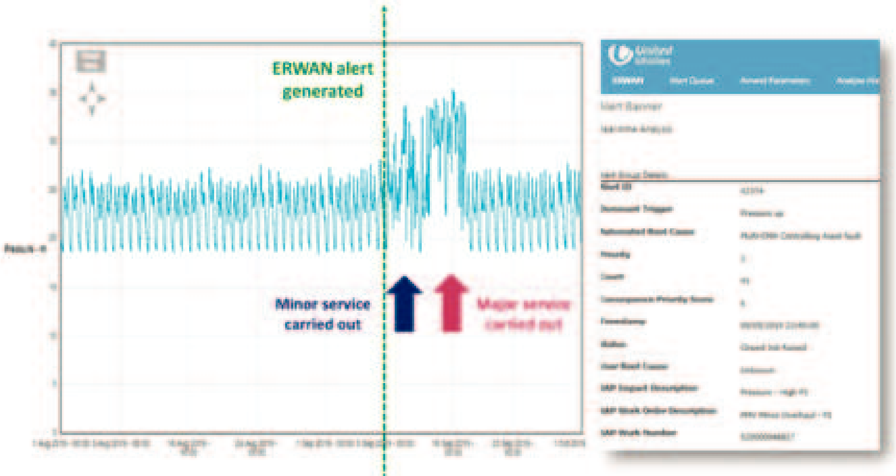



**Figure 1. ERWAN system alert indicating a sudden pressure increase, likely due to a faulty pressure reducing valve.**

customers). It has also reduced asset maintenance costs by informing the need for maintenance prior to asset failure, and avoiding unneeded maintenance visits. Operational costs are also reduced as it enables problems to be dealt with proactively which is much less expensive than dealing with asset and service failures.

Furthermore, the success of the ERWAN system has been important to influencing change in the ways of working (e.g. making better use of data analytics in the daily operation) and the establishment of the EDT in United Utilities' Integrated Control Centre (ICC). The ICC is the hub of United Utilities' operations where a team of highly trained system operators watch over the network 24/7. They use the information and insight provided by ERWAN and other monitoring systems to perform complex event diagnosis and, by making intelligent decisions in the centre, prevent abortive work for field staff and resolve disruption for customers faster. Increasingly, through control and automation, the ICC can intervene remotely to resolve issues faster and more efficiently. This hub is one of the cornerstones of United Utilities' AMP7 (Asset Management Plan five-year time period used in the English and Welsh water industry) Systems Thinking strategy and will catalyse future benefits.

### Event location

After it is established that an event has occurred in a DMA by using automated systems such ERWAN, the next challenge in event management, especially when pipe burst/leak events are considered, is to determine the exact event location. Typically, network resources are deployed to DMAs containing new burst/leak events so that they can be precisely located (or "pinpointed") and then repaired. There are many cases, such as when the size of a burst/leak event is small, where their location is not readily apparent. In these cases, resource intensive pinpointing activities such as acoustic surveys are carried out so that each of the pipes in a DMA can be examined to find the exact burst/leak location. It can take several days to examine all the pipes in a DMA as, in United Utilities for example, the typical total length of mains is about 13 km. This represents a significant investment of labour, equipment and operational expenditure when this approach is used across an entire WDS. In this scenario, a methodology that enables narrowing down the area that must be searched within a DMA (i.e. approximately locate the event) would be greatly beneficial for water companies.

This section briefly presents the details of a novel methodological framework[9] for the approximate burst/leak location that is being developed as part of a collaboration with the University of Sheffield and one example of its application to a burst event simulated by the controlled opening of a fire hydrant in a United Utilities' DMA. This framework assumes that an increased number of pressure sensors can be deployed in the DMA being analysed. Due to the financial constraints placed on water companies and the costs of the additional instrumentation required, however, it is desirable to limit the number of additional instruments to be deployed. Therefore, the methodological framework being developed also encompasses a method for selecting the optimal number and location of sensors to be deployed in a particular DMA to achieve a desired level of event location performance. This tight coupling between optimal sensor placement and approximate burst/leak location is of particular importance as an optimal sensor placement strategy depends on the method that is used to locate the potential bursts/leaks and the efficiency of the burst/leak location depends on the sensor placement.

The novel methodological framework is based upon a Spatially Constrained version of the Inverse Distance Weighted (SC-IDW) geospatial interpolation technique[13]. Generally speaking, geostatistical techniques have the potential to limit the number of instruments which are deployed in a DMA as they can estimate the values of parameters at locations which are not measured based on the measurements from nearby sensors and, hence, to enable higher burst/leak location performance to be achieved for a given number of sensors[14]. Bearing this in mind, the use of SC-IDW enables the overcoming of the obvious limitation of traditional geostatistical techniques of using the Euclidean distance instead of the pipe length between the estimation locations and the instrument locations (i.e. not accounting for the actual network layout of a DMA). The framework makes also use of a hydraulic model and of the GALAXY multi-objective evolutionary algorithm[15] (i.e. a nature inspired AI methodology) to identify a Pareto front of optimal sensor configurations which simultaneously minimise the required number of pressure sensors (cost) and the average size of the areas to be searched (best level of burst/leak approximate location accuracy).

The first step for solving the optimal sensor placement problem involves hydraulic modelling of bursts/leaks at all nodes and building a sensitivity matrix. The valid range of burst/leak event sizes to be modelled is determined for each DMA by considering the accuracy of the pressure instruments being used (to find the smallest burst/leak event sizes) and a maximum allowable increase in flow (to determine the largest burst/leak event sizes for each burst/leak event location). The aforementioned sensitivity matrix is based on the changes in pressure for each potential sensor location, which are calculated by comparing the pressure in the hydraulic model with no burst/leak modelled with the pressure in the model with each burst/leak modelled. Additional computations are then conducted aimed at reducing the search space of the optimisation (i.e. grouping together events that cannot be distinguished given the pressure instruments' accuracy). Following this, the values of the pressure changes in the 'grouped' sensitivity matrix are used for building various interpolation surfaces during the optimisation step, which aims at maximising (using an objective function also based on the SC-IDW interpolation technique and a threshold that defines the burst/leak search area on an interpolation surface) the location performance of each configuration of sensors for every burst/leak being modelled. After determining the optimal sensors configuration by looking at the results of the optimisation step (and after deploying the pressure sensors in the field), the SC-IDW interpolation technique can be used operationally to calculate the approximate location of an actual burst/leak occurring in a DMA (once a burst/leak has been detected or is suspected) based on the actual changes (from 'normal') in pressures measured at the sensor locations. The calculated search area is then highlighted on a map of the DMA, which is passed to network resources to aid with pinpointing the burst/leak event.

Figure 2 shows an example of such a map generated for the approximate location of a burst event simulated on the 14th of February 2020 by the controlled opening of a fire hydrant (so that the exact size and start time are known) in one of United Utilities' DMAs. This DMA contains approximately 2,100 properties and 25 km of mains. A PRV controls the pressure in one section of the DMA because of the highly variable elevation in the area. The fire hydrant opening was adjusted to achieve a flow rate of 0.6 l/s which is equivalent to approximately 6% of the average flow rate into the DMA calculated over a normal week. In Figure 2, the locations of the three optimally placed pressure sensors (determined by considering a total of 934 potential burst/leak event scenarios across 7 burst/leak event sizes) are shown as blue dots. The location of the opened fire hydrant is shown as a green dot. The pipes and nodes within the calculated search area are coloured in red. It can be noticed that this event was successfully approximately located within a search area that is less than a quarter of the total length of mains in the DMA. This example demonstrates the potential of the methodological framework being developed to allow successful approximate location of relatively small burst/leak events by using only a few additional optimally placed pressure sensors. This said, it is expected that the search areas can be further reduced by deploying more sensors. Nevertheless, by reducing the search area to a sub-region within a DMA, significant reductions in the time taken to pinpoint burst/leak events can be achieved (e.g. by ¾ as exemplified here).

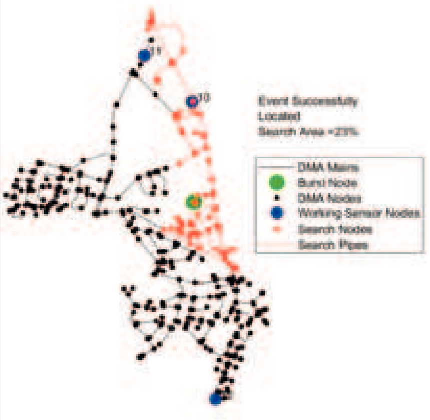
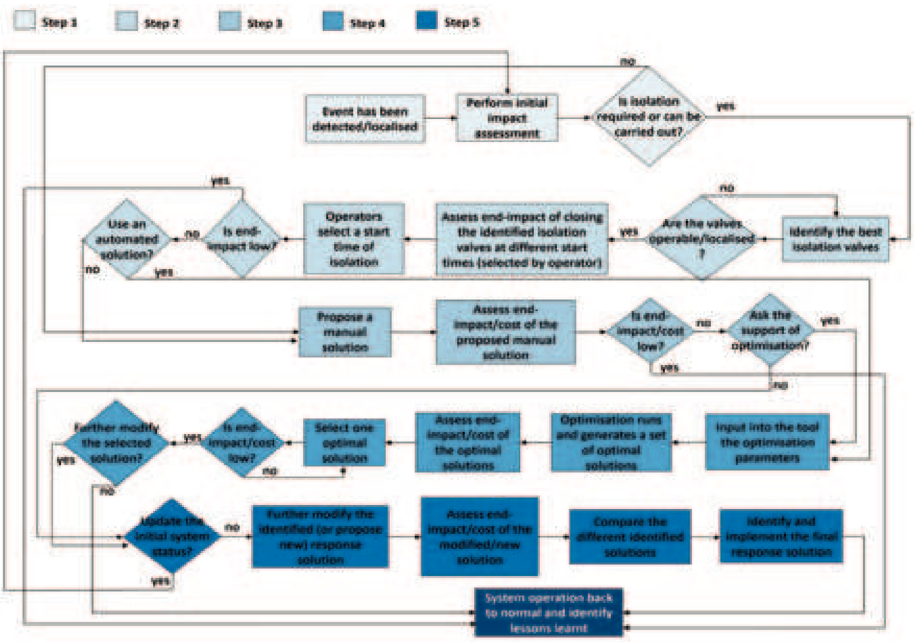


**Figure 2. Example of a successful approximate burst location.**

**Figure 3. New response methodology's flowchart.**



**Post event response**

After successful detection and location of events, the next considerable challenge for water companies during the event management process is the identification of a suitable strategy to respond to those events in near real-time. This section briefly presents the details of a novel methodology[11] for the response to water network events that is being developed as part of a collaboration with the University of Exeter and the initial, promising results obtained from its application on a semi-real case study.

The novel event response methodology presented here aims at improving United Utilities' current event response practice by supporting/guiding the ICC operators in the identification of low end-impact (i.e. the total impact after implementation of the response solution) and low cost response solutions. It consists of the following main steps: (1) robust initial event impact assessment (over a set horizon), (2) identification of a suitable isolation plan, (3) human-based, but computer-aided, identification of a response solution (i.e. manual solutions proposed by an operator), (4) automatic identification of a response solution generated using Genetic Algorithms (GAs) optimisation, and (5) selection of the response solution to be implemented in the field. Note that these five steps do not need to be necessarily carried out in a sequential manner. The following three-stage routine is performed in each of the aforementioned step: Stage 1) involves obtaining various operators' inputs (e.g. impact horizon, earliest time the repair can be initiated, etc.), Stage 2) involves carrying out hydraulic simulations to assess the end-impact and cost of each solution, and Stage 3) involves visualising the calculated end-impact and computing the cost of each solution. The new response methodology's steps are shown as a flowchart in Figure 3.

The above event response methodology is implemented in the Interactive Response Planning Tool (IRPT), which has been developed in Matlab. In the IRPT, the hydraulic simulations are carried out by using EPANET2[16] and pressure-driven network modelling based on the methodology developed by Paez et al.[17]. The Non-Dominated Sorting Genetic Algorithm II or NSGA II[18] (i.e. another AI tool/technique) is used to solve the multi-objective optimisation problem (albeit work has also been done to develop and use a new heuristic method that offers the advantage of significantly reducing the time taken to find near-optimal response solutions). The IRPT also links to the Quantum Geographic Information System (QGIS) software to visualise the spatial distribution of end-impact on a suitable map of the analysed WDS.

The IRPT facilitates an operator's decision-making by considering/providing: (i) structured yet flexible approach that supports and guides the operator throughout the entire response process, whilst allowing the operator to have a final say, (ii) novel interaction with the operator in near real-time via the simple IRPT graphical user interface (e.g. allowing operators to propose different 'what-if' scenarios without being hydraulic experts), (iii) provision of automatically generated advices (e.g. optimal response solutions and assessed end-impacts/costs), (iv) improved impact assessment using realistic (i.e. based on real-life metrics used by water utilities) impact indicators that cover different aspects of the event, which are consistently calculated for every considered response intervention, (v) capability to select multiple common operational intervention types such as rezoning and water injection (based on operational costs, availability of different types of interventions, etc.), and (vi) capability to easily compare different response solutions by visualising, inter alia, the impact coverage (using maps) and cost of different solutions. As a result, low end-impact and cost solutions can be effectively identified. This has multiple benefits for a water company. The most important benefit is reducing the impact on the customers, which can be costly in many ways (financially but also in terms of reputation, etc.). Other benefits related to costs include: a) operational savings in the long-term as many events may occur each year - although the cost of a single response solution may be small (e.g. hundreds of pounds), and b) less time spent on site for opening valves or injecting water - this could benefit water companies in terms of more efficient scheduling of the network resources' activities.

The IRPT is illustrated here on a semi-real case study to demonstrate the benefit of a response solution identified through interaction with the IRPT (hereafter referred to as the 'new methodology response') by comparing it to a response solution based on typical water companies' current practice (hereafter referred to as the 'current practice response'). Note that the case study under scrutiny is referred to here as "semi-real" because, despite being based on a real system and event, several simplifications were made with regard to the actual response actions taken by the ICC operator in real-life. This is primarily because the IRPT is still in development and did not yet offer the capability of exactly replicating those real-life response actions. Bearing this in mind, note that the used 'current practice response' label should also be construed accordingly. The considered event was a shutdown of a Water Treatment Work (WTW) (serving multiple DMAs and approximately 100,000 customers) due to a burst on a main within the WTW. The shutdown resulted in intermittent supply and low pressure to some customers. The WTW remained shut until the quality of the water leaving the WTW could be assured to meet the required standards. United Utilities mobilised ASVs to the area, which injected water at various points in the affected area and at different times during the incident.

Furthermore, United Utilities implemented a number of network changes (i.e. rezoning) in order to minimize customer end-impact. Bottled water was delivered directly to priority services and sensitive customers. The repair was completed 24 hours after the shutdown. Table 1 summarises the result obtained on this case study in terms of the total end-impact and the cost calculated by the IRPT for the 'new methodology response', 'current practice response' and 'no response' (i.e. initial condition of the system after the event) scenarios. For each of those scenarios, Table 1 also presents the calculated values of the various impact indicators (which make up the total end-impact), namely: a) CML, b) Average Minutes Low Pressure (AMLP), c)

*continued on page 119*

**Table 1. Total end-impact, cost and values of the considered impact indicators for the 'no response', 'current practice response', and 'new methodology response'.**

| | *CML (mins/cust)* | *AMLP (mins/cust)* | *UW ($m^3$)* | *DRI (-)* | Cost (£) | Total end-impact (%) |
|---|---|---|---|---|---|---|
| **No response** | *4* | *3.6* | *3330* | *14* | **0** | **11.1** |
| **Current practice response** | *2.1* | *2* | *1825* | *273* | **894** | **6.5** |
| **New methodology response** | *1.6* | *2* | *1475* | *92* | **55** | **5** |

# REAL TIME FORECASTING AND AUTOMATIC SPECIES CLASSIFICATION OF HARMFUL ALGAL BLOOMS (HAB) FOR FISHERIES MANAGEMENT

BY JOSEPH H. W. LEE, J. H. GUO, TREE S. N. CHAN, DAVID K. W. CHOI, W. P. WANG AND KENNETH M. Y. LEUNG

**Fish is an important source of animal protein in the diet of the Asian population and 60 percent of this is from aquaculture. Asia contributes about 90 per cent of the global aquaculture production and has become the most important supplier to the global seafood trade [7]. It is expected that population growth and economic development will lead to increasing fish consumption and global demand for food fish. In Hong Kong, marine fish culture (mariculture) has been a major supplier of high value fish including groupers, snappers and sea breams. Local mariculture is carried out in cages suspended by floating fish farm rafts in designated fish culture zones (FCZ) which are typically weakly-flushed tidal inlets.**

In subtropical eutrophic coastal waters around Hong Kong and the region, the explosive growth of phytoplankton (algal blooms) is often observed. These blooms can lead to water discoloration (e.g. red tides), severe dissolved oxygen depletion, and shellfish poisoning – resulting in beach closures and massive fish kills [1]. For example, in April 1998, a devastating red tide resulted in the worst fish kill in Hong Kong's history - over 80% (3,400 tonnes) of fish stocks in Hong Kong were wiped out, with an estimated loss of over USD 40 million. Despite significant upgrades of the water pollution control infrastructure over the past two decades, massive harmful algal blooms (HAB) still recur and present formidable challenges to fisheries management (Figure 1). Worldwide, HAB is an important problem related to the global challenges of water and food security. The onset of a HAB is also notoriously difficult to predict.

**Figure 1. Typical marine fish culture zone located in a coastal tidal inlet and examples of coastal algal blooms and fish kills.**
**(a) Examples of coastal algal blooms.**

**(b) Typical marine fish culture zone and massive fish kill in April 1998.**

Traditional approaches of red tide monitoring and fisheries management rely on field sampling and laboratory analysis of chlorophyll-*a* concentration (Chl-*a*) - an indicator of algal biomass - and manual cell counting and species identification, which are resources intensive and time consuming. With the increasing availability of real time water quality sensors, the development of HAB early warning systems has become a practical possibility. In this article, an overview of recent research on the use of remotely sensed data in a HAB early warning system is described. Two aspects of the system are presented: (i) daily forecast of algal bloom risk based on prediction of vertical density gradients using *in-situ* real time (10 min sampling period) water quality data; and (ii) use of machine learning to automatically detect target HAB species from images (30,000 numbers/hour) monitored by a submerged Imaging Flow Cytometer at a marine fish farm. Further details can be found in the cited references.

### Real time forecasting of algal blooms using real time water quality data

The occurrence of HABs in eutrophic coastal waters depends on the complex interaction of physical and biological factors that include: nutrient supply (e.g. inorganic nitrogen and phosphorus), algal growth rate, hydro-meteorological conditions (e.g. solar radiation,

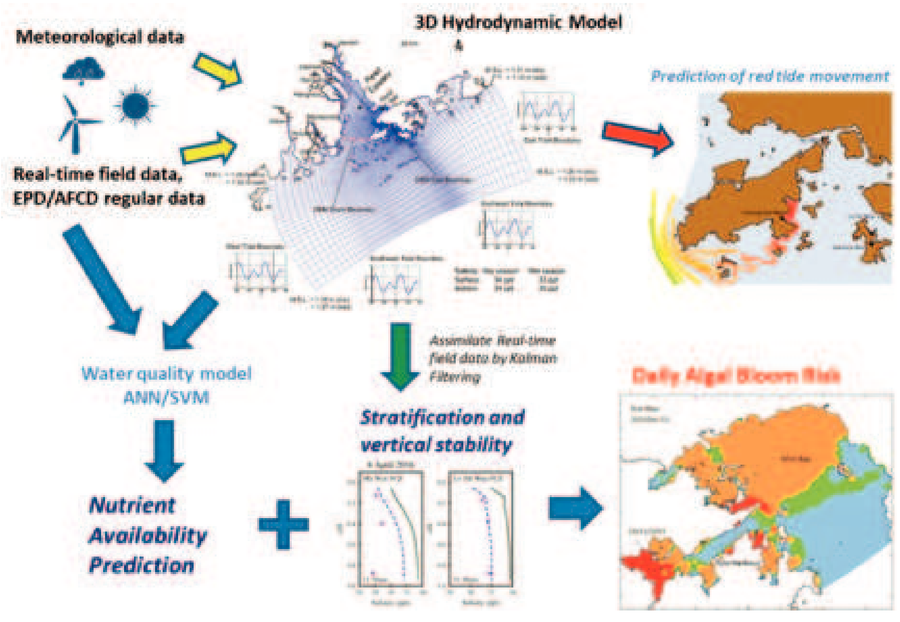



Figure 2. Conceptual framework for a harmful algal bloom (HAB) early warning system for prognostic forecast of algal bloom.

rainfall, air and water temperature, wind), tidal currents, water column transparency (light extinction) and turbulent mixing which is strongly affected by density stratification. The impacts of HAB on water quality also depend on algal and dissolved oxygen dynamics, and nutrient recycling. An early warning system of HAB occurrence (even with a lead time of 1-2 days) can benefit fisheries management and emergency response greatly.
Building on field observations of algal blooms, the use of data-driven methods such as Artificial Neural Networks (ANN) to predict coastal algal blooms has been attempted [2], [9]. However, the measurement frequency (typically monthly or biweekly) of most water quality monitoring protocols was insufficient to capture the highly dynamic variation of hydrodynamics and water quality, and in particular algal biomass. In recent years, HAB early warning systems have increasingly been reported [5], [6], [10]. Nevertheless, the development of field validated HAB forecast systems remains a formidable challenge.

Recently we have developed a daily algal bloom risk forecast system based on: (i) a vertical stability theory; and (ii) a data-driven artificial neural network (ANN) model that assimilates high frequency data to predict sea surface temperature (SST) and vertical density stratification on a daily basis. The model does not rely on past chlorophyll measurements and has been validated against extensive field data.

Field observations show that a stable water column is necessary for an algal bloom to form. In weakly flushed tidal inlets, it can be shown that the vertical turbulent diffusivity, $E$, must be less than a turbulence threshold defined by the net algal growth rate and the euphotic depth – with $E<E_c=4\mu l^2/\pi^2$, where $\mu=$ net algal growth rate and $l=$euphotic depth (proportional to Secchi depth) [13], [14]. If the vertical mixing exceeds the critical turbulence threshold, too much algae will be mixed out of the photic zone into the non-productive lower layer, and a bloom cannot be formed. The vertical stability criterion has been verified against 191 algal blooms over the past three decades [8].

In addition to the water column stability condition, a nutrient threshold, i.e. total inorganic nitrogen > 120 μg/L and orthophosphate > 18 μg/L should be met. If both the stability and nutrient criteria are fulfilled, there is no restriction for the algal population to grow in either physical or biological aspects

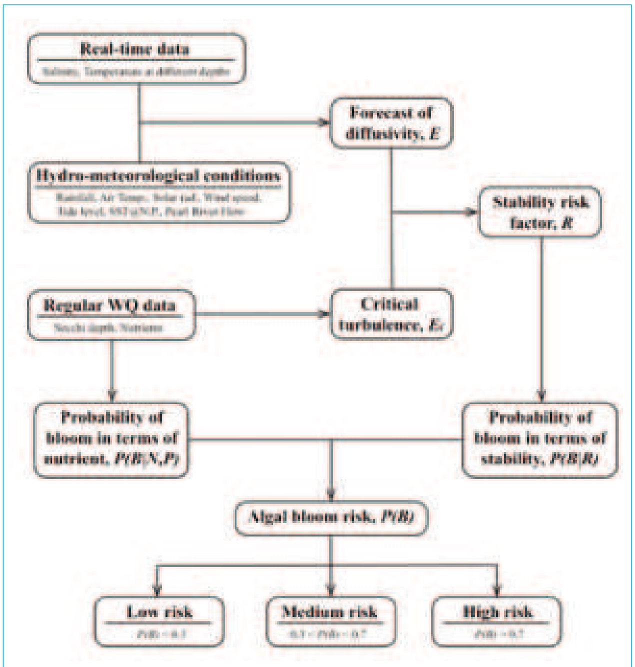



Figure 3. Daily algal bloom risk forecast framework as a function of hydro-meteorological and water quality data expressed in terms of a hydrodynamic stability risk factor and nutrient availability for the Yim Tin Tsai (YTT) Fish Culture Zone, Tolo Harbour, Hong Kong.

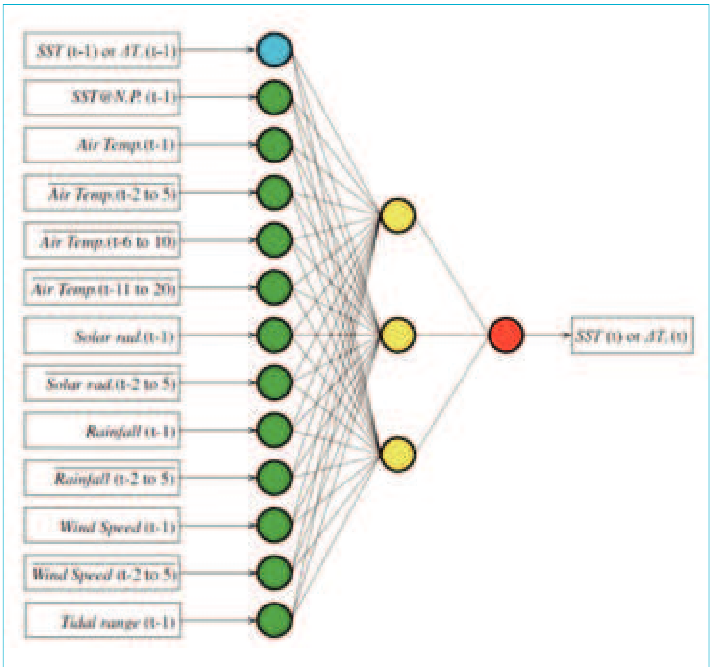



Figure 4. Artificial Neural Network (ANN) for daily prediction of sea surface temperature (SST) and vertical temperature difference ($\Delta T_z$); the uppermost neuron in the input layer shows the most current real time measurement (when data is available). Time averages over several days indicated by over bar.

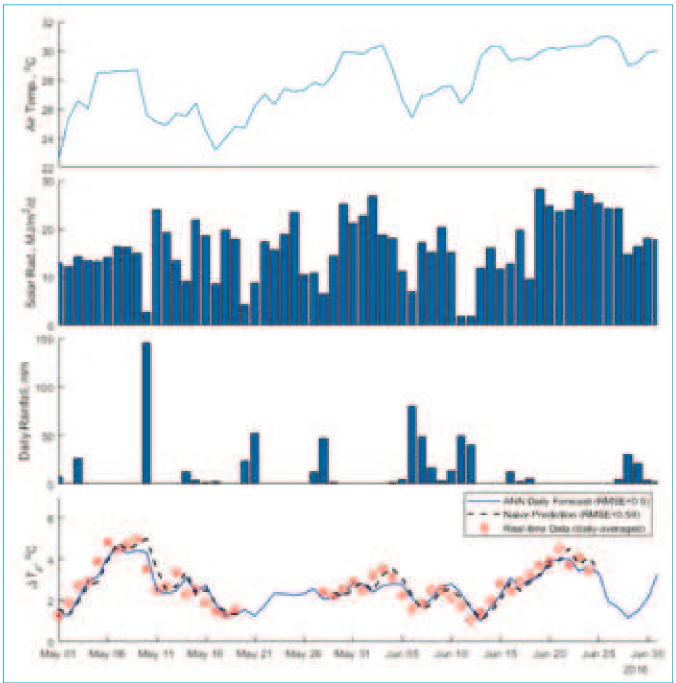



Figure 5. Example daily forecast of vertical temperature differential $\Delta T_z$ using hybrid ANN model, compared with daily-averaged real-time data and naive prediction given by data on the previous day. Note that the ANN daily forecast is continuous while naive prediction is limited by gaps of real-time data.

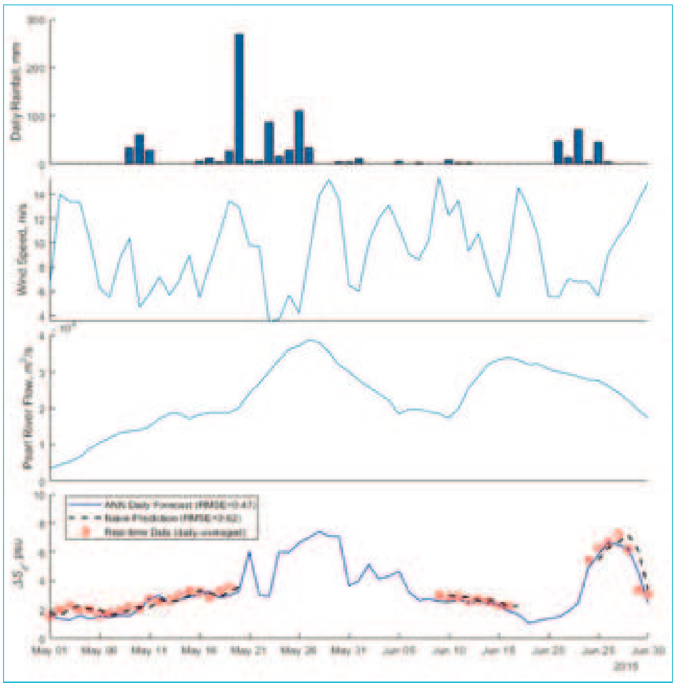
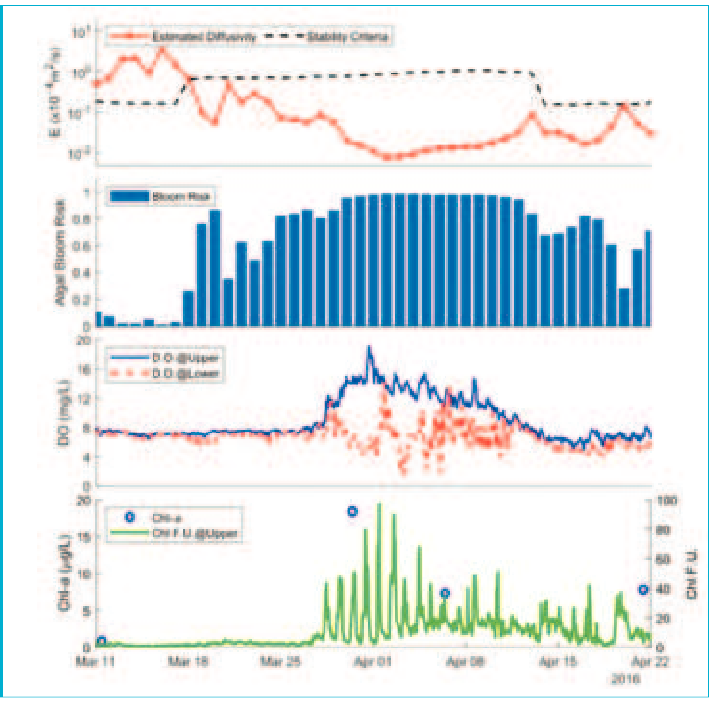



Figure 6. Example daily forecast of vertical salinity differential $\Delta S_z$ using hybrid ANN model, compared with daily-averaged real-time data and naive prediction given by data on the previous day. Note that the ANN daily forecast is continuous while naive prediction is limited by gaps of real-time data.

and hence a bloom is likely to occur. Based on long term data, the vertical stability criterion and the nutrient threshold can be cast into probabilistic or risk terms and combined to give a prognostic forecast of algal bloom risk (high, medium, low) levels. Figure 2 shows a conceptual framework of a possible data assimilation system based on the integration of 3D and data-driven models, and field data.

**Figure 7. Example daily forecast of vertical turbulent diffusivity and bloom risk compared with measured surface and bottom dissolved oxygen and chlorophyll fluorescence for a dinoflagellate bloom observed at YTT FCZ in Mar-Apr 2016 (causative species: *Akashiwo sanguinea*; cell count:1,000-10,000 cells/mL).**




The availability of high-frequency real-time temperature, salinity, dissolved oxygen (DO) and chlorophyll fluorescence data (at 10-minute intervals) opens the possibility of forecasting algal bloom risks on daily basis. Real-time telemetry data monitoring stations have now been set up in 12 key fish culture zones in Hong Kong, with spatial distances ranging from 2.5 to 20 km. Figure 3 shows the flow chart of the implementation of the forecasting framework for the Yim Tin Tsai marine fish culture zone in Tolo Harbour, Hong Kong. The vertical temperature and salinity gradients (and hence the density gradient) can be forecast by assimilation of data and/or model predictions using an Artificial Neural Network (ANN). Figure 4 shows an ANN model with three layers (input, hidden and output layers) for daily forecast of SST and vertical temperature difference using inputs of daily averaged real-time data in the previous day together with past hydro-meteorological data. A similar network can be obtained for the vertical salinity difference. The tidally and wind-induced vertical diffusivity $E$ can then be estimated (based on 3D hydrodynamic models and predicted density stratification) and compared with the critical turbulence criterion $E_c$ to give a stability risk factor $R$. By analysing all historical algal bloom events, the likelihood of a bloom occurrence based on hydrodynamic stability can be cast in terms of a probabilistic risk, $P(B|R)$. Similarly, the likelihood of a bloom based on nutrient availability (i.e. concentration of total inorganic nitrogen and orthophosphate) can be obtained as $P(B|N)$ and $P(B|P)$. The algal bloom risk for the next day can then be obtained using the multiplication rule and the Liebig's Law of the Minimum: $P(B) = P(B|R) . min[P(B|N),P(B|N)]$.[8]

Figure 5 and Figure 6 show respectively a daily forecast of vertical temperature and salinity differential (at two levels). Based on

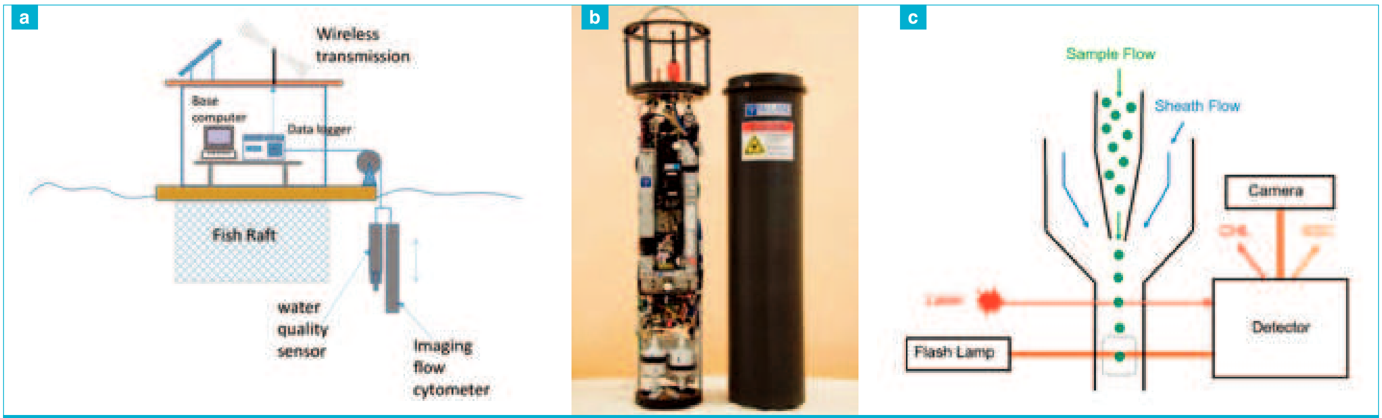



Figure 8. HAB species monitoring at fish culture zone using Imaging Flow CytoBot (IFCB). (a) Field deployment of IFCB at fish raft. (b) IFCB (c) Hydrodynamic focusing.

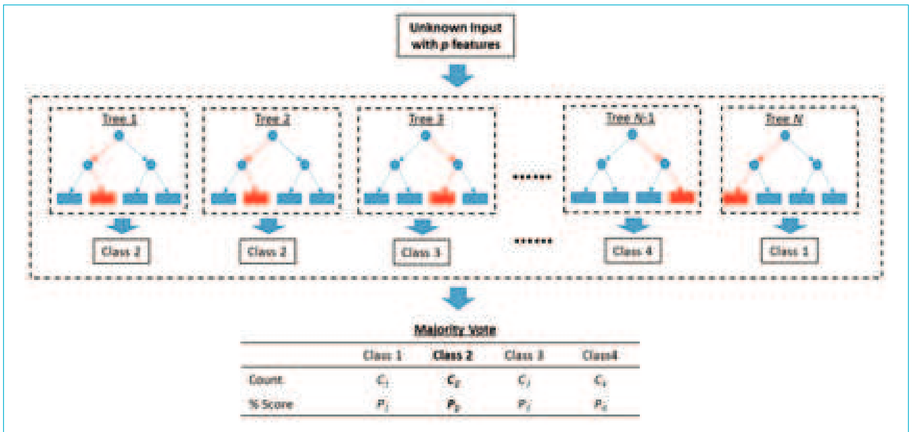



Figure 9. Classification using a random forest classifier (ensemble of decision trees trained with bootstrap sampling and random feature subspace methods). Extracted features of input image are presented to classifier and each tree makes a prediction independently. The number of instances that each class $i$ being predicted are counted ($C_i$) and a percentage score is obtained ($P_i$). The final decision is the class with the maximum score (majority vote).

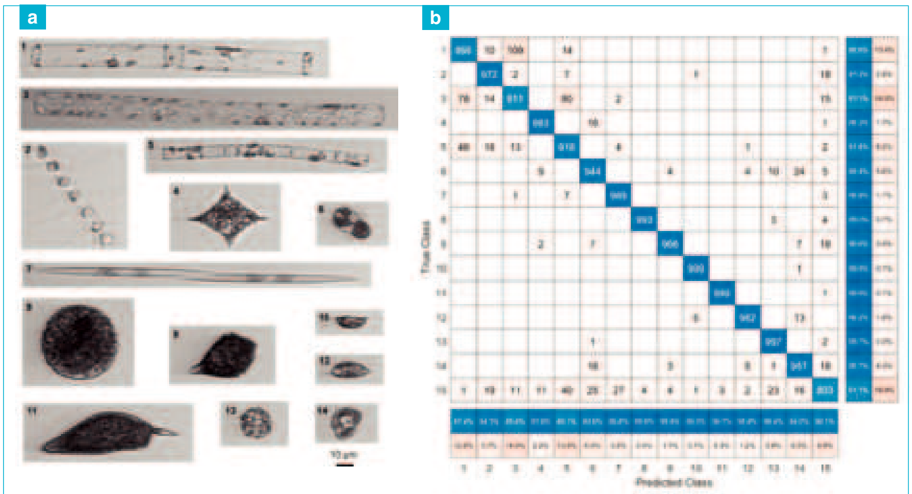



Figure 10. Automated classification of 14 target harmful algal bloom (HAB) species using machine learning. (a) Examples of IFCB images for 14 target HAB species. (b) Confusion matrix of classification result of test images. Numbers in blue boxes along the diagonal line indicates the correctly classified images. Class No. 15 refer to all species other than the 14 targets in (a).

the forecast, the vertical density gradient at the site can then be determined. The ANN model is a hybrid model that is capable of making short term forecasts even in the absence of *in-situ* data (e.g. due to data logger failure, system malfunctioning or equipment maintenance). The system has been validated against four years of field data, with an accuracy comparable to the field performance of commercially available systems (0.51 ˚C and 0.58 psu for the temperature and salinity, respectively). It should be noted that the model is clearly superior to the naïve prediction (prediction of today's conditions being same as yesterday). In practical deployment, the presence of real-time data gaps is the norm rather than the exception and it is essential to have a model that can perform short-term forecasts even in the absence of *in-situ* real-time data.

Figure 7 shows the variation of the estimated vertical diffusivity, algal bloom risk, DO and chlorophyll fluorescence in March-April 2016. It is seen that with the decrease in vertical diffusivity towards the end of March 2016, the bloom risk becomes steadily high ($P(B)>0.8$) around 26 March, and the stable water column resulted in an algal bloom which was sighted on 29 March, 2016. The onset of the dinoflagellate bloom was indicated by the sharp rise in chlorophyll fluorescence and was confirmed by direct onsite measurements which revealed the causative species to be *Akashiwo sanguinea* with cell counts of 1,000-10,000 counts/mL and chlorophyll-*a* > 10 $\mu g/L$. The photosynthetic production in the surface layer resulted in DO supersaturation (up to 16 mg/L) and a marked DO differential between surface and bottom of 4-10 mg/L. The bottom DO was depleted to a low level of around 4 mg/L during the bloom which subsided after about two weeks. The algal and DO dynamics is also associated with nitrogen and phosphorus uptake [8].

The vertical turbulence at the site is dominated by wind-induced mixing prior to the bloom which was coincident with a period of low wind (< 2 m/s), neap tide, high water transparency (large Secchi depth), and increasing temperature and vertical temperature (salinity) differentials of 4 ˚C (2 psu) respectively. The bloom occurrence is clearly correlated with the predicted algal bloom risks. As a bloom will occur if nutrients are sufficient, it is found that the bloom risk due to stability risk is often a good indicator of a bloom.

### Automated classification of high-frequency microalgae images

High-frequency microalgae image data can be acquired *in-situ* through an imaging FlowCytobot (IFCB) that enables the identification of HAB species and estimation of cell abundance in real time. The IFCB is an automated, submersible equipment that can be continuously deployed underwater for months [11]. Designed using the principle of hydrodynamic focusing and flow cytometry, the IFCB is able to capture up to 30,000 high-resolution images (3.4 $\mu m$/pixel) in an hour (three 5 mL samples). The observation range is from 10 $\mu m$ to 150 $\mu m$, which covers most of the common algal bloom species in Hong Kong. Analysis of image data at such a high sampling rate requires automated taxonomic classification using machine learning techniques [12].

Since March 2019 we have been deploying an IFCB at the Yim Tin Tsai (YTT) Fish Culture Zone in Tolo Harbour, Hong Kong, to collect algal image data and monitor algal species. The system is equipped with a 4G cellular network connection to facilitate remote equipment control and data transfer (Figure 8). To collect training samples for development of auto-classifier, we have performed manual annotation of over 330,000 images collected by IFCB during the deployment in YTT. These images cover 40 categories from species to group levels, including diatoms and dinoflagellates. Automated classification approach of IFCB images has been developed using both (i) random forest algorithm with robust image processing and feature selection techniques; and (ii) state-of-the-art transfer learning with a pre-trained Convolution Neural Network (CNN) (i.e. GoogLeNet). The random forest (RF) [3] is an efficient machine learning approach predicting the label of an unknown image based on extracted image features. As illustrated in Figure 9, an ensemble of decision trees trained with bootstrap sampling and feature bagging make predictions independently and the final decision is based on majority votes. Fourteen commonly observed HAB species of particular interest are selected as the training targets (Figure 10(a)). Both RF and CNN approaches reach classification accuracies of over 80% for all target species. Figure 10(b) shows the confusion matrix of classification results (using the RF approach) of 1,000 test images for each species. The columns of the confusion matrix represent the number of predictions in each class while its rows represent the actual observations in each class. Testing against unlabelled IFCB samples shows that our developed classification approach is very efficient with near real-time cell abundance estimation of prevailing species - results can be obtained within 1-7 minutes after a sample is acquired. This opens the possibility of adapting IFCB into a real-time HAB detection and early warning system.

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# SMART WATER METERING AND AI FOR UTILITY OPERATIONS AND CUSTOMER ENGAGEMENT: DISRUPTION OR INCREMENTAL INNOVATION?

BY ANDREA COMINOLA, IAN MONKS AND RODNEY A. STEWART

**Digital technologies are disrupting several economic sectors and creating new business opportunities. As part of this transformation, the utility sector is also becoming more digital. However, water businesses have been slow to change paradigm and so far adopted digital technologies with incremental steps, often acting reactively to water scarcity conditions. Technologies such as smart water metering and Artificial Intelligence now offer water businesses the opportunity to focus on customer centric solutions to reap both operational and customer satisfaction benefits.**

Digital sensors and communication technologies have rapidly gained momentum with the transformation of our urban centers into smart cities. New digital products and data communications have revolutionized several urban services and enabled new economic models, as demonstrated, for instance, by the gig economy subverting the consolidated paradigm of the highly regulated taxi industry. Comparably, technological development coupled with existing demographic, economic, and climate challenges is giving traction to the utility sector to transition to the digital age. Both smart water metering and the associated data processing techniques, including advanced analytics and Artificial Intelligence (AI), are often mentioned as key transformative digital technologies of the utility sector [1]. However, we acknowledge that the uptake of digital technologies has been more gradual in the water sector, compared, for instance, to the energy sector. Smart water meter development and experimental trials started more than 20 years ago. Yet, large-scale smart water meter rollouts, as well as commercial applications of AI technologies coupled with smart water meters, are still limited.

Here, we analyze the role of smart water metering and AI in water business applications, and ultimately inquire: are they disruptive or incremental innovations for the digital transformation of water businesses? In this paper, we first investigate and provide examples on how smart meters and AI have been so far applied to support utility operations and customer engagement. We then formulate motivations and identify the benefits for using smart water meters in customer applications. Finally, we propose a pathway to best practice for water businesses to assess the maturity stage of their metering technologies and their capacity to innovate.

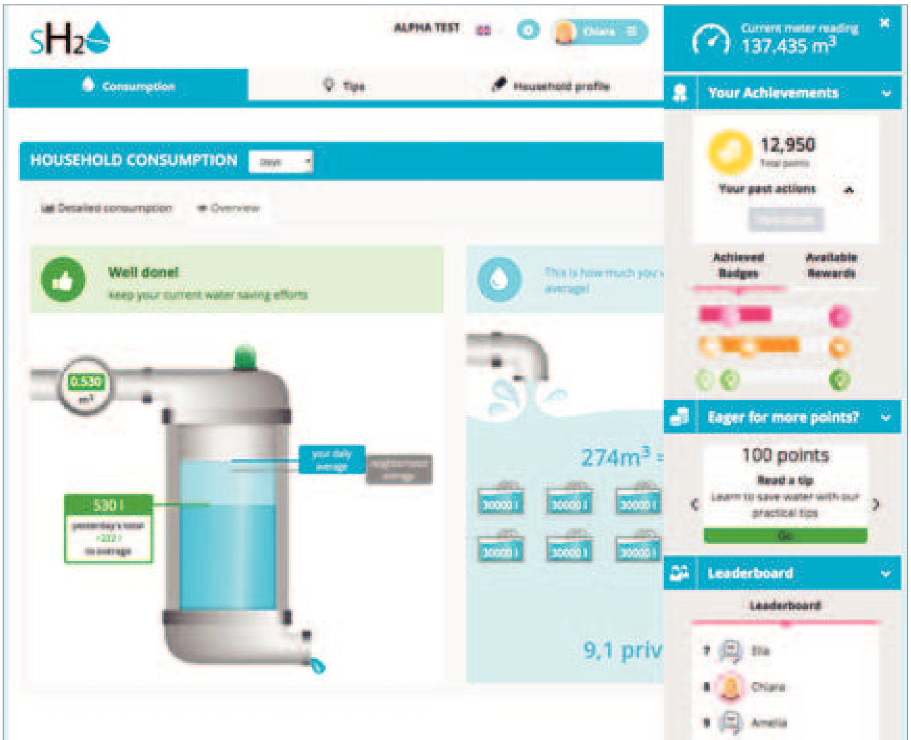



**Figure 1. User interface of the SmartH2O platform with household consumption goal setting mechanisms [4].**

### Advent and future of smart water meters

Smart water metering technologies have been developed since the late 90s, allowing for gathering of water consumption data with high spatial and temporal resolution. Pioneering studies to advance smart meter technologies and run smart meter trials emerged primarily in Australia and the United States, fostered by prolonged drought conditions requiring campaigns and incentives to promote water conservation [2]. As reported in a recent review paper on the benefits and challenges of using smart meters for residential water demand modelling and management [3], different smart water meter technologies have been developed since the first prototypes. Along with their technological development, several modelling applications have been implemented, closing the loop between water consumption data gathering and water demand management. Smart water meters have been used to promote short-term water conservation, simply by enabling water consumers to gain more information and control over their water consumption and water bill. Moreover, the usage of smart meters to retrieve end use level information, characterize water consumption profiles of individual households, and monitor changes in water consumption has fostered the development of tools to analyze the different water consumption behaviors of individual customers, obtain insights on water consumption and conservation drivers, and ultimately design customized water demand management programs. Interactive web portals and customer engagement tools have been implemented as part of new customized demand management programs to enable data visualization and facilitate the two-way communication between water consumers and utilities (see, for example, the user interface of the SmartH2O platform in Figure 1 [4]).

Overall, several studies and applications analyzed the information content of smart meter data to characterize and model water consumers' behaviors. However, uncertainties related to return of investments, meter battery life, data management, data privacy, product availability, and the long-term persistence of conservation behaviors have so far slowed a complete rollout of smart metering technologies [5]. This does not mean that smart water meters are not revolutionizing the water utility sector, but rather that their benefits and business cases for water utility applications are becoming evident only gradually. Water businesses are beginning to view smart water metering as a valuable technology for them to manage water demand, reduce infrastructure costs and streamline operational functions.

The global smart water meter market is expected to grow in the next years, reaching a value of more than 10 billion USD before 2030.[1] As smart water meters are now being considered "smart" not only because of their possibility to enable remote data reading, but also because of the wealth of applications enabled by their associated informatics, water businesses are adapting and starting to acquire new skill sets for their employees. A best-practice smart metering system goes beyond automated meter reading and rudimentary presentation of hourly consumption data to provide deeper insights on customers' usage of water and the associated costs [6]. IT, data science, and analytics skills are needed to fully exploit smart meters coupled with advanced analytics and AI to support utility operations and customer engagement.

#### Smart water meters coupled with AI to support utility operations

AI-based models have been used already to support utility operations independently from the development of smart meter data. Typical applications regard metamodeling of water distribution networks with black-box models, such as Artificial Neural Networks (ANNs), or urban water demand prediction. Accurate predictions of urban water demand are key inputs for designing optimal planning and management decisions. Several techniques have been used in the literature to identify and infer existing relationships between water demand and sets of heterogeneous variables representing potential water demand determinants. Among these, the last two decades have seen a rapid increase in the usage of ANN-based methods. The success of such methods is primarily due to their flexibility of use, their ability to capture unknown nonlinear relationships between the predictand, i.e., water demand, and its potential determinants, and their predictive capabilities demonstrated by benchmarking with alternative methods.

The availability of smart water meter data is facilitating the full potential of such data-driven methods, especially for applications related to high-resolution descriptive and predictive modelling of water demand. For instance, Bennet et al. [7] demonstrated the suitability of ANN-based methods to forecast water demand at the household level for a sample of over 200 households in Australia. Besides the usage of ANN to forecast water demand, other advanced Data Analytics (DA) techniques have been adopted to create value from smart meter information. Data-driven customer segmentation enabled by data dimensionality reduction, clustering techniques, and pattern analysis, has been developed to support water businesses obtaining detailed insights about the heterogeneous behaviors of their water consumers, along with their socio-demographic drivers and, thus, to better design demand management interventions.

Moreover, some studies primarily conducted in drought-prone areas exploited advanced analytics and smart meter data to monitor behavioral responses to demand management interventions, pinpointing water use shifts correlated with climate-related mass media and policy events, and identify rebound effects (e.g., [8]).

Finally, pattern analysis of smart meter data allows better identification of anomalous consumption levels and more accurate billing. Utility operations can even take advantage of smart meter applications that are apparently only customer oriented. For instance, the practice of service recovery leading to compensatory refunds for concealed leaks continues to cost water businesses as do disputes over accounts and compensation paid for water damage from network leaks and bursts.[2] This is particularly the case in complex, multi-metered properties such as high-rise and multi-unit communities where both individual unit and communal consumption occurs.

All the above examples illustrate a range of operational cases where water businesses benefit from advanced analytics coupled with high-resolution smart meter data. As a result of such coupling, water businesses can better inform their water demand and supply strategies, and therefore increase the efficiency of their operations. However, differently from other sensors distributed in the water distribution network (e.g., pressure sensors), smart water meters inherently record information on individual customer behaviors and consumption habits. This provides water businesses with further opportunities to exploit such information to develop customer engagement programs that include water consumers in their efficiency loop more transparently and proactively.

*"Digital transformation in the water sector will be incremental, but successful citywide rollouts will accelerate change through pressuring adjoining water businesses to step-up and provide similar solutions and efficiencies."*

#### Water businesses must engage customers better

Digital disruption has already revolutionized many industries and allowed much better engagement with customers through web and phone interfaces. Travel, banking and finance, education, retail, food, etc. are all industries that have used digital technologies and DA to capture and push useful information to customers and engage them better. However, the urban water sector is still largely engaging with customers in the same way that they have over the last few decades, where a single water usage data point is collected by human meter readers on a quarterly basis and paper bills are distributed to customers with limited useful information. Water bills are paid and engagement rarely occurs, and when it does, it is often to discuss high water usage from months past that may be due to a range of reasons such as an unknown leak, high usage, meter or reader error, meter read estimations, to name a few. Sadly, due to the present limited information collected on water

1) https://www.reportsanddata.com/report-detail/smart-water-meters-market

2) https://energycentral.com/c/iu/advances-artificial-intelligence-ai-and-machine-learning-coupled-smart-water

usage in most jurisdictions, it is not possible to meaningfully engage with customers on high water usage, hidden leakage events, incentives to reduce total and peak period demand, water affordability, custom conservation opportunities, etc.

Given that water businesses are often government-owned water service provider monopolies having no direct competition that can provide a superior customer experience, they often forget about the customer and the opportunities and benefits of smart water metering for them. However, modern business survival is often premised on their ability to engage with customers and provide them a fulfilling experience with the product or service provided. A recent paper by Monks et al. [9], identified a total of 75 benefits from smart water metering. These benefits help either the water businesses, or customers, or are shared by both water business and customer. Many benefits had not previously been revealed in the literature. Of the reported benefits, 40 benefits directly impact customers and of these, 18 are considered exclusively benefits to customers, such as the reduction in costs to customers due to leak alerting or the availability of customized product offers, and the other 22 as benefits delivering to both customer and the water business, such as reduced customer billing complaints, enhanced communications, and improved meter failure analytics (shared benefits). Monks et al. [10] examined the extent to which smart metering would improve levels of customer satisfaction.

Most operational smart water metering benefits can be quantified in monetary terms. Customer Satisfaction (CS) related business impacts are more easily distinguished in a comparable privately operated telecommunications business due to lost customers when service is comparably lower than competitors. These impacts are not directly discernable in a monopoly water business market arrangement where customers are not lost due to poor CS. However, in such market arrangements, while customers and revenue may not be lost in the short term, customer trust and relationships are being eroded over time, and dissatisfaction may culminate in pricing caps, government penalties, political backlash, and a lack of community cooperation. Not sufficiently engaging with customers and not providing them with a comparable level of service to other best-practice water businesses presents an unpalatable long-term risk to contemporary water businesses.

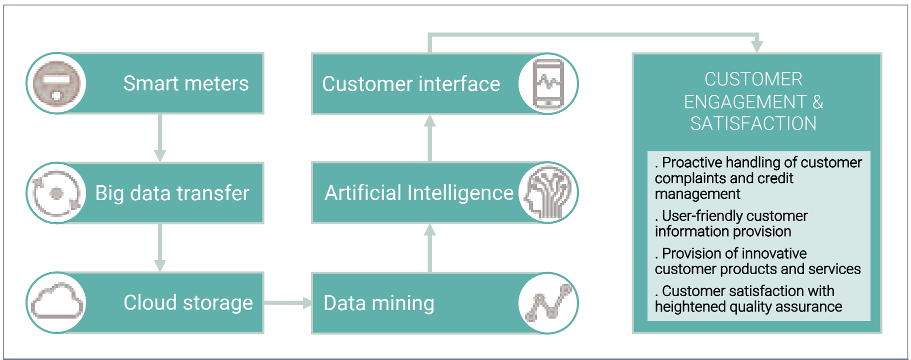


**Figure 2. Pathway to harness customer engagement and satisfaction from smart metering.**

The advent of smart metering technologies and near real-time communications of high-resolution data has enabled many leading water businesses to provide to their customers superior levels of service that are best practice. Deeper insights from smart meter collected big data, supplemented with other internal and external datasets, can only be realized through the development and deployment of advanced data mining methods and AI techniques. Figure 2 outlines a pathway to harness customer engagement and satisfaction benefits from smart metering.

> *"Water businesses that can effectively harness digital technologies like smart meters and AI techniques, will reap both operational and customer satisfaction benefits"*

## Artificial Intelligence to facilitate customer data interpretation

Understanding and interpreting customer data requires the development of AI through a range of DA and Machine Learning (ML) techniques. Smart water meters are now affordably deployable to provide the necessary data to interpret and report individual customer data in a proactive and meaningful way. Near real-time personalized water usage information and feedback has the potential to increase CS substantially [10]. Various AI approaches are being investigated to deeply analyze customer data, and they can be considered within the following four categories: Neural Network (NN) methods, regression methods, stochastic methods, and hybrid methods [6].

The dominance of NN-based methods is notable in customer data interpretation because of the large volume of smart metering data. Various researchers have employed a range of ANNs in their proposed methods, including more advanced deep learning (DL) NNs. Regression-based methods are also commonly used. Regression-based approaches are good for identifying key factors contributing to customer water consumption. Some regression-based methods include Support Vector Regression (SVR), Support Vector Machine (SVM)-based regression, Multivariate Adaptive Regression Splines (MARS), and Projection Pursuit Regression (PPR). There is a growing use of sophisticated stochastic-based techniques such as Hidden Markov Models (HMM) to forecast customer water usage information. Recently reported methods are hybrids, i.e., they employ more than one technique and are often required for complex customer interpretation and reporting requirements. Some hybrid methods already adopted by water researchers and industry professionals for customer water usage profiling include General Regression NN (GRNN), Extreme Learning Machine (ELM) integrated with Variational Model Decomposition (VMD), Singular Spectrum Analysis (SSA) coupled with linear autoregressive models, spatiotemporal Gaussian process models, Gaussian mixture models and K-means clustering Generalized Additive Models (GAM), hybrid Particle Swarm Optimisation–ANN (PSO-ANN), Bayesian Additive Regression Trees (BART), Gradient Boosting Machines (GBM), to name a few examples. Each of these techniques fosters the creation of sufficient AI to feedback customized information to customers, such as their quasi real-time water consumption, time-of-use or exceedance of high demand thresholds, and leak alerts.

## Smart meter and AI customer applications and benefits

Smart meters and AI will enhance existing customer engagement activities and provide a whole new range of applications [10]. These applications will provide various benefits for both customers and their service providers. The key applications and benefits are discussed below.

- **Proactive handling of customer complaints and credit management:** in addition to the elimination of reading errors, estimated reads, self-reads and meter-reader access, customers will have access to web portals and phone applications that provide detailed information on their water usage and alert them of high water usage and bills well before payments are required, thereby allowing customers to reduce consumption to fit within their monthly available budget.

  Benefits of this enhanced customer engagement application include**:** reduced customer billing complaints; reduced external and internal costs of ombudsman referred complaints and legal costs; improved outcomes from billing disputes; and reduced requirement for customers to contact bill relief agents.

- **User-friendly customer information provision:** information is power, and when customers have tailored water usage information for them, they are able to make better decisions and more timely actions [11].

  Benefits of this application include: reduced leaks and associated costs at properties; water usage awareness and education; greater water efficiency and reduced bills; choice of billing frequency (e.g., monthly, quarterly, etc.); information on appliance efficiency; increased goodwill from information sharing with their customers; and the ability to be notified of internal leaks that may cause building damage and insurance claims.

- **Provision of innovative customer products and services:** big data from smart meters opens opportunities for water service providers to offer a range of new products and services to their customers. These products and services may generate new or improved revenue streams or be used to increase levels of CS such as billing day flexibility. For example, through under-standing water usage within a customer's premises, providers may be able to refer required services (e.g., plumbers to fix identified leaks, efficient appliances where high water use, etc.). Water service providers may also seek to offer complete water monitoring solutions where they sub-meter their larger water usage customers or the provision of algorithms to provide end-use data (e.g., shower, tap, etc.) on residential properties [12]. Other services could include tailored benchmarking, increased security through monitoring of water usage, to name a few.

  Customer benefits of this application include: billing day flexibility; provision of complete customer end-use data logging and analytics services; new suites of online products and services; and increased goodwill from new products and services provision.

- **Customer satisfaction with heightened quality assurance:** current urban water management approaches adopted by industry professionals are reliant on many assumptions (e.g., water bill estimates) and are subject to error. Customers expect others to pay their fair share through accurate metering. This relatively low level of quality assurance due to decision making based on incomplete information has been accepted by captive customers for some time. However, smart metering and big data analytics provides an opportunity to signifi-cantly enhance the level of quality assurance related to water usage, which will generate goodwill with customers.

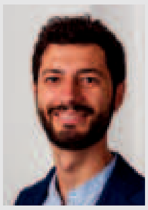
  Customer benefits of this application include: the ability of large smart meter datasets to help detect faulty meters and improve meter sizing for non-residential customers; water theft; automated regulation compliance monitoring; improvement in value of goodwill customer recognition of better capital management and operational efficiency.

## A pathway to best practice

We suggest that there is a "best practice" that water businesses might strive for that maximises the return on investment on smart water metering. The collected meter readings need to be assembled into a data repository along with other sensor and operational data, and complemented with external weather, demographic, property, and various other data sources. Digital twinning of physical and virtual city infrastructure is already driving the push for an open source Common Data Environment (CDE) for all static and 'live' data sources.

The level of business transformation based around the metering technology might be recognised through a capability model. The Intelligent Metering Maturity Model is suggested and a prototype is illustrated in Figure 3. Capability models have provided observers with a method of comparing businesses against each other and best practice, and they have provided a roadmap to improvement.

At the lowest level, water businesses would score zero with 100% manual metering and no digital metering, or incomplete metering (e.g., it is estimated that only 50% of the domestic properties in the UK were metered in 2015; differently, in Australia almost all properties in urban areas are metered, but the penetration rate of digital metering is roughly 10%). The score rises to 1 when digital metering is raised to 100% replacing all manual metering, but without any in-depth exploitation of the data other than automated billing, as is the current situation with metering of high-rise buildings in many utilities. Applying basic DA and AI approaches for leveraging of the data for

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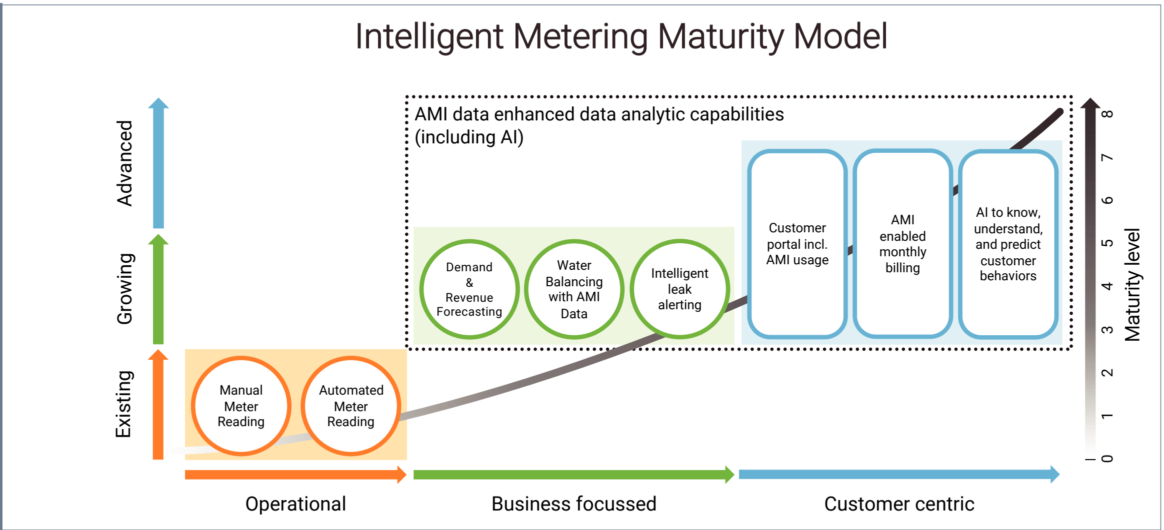
**Rodney A. Stewart** is the Digital Utility Transformation Professor at School of Engineering and Built Environment, Griffith University, Australia. Prof. Stewart conducts research in the applications of smart metering technology and big data informatics for re-engineering the water and energy utility sectors. In the water utility sector he has completed a number of high resolution smart water meter studies that provided the 'big data' to underpin detailed water end use studies, demand management strategies, bottom-up forecasting models, just-in-time pipe network infrastructure planning, water-energy nexus studies, post-meter and network leakage studies, to name a few. His goal is to conduct the necessary evidence-based research to demonstrate the numerous applications and benefits of intelligent water and electricity networks in order to accelerate the rate of diffusion of these technologies in the utility sector.

Figure 3. Suggested capability model and pathway to best practice.




processes that are essentially operational (e.g., network leak detection, planning and peak demand analytics, meter sizing and meter failure analytics) raises the score. Higher scores are achieved by providing leak alerting and a customer portal for accessing their data and offering frequent (e.g., monthly) billing. The highest scores can only be achieved when water businesses introduce sufficient predictive AI to accurately understand and predict network and customer functions without manual human data manipulation and interpretation.

## Disruptive or incremental innovation?

Two technologies are under consideration here: smart water meters and AI. At times both would be considered disruptive in their own right and have improved CS. A demonstrative case study is given by a smart meter installation rolled out in Kansas City, Missouri in the United States, along with an extensive process re-engineering undertaken to leverage the technology [13]. The published customer satisfaction level reported over the following four years from 2013 show an uplift of the percentage of customers satisfied from the high sixties to the mid-nineties. Another case study in Newmarket (UK) reports 8% water savings achieved by combining a smart metering program with data and behavioral science.[3] Townsville (Australia) avoided a costly engineering solution saving USD 4M when they used sensors and data analytics across their network to identify the true cause of low-pressure supply issue and resolved the issue through better valve operation. Longer term water savings of 6.8% were achieved in Sydney (Australia) when smart meter data is presented back to the customer via in house displays [14]. To realise the CS improvements the technology needs to be enabled, first.

Most of the 75 benefits identified from smart water metering in reference [9] rely on the use of data analytics to mine the data for insights. Indeed, one of the pre-conditions is the resourcing of a data analytics capability, whether through deploying in-house expertise or by out-sourcing to their digital metering supplier or to consultants. An example of best practice in this regard is the recent smart meter rollout of the city of Gandía (Spain), where the joint effort of the local utility, city council, and a telecommunications company is leading to the collection of hourly water consumption data from over 40,000 smart meters and this data is standardized in a Big Data platform.[4]

The willingness of a water business to enable the benefits would depend on their appetite and capacity for change and, in some cases, may require change approval by their regulator. Where metered billing is not the social norm, water businesses might still move to smart metering (or data logging) having recognized the potential to deliver the detailed data needed to overcome operational and water quality issues, and assist water conservation efforts. Indications from past and recent surveys of water businesses, and inclusions in recent pricing submissions to regulators, show that the larger water businesses are actively considering a move to digital metering. Many smaller regional water businesses with less capital and capacity for risk, are waiting to see the direction taken by larger utilities. However, there are some smaller agile water businesses that are better able to exploit the benefits of digital technologies, and they are technologically leapfrogging the larger metropolitan water service providers in their country.

## Hence, can we ultimately say whether smart water meters and AI are disrupting or incrementally innovating the water sector?

Generally, water businesses do not compete against each other by virtue of their exclusive rights of service and natural monopoly status, being government-owned or tightly regulated, and sometimes having common owners, making their relationship more collegiate than competitive. Knowledge and experience are shared through formal and informal channels. However, a technological laggard will eventually be found out by their customers as they become aware of superior services offered by adjoining water businesses, through various channels such as media, government reports, discussions with friends and family, moving to a new address, to name a few. Water businesses that are slow to embrace change, are merely widening the technological gap that will need to be addressed at some point in the future.

Examining the theory of disruptive innovation [15], a gap has been identified with mission driven institutions that have a higher calling, among which water services might consider themselves. While both the take-up of smart water metering and AI within water businesses may be slowly growing after a stuttering and fragmented start, we feel they should now be considered embedded technologies among progressive companies. Following a long gestation period, smart water meters and AI should now be treated as mature Business As Usual (BAU) tools, rather than as must-use disrupting technologies. In the absence of data warehouses being utilised by utilities [6], smart

3) https://www.advizzo.com/portfolio/anglian-water-case-study/

4) https://www.idrica.com/blog/gandia-smart-water-city-2/

water meter technology vendors or private software companies are providing cloud-based data repositories, customer portals, and offering to fill utilities' AI gaps as an add-on service. In this regard, the development of smart metering and AI can be considered disruptive, as it created opportunities for new economic models, tech actors, and investors previously not attracted by the water sector. The next significant innovation and business step will be materialized when synergies between the water sector and other utility sectors (e.g., electricity, gas, telecommunications) will be exploited in a cost-effective manner to realize the vision of a digital multi-utility service provider [16]. Exploiting multi-sectoral synergies will reduce asset and operational costs by collecting concurrent water-energy data efficiently, implementing flexible and data agnostic processing techniques, and ultimately designing integrated tailor-made services to customers. ■

*"At a minimum, water service providers must embrace incremental digital transformation, or government sanctioned alternative retail models offered by innovative private technology providers will be pushed upon them and strip back their function to heavily constrained water asset operators."*

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# AI–BASED EVENT MANAGEMENT AT UNITED UTILITIES

*continued from page 108*

Unaccounted for Water (UW), and d) Discolouration Risk Increase (DRI). It can be noticed that even though CML, AMLP and UW are reduced when compared to the 'no response' scenario, the 'new methodology response' offers further improvements over the 'current practice response'. Indeed, the 'new methodology response' further reduced all impact indicators except AMLP that remained the same. The 'new methodology response' also suggested a smaller number of interventions to implement as evidenced by the significant improvement in DRI and cost. In light of the above, it can be concluded that through interaction with the IRPT operators could have identified a more effective response solution. Hence, this case study shows the potential of the IRPT to be beneficially used by United Utilities to make better and more informed decisions.

## Summary

This paper describes an AI-based approach for managing events in WDSs such as pipe bursts/leaks and equipment failure. The key pieces of new technology are comprised of a series of ML and other advanced analytics methods that are used to detect and locate these events and then identify an optimal response strategy, all in (semi) automated fashion and in near real-time. This new technology, developed in collaboration with two leading UK universities in water engineering, works by extracting useful information form pressure and flow sensors and other data sources available.

The new technology enables United Utilities to manage the above events much more pro-actively than before by reducing the time of awareness to these events but also, in some cases, preventing events from taking place altogether. This combination has resulted in a range of benefits achieved, from major operational cost savings to reduced interruptions to supply and hence improved service to over 7 million people and 200,000 businesses in the north west of England. As the new technology has also demonstrated the potential to more efficiently guide United Utilities' personnel to the problem areas and to support the ICC operators to make better and more informed decisions when tasked with the identification of a suitable strategy to respond to those events, further benefits arising from the pursued fully managed life-cycle of events approach are expected. ■

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# THE HISTORY OF THE MAR DEL PLATA OUTFALL SYSTEM: A TALE WORTH TELLING

BY MARCELO SCAGLIOLA, ANA PAULA COMINO, PHIL ROBERTS AND DANIEL BOTELHO

**In a previous issue of Hydrolink, we discussed the contribution of marine outfall systems as part of the solutions for the UN Sustainable Development Goals (SDGs), and introduced general guiding principles for system design, construction, and operation [12]. Because they convey the effluent to the ocean, outfalls are frequently (and erroneously) perceived as a pollution source. As a result, all too often the adoption of marine outfalls encounter fierce social and political resistance taking many years for their construction and implementation, preventing the affected communities from enjoying better sanitation outcomes [15].**

This article presents a similar history, of the design and construction of the Mar del Plata, Argentina, Outfall System. But here, we show how the improvements to the water quality of the Mar del Plata's beaches were immediately felt following the outfall construction and commissioning [5], propping up the city's success as one of the premier touristic destinations in Argentina. More than that, Mar del Plata is a great example for reflection and evaluation whether such long times for implementation of solutions can be afforded if we are to achieve the SDGs by 2030.

### The City

Founded 146 years ago, the coastal city of Mar del Plata is the most popular vacation destination in Argentina. Its beaches (Fig. 1) are a main attraction to both local residents and tourists, making Mar de Plata one of the largest urban settings in the country [5] with a population nearing one million during the holiday season. As tourism is a vital part of its economy, protecting the water quality of its beaches is paramount to the city.

With over 95% sewerage coverage, a submarine outfall operating since 2014, and a new wastewater treatment plant since 2018, Mar del Plata can be considered to have an advanced level of sanitation. This effort resulted in greatly improved water quality for primary recreation, safeguarding public health and promoting touristic activity. Regular monitoring programs indicate the entire city's coastal waters meet local and international guidelines for primary contact recreation.

We would like to highlight the immediate improvements of the recreational water quality of Mar del Plata since the commencement of the submarine outfall operation. Fig. 2 presents 30 years of entorococci monitoring in Mar del Plata's beaches. It can be readily seen that the water quality standards for indicators of fecal contamination were met almost immediately following the outfall construction. For example, at Delicias Beach approximately 0.9 km from the discharge, the monitored enterococci concentrations reduced considerably from 50,000 to 27 entoro-

Figure 1. Aerial view of Mar del Plata's beaches.

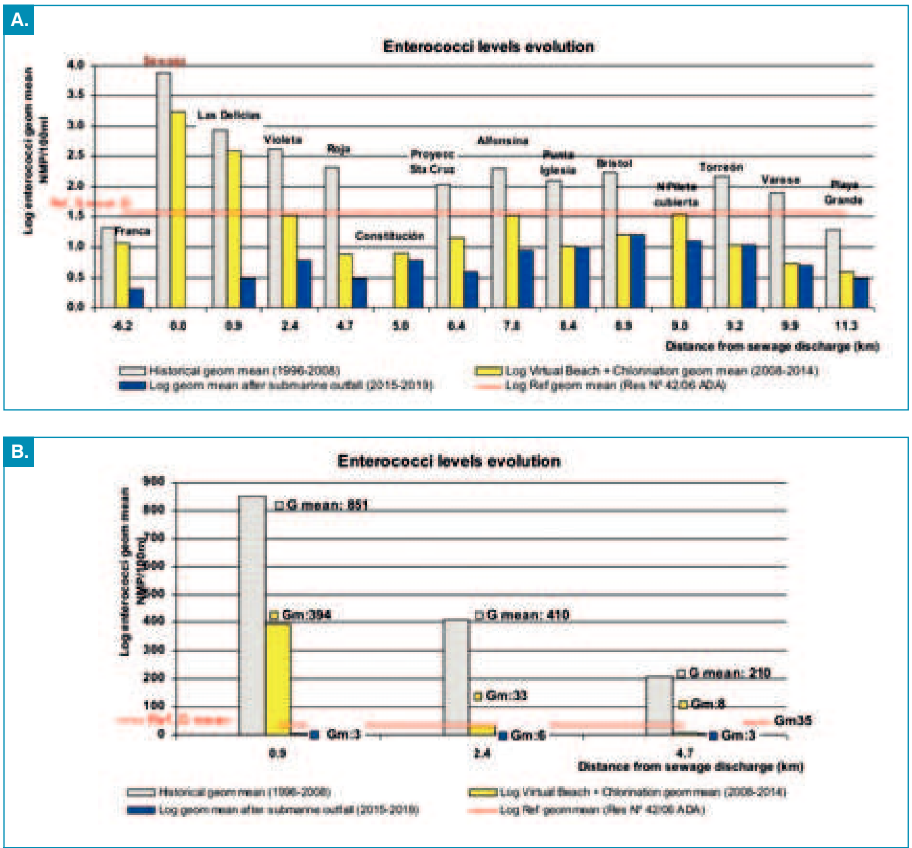



**Figure 2. A. Faecal contamination indicators in Mar del Plata's beach before and after the outfall (log scale). B. Details at Las Delicias, Violeta e Roja Beaches. The yellow bar shows monitoring results from the Contamination Monitoring Program (CMP) supported by the Virtual Beach modelling before the outfall operation commenced.**

cocci/100 ml following commencement of the outfall operation (Fig. 2b).

In hindsight, one can readily observe the benefits of the outfall operation. However, the project history dates back to the beginning of the 1980's, owing to several serious impediments along the way. It is therefore important to look back at this period to identify and reflect over the reasons why it took so long to complete the outfall project. In doing so, it is also opportune to present the mitigation measures undertaken for recreational water quality improvements before concluding the outfall installation.

### Vision and early project stages

In the early 1980's, the sewage discharge was located approximately 10 km north of the city at the existing outfall starting point. Tasked with the challenge of protecting Mar del Plata's beaches, Eng. Alberto Baltar, director of Obras Sanitarias Sociedad de Estado (OSSE) at the time, had the initial vision for a submarine outfall and diffuser system. His vision was based on his knowledge of similar technology applications around the world. Further, Eng. Baltar had a strong perception of the self-purifying capacity of the sea in Mar del Plata, noting its open coast, energetic surf zone, and intermittent storms and erosive processes, all of which indicated a favorable system for assimilation of the organic loads from the urban effluent (Baltar, pers. comm.).

With this initial vision, almost exclusively Eng. Baltar's, the city of Mar del Plata commissioned a study to present an outfall system as an alternative for adequate effluent disposal in the area [9]. The study comprised several field studies, which were the first to characterise the physico-chemical and bacteriological composition of both the wastewater effluent and the water near the discharge. These studies also quantified relevant local oceanographic processes to conclude that a marine outfall could be adopted as a solution for the city's effluent discharges.

Following these preliminary investigations, OSSE hired Eng. Russell Ludwig, a renowned consultant on outfalls, who reviewed the Instituto Nacional de Ciencia y Técnicas Hídricas (INCyTH) [9] studies and recommended additional engineering elements to the diffuser system [11]. Of particular relevance was the recommendation for application of new advanced modeling techniques for assessment of nearfield dilution considering local currents [12]. These new formulations had been proven to be the most accurate when compared to field data of operating outfalls and later became the basis for the model PLUMES [2] that was subsequently adopted for the Mar del Plata outfall design.

### New treatment plant and delays

As a first step preceding outfall construction, an effluent pre-treatment plant (later named the Eng. Baltar plant) was tendered and constructed. Starting operation in 1989, this pre-treatment plant comprised 0.5 mm screen filters designed to work in tandem with the submarine outfall. However, the plant and outfall worked together for only four years. In 2019, the plant was dismantled and replaced by a new pre-treatment plant.

Since inception of the outfall system, it took almost an entire decade for the construction of the first pre-treatment plant. Over this period, a series of debates were held between proponents of the outfall and those who were opposed to it in favor of a secondary wastewater treatment plant. (Sarandón, pers. comm.). These discussions, in part responsible for the delays over this first decade, presented convincing arguments for a submarine outfall as the best disposal alternative for Mar del Plata.

While economic factors always permeate large infrastructure projects, technical aspects were at the forefront for selection of the best alternative. Notwithstanding this, shortly after commissioning the first pre-treatment plant, Eng. Baltar retired, which proved to be crucial for the project delays. The project benefits were questioned, discussions effectively returned to ground zero, and new technical and political arguments were put forward probing whether a secondary treatment plant would be a better solution than the combined pre-treatment and outfall system.

### Secondary treatment or outfall system?

Results obtained in Mar del Plata up to the current day show that these discussions were counterproductive, and that the focus should have been on recreational water quality. Independent of the level of wastewater treatment (primary, secondary, or tertiary), existing marine outfall technology is not only adequate but it can be argued is essential for maintaining water quality for primary contact recreation. Even advanced levels of treatment will still require an outfall that removes the effluent far from shore [13].

Existing mathematical models can be used to define discharge location and diffuser design, to ensure that the self-purifying capacity of the receiving waters is sufficient to maintain water quality in bathing zones. Human enteric bacteria are not endemic to marine systems and as a result undergo significant die-off once discharged in the ocean. A well-designed outfall system takes into consideration bacterial mortality and ensures recreational waters are free from harmful enteric bacteria, thus precluding the need for additional disinfection. Furthermore, the rapid dilution achieved with a marine outfall diffuser (approximately 1:100) greatly improves the assimilation capacity of the receiving marine ecosystem.

A secondary wastewater treatment plant reduces biochemical oxygen demand (BOD) by oxidation of the organic load through a series of distinct microorganisms in succession within a controlled environment. The same result can be achieved by dilution with an outfall diffuser allowing the marine environment itself to undertake the oxidation process, and, as a result, reducing the level of treatment required. Therefore, the type of treatment and outfall design should be thought of as parts of an overall system to be evaluated, and not competing options as often argued.

Unfortunately, this old discussion of 'secondary treatment vs outfall is still common in many proposed sanitation projects. The precedent of Mar del Plata shows that discussions must be supported by an assessment of the marine environment not only as a receptor of effluent discharges, but as a nature-based solution and part of an integrated sanitation system. The assimilation capacity of the receiving environment has enormous implications for the choice of treatment system.

Determination of assimilative capacity requires evaluation of the marine ecosystem centered on baseline data collected prior to discharge and identification of potential ecological vulnerability points. This evaluation permits the design of post-discharge monitoring programs to continuously assess the environmental disturbance resulting from the effluent disposal. Such monitoring programs are important components within the broader context of an Integrated Coastal Management (ICM) system [4].

Sanitation planning within an ICM strategy, which continually evaluates the environmental impact of sewage disposal through ecological studies and monitoring of the receiving environment (both water and sediment water quality variables), allows constant assessment of ecosystem health as well as identification of requirements and opportunities for interventions in case of environmental harm.

Significant savings can result from this continual environmental diagnosis method without necessarily relying on more advanced levels of effluent treatment. These savings can be used for extending the sewerage network to regions with limited coverage, a common situation in developing nations. As such, scarce resources can be better spent on infrastructure and social development to satisfy the basic sanitation needs to be delivered by the Sustainable Development Goals (SDG) initiatives.

Guaranteeing 100% water supply, sanitation and hygiene for the world's population by 2030 will require optimal application of economic resources. Recognised as a solution to protect human health from effluent-borne infections, submarine outfall systems require relatively low capital and operational costs. Our history strongly suggests that, at least initially, economic resources should be used to extend the coverage of sewerage networks in combination with an outfall system (provided there is adequate environmental assimilation capacity). As a result, local communities will enjoy the benefits of proper effluent conveyance and disposal, as well as the ocean as an environmental treatment resource. Mar del Plata is living proof that this strategy for sanitation works.

### More on history and additional environmental studies

Returning to our outfall history, it is important to mention that the INCyTH study not only focused on a preliminary assessment of the receiving water but also recommended additional studies that included continual and permanent monitoring for the beach's recreational water quality and the wastewater effluent parameters.

Following Eng. Baltar's retirement, despite the decision-making delays regarding the sanitation alternative choice, data collection for preliminary studies continued and was augmented. Studies looked at a range of environmental aspects, including heavy metals in sediments [16], effluent assimilation capacity [10], permanent bacterial monitoring at the city's beaches [16], [17], [21], permanent monitoring for effluent and pretreatment solid waste characterisation [21], ocean currents [20], marine receiving environment monitoring [21], as well as intertidal and subtidal physico-chemical characterisation [21]. These studies further confirmed the conclusions obtained in the earlier study by INCyTH [9], supporting the recommendation that an outfall and diffuser was the best solution for the city's effluent disposal. These studies were also of fundamental importance in that they determined the baseline conditions prior to outfall construction, and could therefore be used for evaluation of the outfall performance.

### Reenactment of the submarine outfall project as part of the sanitation solution for Mar de Plata

Almost one decade after the Eng. Baltar plant commissioning, OSSE with the help of the National Entity of Hydraulic and Sanitation Works [7], recruited an experienced international consultant (Eng. Martí) to review the previous studies and deliberate on whether a secondary treatment plant or an outfall should be adopted as part of the sanitation solution for Mar del Plata. Eng. Martí concluded an outfall would be the most appropriate option for Mar del Plata and himself executed the modeling required to define the outfall design parameters and additional specifications to prepare the corresponding construction tender. The tender was issued in 1999 for the second stage of the treatment plant, comprising upgrades to the existing pretreatment plant and construction of the submarine outfall.

It is to be noted that **another decade had passed** since inauguration of the initial pretreatment plant before tendering for the outfall construction. These delays were largely due to lack of project technical support following Eng. Baltar retirement and recommencement of the old discussions. As a result of this chronology, it is concluded that such important projects cannot be solely vested in a single person for its execution. **When there is a network of professionals to provide support for the project, eventual project impediments can be readily and efficiently overcome, resulting in project improvements and its timely conclusion**. A series of examples in this regard were essential for completion of Mar del Plata's outfall.

### First attempt at outfall construction

Tendering for outfall construction started in 1999, financed by OSSE. However, a series of complex tendering processes, technical issues, and a serious economic crisis in Argentina in 2000, rendered the project no longer viable. Once again, the project was delayed and a new tender process could only be undertaken in 2008, thus wasting another decade.

Nevertheless, the effluent and marine environmental monitoring programs continued and were showing serious contamination of Mar del Plata's beaches by the discharge plume. The monitoring data comprised an important environmental baseline to influence decision-making with regards to the sanitation of the city.

**Second and successful attempt at outfall construction**

Following more favorable economic and political conditions, supported by the monitoring information, a second attempt to construct the marine outfall was set in motion in 2006. The Argentinean Government and the Municipality of Mar del Plata signed a covenant for the outfall construction, based on the recognition of the importance of Mar del Plata's beaches as a tourist resource for the entire country. Another six years had passed since the first failed construction attempt in 2000.

By this time, 10 years of monitoring data were available, providing an excellent environmental baseline prior to outfall operation with great scientific value. It was the perfect opportunity to present the monitoring data and announce the Mar del Plata outfall construction to the international community at a specialised conference in Antalya, Turkey [19]. Shortly after, a new outfall and diffuser design commenced, including diffuser modeling and pipeline material re-specification. This time, taking the lessons learnt from the first attempt, collaboration was established between ENOHSA, OSSE, international consultants, and the University of Cordoba. A new tender process was established, a contract was awarded and outfall construction finally started in 2008. The works were financed by Argentina's National Treasury and executed under the management of Mar del Plata's municipality government.

Figure 3. Final section of the Mar del Plata outfall showing diffuser ports ready for installation.

**Interaction with Marine Outfall Technical Committee**

**Virtual Beach Model Calibration**

As a result of participation in Marine Waste Water Disposal (MWWD) conference in 2006 [19], a fruitful collaboration between OSSE and the IAHR-IWA Technical Committee on Marine Outfall Systems was initiated, which was fundamental for the completion of the outfall project. Over the same period, in 2006, new regional recreational water quality norms were enacted for recreational water quality in Argentina. Suffice to say, the water quality of Mar del Plata's beaches did not meet the standards at the time [1]( see also Fig. 2). It was then decided that a mitigation strategy to protect the recreational water quality was required while outfall construction was underway [3].

Data from the 10-year environmental monitoring were adopted for calibration of the Virtual Beach bacterial dispersion model [8], such that bacterial contamination levels at Mar del Plata's beaches could be predicted one day in advance [11]. This same model was then adopted with other studies undertaken by OSSE on local water currents (Scagliola et al. 1998) and bacterial decay [18], [23] to design a Contamination Mitigation Program based on sewage effluent hypochlorite dosing.

A central aspect of the Mitigation Program was the identification of days requiring effluent chlorination, the level of dosing, and the start and end times of the operation. This Program, which was in place between 2008 and 2014, was an effective effluent management measure that ensured Mar del Plata's beaches met recreational water quality standards prior to outfall construction [24], [25]. On average, chlorination was undertaken in 25 of the 90 summer days considered in the Mitigation Program, allowing not only significant cost savings but also minimization of secondary detrimental chlorination effects [4], [6]. The Mar del Plata effluent disinfection based on the Virtual Beach predictive model proved to be a valuable innovation that can be recommended to locations that do not meet water quality standards while sanitation solutions (i.e. a marine outfall) are yet to be completed. Such innovation could only be accomplished by collaboration between local investigators with water quality modeling experts.

The interaction between OSSE and the IAHR-IWA TC on Marine Outfall Systems culminated in the organisation of the International Symposium of Marine Outfall Systems in Mar del Plata in 2011 congregating over 300 participants from across the globe to share their experiences on diverse aspects of outfall design, construction and operation.

**Outfall installation problems**

The Mitigation Program proved to be efficient in improving the city's recreational water quality while construction of the outfall was underway. However, over this second construction attempt, new problems came to light. Originally, the design considered a buried manifold across the entire outfall reach. However, due to the vigorous local sediment dynamics, the dredged trench was reburied before installation of the pipeline could be undertaken.

As a result, an alternative trenchless design was presented as a solution to the problem. The new design comprised anchoring the outfall to the seabed and adjustment to its last 700 m alignment. Given these modifications, OSSE consulted the IAHR-IWA TC on Marine Outfall Systems who recommended a qualified consultant to review the alternative design. The positive interaction between the construction team and the design reviewer permitted continuation of construction through to completion in 2014 (fig. 3).

**New wastewater treatment plant**

Simultaneously to the submarine outfall design and construction, a new treatment plant design was undertaken to replace the Eng. Baltar pretreatment plant. Installed in a nearby larger building, the new location could accommodate future upgrades that might become necessary, depending on either the receiving marine water quality monitoring indicators or in case new and more stringent water quality standards are put in place. This plant, functioning since 2018, adopts new technology, including primary treatment followed by a pre-staged de-aerator and degreaser system, all of which are essential to dealing with the urban effluent characteristics that are highly affected by the local fishing industry.

The plant discharges to the 4.2 km long marine outfall. The outfall terminates in a diffuser along its final 500 m that consists of ninety 15 cm diameter ports. Together, the sewage collectors, new treatment plant and outfall form Mar del Plata's sanitation system. With these installations, the environmental monitoring of Mar del Plata's beaches showed that recreational water quality standards for fecal *Enterococci* were not exceeded (fig. 2). Further, near field monitoring shows there is neither organic enrichment nor heavy metal and hydrocarbon contamination in the sediments [22]. Moreover, benthic organism studies indicate good conditions and a healthy marine receiving environment [5], [25]

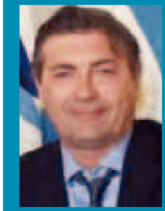
**Discussion and conclusions**

We have described an extensive project process that involved multiple technical and institutional actors. Noting the long times to complete the outfall construction, as well as past and current wastewater treatment plants, the sanitation plan for Mar del Plata had to progress at all levels (local, provincial, and national), as a state policy independent of government changes.

For more than 30 years, different city mayors, hundreds of technical professionals and workforce from OSSE, local and international consultants, and National and Provincial Entities and Authorities participated and contributed to the sanitation project. It is impossible to name every single person without unjustly missing important contributions, but it is fair to say those involved were genuinely interested in obtaining the best solutions. There were long periods during which the project was put into question. The doubts with regards to the project were generally of a technical nature, whereby the choice between outfall and a secondary treatment plant promoted a debate that ultimately allowed the project's continuation. Therefore, the technical basis behind such projects must be sustained by a network of professionals that are able to understand and solve the myriad of problems that may occur throughout a project's lifetime, from inception through construction and into operation, and eventually until decommissioning.

Today's accomplishments were only possible thanks to the assembled network effort, knowledge and will to see the project to completion. Specially, the concerted actions from OSSE and successive local and national governments were crucial to overcome obstacles to the outfall construction. These institutions had the foresight to prioritise the development and implementation of public policies as a vehicle to guarantee the water quality of the beaches enjoyed by visitors from across the country. It is therefore imperative to have water quality objectives and receiving environmental values ahead of any specific technical solution, and not the other way around.

Likewise, the implementation of the Marine Environment Monitoring Program in conjunction with adequate assessment of its

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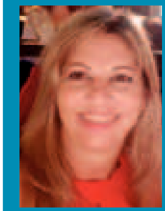

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results were fundamental, not only for evaluation of ecosystem health and recreational water quality during the project progression, but also for recognition that the outfall construction was essential for the sanitation needs of the city. The program was also crucial to demonstrate that, once the project was initiated, no additional steps would be required to complement the overall city's sanitation plan. Further, the monitoring allowed the design of a Contaminant Mitigation Program using the Virtual Beach system that was based on sampled parameters, maritime conditions and modeling predictions. For other localities still requiring completion of their sanitation programs, application of a similar system is recommended as an effective means of reducing the risk of beach fecal contamination.

Possibly, the most important conclusion from this story is the importance of networks to advance, improve, and finalise projects. Along the way, the project largely benefited from the interaction of professionals through the IAHR-IWA TC on Marine Outfall Systems. These interactions culminated in the adoption of tools developed by Committee members, as well as the identification of experienced consultants for crucial project adjustments. Further, the meetings organised by the TC and other relevant organisations created optimal conditions for the establishment of an effective network of professionals, which proved to be the best conduit for reduction of project uncertainties and timelines, and for the development of solutions to drive the project towards its final objectives.

This experience shows how Technical Committees are invaluable for the collective construction of sanitation projects around the world. Technical meetings, such as the International Symposium on Outfall Systems held in Mar del Plata in 2011, are not only important for the outfall technical community but also offer an important vehicle for communication of sanitation activities to the public at large, and are therefore an integral part of achieving SDGs 6.6*.

As previously discussed, marine outfall systems can play an important role to achieve SDG's by 2030. However, long periods of inaction cannot be justified nor afforded. The professional networks and dissemination of learned lessons between projects were demonstrated to be the best approach to reduce delays and conclude projects. The cost-benefit ratio provided by marine outfalls is likely to lead to improved sanitation conditions for achievement of SDGs.


## Special acknowledgments

Dr. Walter Frick not only made the Virtual Beach system available but also assisted us in its calibration to Mar del Plata conditions without any financial interests. He also accompanied and helped the design of the Contamination Mitigation Program and assisted us in the presentation of our Works in relevant Conferences and Symposia. Above all, he and his wife Anne graced us with their affection.

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Finally, to the successive OSSE board of directors, who trusted and believed the participation in IAHR technical meetings, as well as other networks (IWA, AIDIS and MWWD), were important to reach our achievements. The successive OSSE presidents Arch. Carlos Katz, Eng. Mario dell Olio and Arch. Alejandro Pozzobón and Syndical Counsel Mabe Segura who foresaw our participation in international networks as the support for best decisions. ■


On behalf of the IAHR-IWA Joint Committee on Marine Outfall Systems, COFES (Federal Council of Sanitary Entities of Argentina) and OSSE (Public Water and Sanitation Company of Mar del Plata - Argentina) the authors would like to cordially invite all IAHR members to the 3rd International Symposium on Outfall Systems to take place in Buenos Aires from 12 to 19 September 2021. Further details can be found at https://www.cofes.org.ar/simposio/.

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* Goal 6.6.a: Expand international cooperation and capacity-building support of development countries in water and sanitation related activities and programs, including water harvesting, desalination, water efficiency, wastewater treatment, recycling and reuse technologies.
Goal 6.6.b: Support and strengthen the participation of local communities in improving water and sanitation management

# FROM LABYRINTH TO PIANO KEY WEIRS: THE STORY

BY SÉBASTIEN ERPICUM, FRANÇOIS LEMPÉRIÈRE, AHMED OUAMANE, MICHEL HO TA KHANH, FRÉDÉRIC LAUGIER, BLAKE TULLIS AND BRIAN CROOKSTON

**Labyrinth weirs are an efficient solution for free surface flow whose development has been initially favored by a close collaboration between research and industry in the United States. Piano Key weirs improve the traditional Labyrinth concept and have been developed with the same collaborative spirit at an international level. Both structures have a huge potential of development and application worldwide, which has been exploited yet only in a few countries.**

**Figure 1. Hope Mills dam spillway with a 4.6 m high Labyrinth weir in North Carolina, USA (commissioned 2018). Photo courtesy of Schnabel Engineering.**

**Figure 2. Charmines dam spillway in France with a 23 m wide type-A piano key weir section on both sides of the crest gates (PKW commissioned in 2015). Photo courtesy of EDF.**

Spillways are key dam safety structures releasing excess water from reservoirs, in particular during floods. Weirs control the discharge through free flow spillways and corresponding reservoir levels. A high discharge capacity spillway allows for more reservoir water storage while keeping dam overtopping and other upstream flood related risks at acceptable levels. Since the discharge capacity of a weir is proportional to its crest length, engineers and scientists early on developed solutions to maximize this crest length [5] while responding to projects goals or sites limitations (restricted spillway width, project economics, etc.). In this respect, Labyrinth weirs, firstly formally studied in 1941 by Gentilini, place the crest of a thin vertical wall along a triangular, trapezoidal or rectangular path (in plan view) to maximize the crest length within a limited footprint (Figure 1). The number of Labyrinth weir projects increased exponentially after the publication of key research by the US Bureau of Reclamation and the American Society of Civil Engineers (ASCE) in the eighties and the construction of Ute Dam (USA). Additional noteworthy studies that have advanced the state-of-practice regarding Labyrinth weirs have been conducted at the Laboratório Nacional de Engenharia Civil (Portugal) and at the Utah Water Research Laboratory at Utah State University (USA). More than one hundred structures have been built to date [1] and Labyrinth weirs remains an active research topic today.

From 1999, the NGO Hydrocoop began investigations to improve the traditional Labyrinth concept, in close collaboration with the Electricité de France - Laboratoire National d'Hydraulique (EDF-LNH) in France and then the Indian Institute of Technology Roorkee in India and the Biskra University in Algeria [3]. Their objective was to develop a new type of labyrinth weir with an even smaller footprint while maintaining a structurally simple and economical structure that could readily be constructed. Such a weir could be placed atop gravity dams in addition to the various applications common to Labyrinth weirs (embankment dams, run-of-river, etc.). In 2003, based on the results of many tests with selected shapes at University of Biskra and some experiments at EDF-LNH, Lempérière and Ouamane proposed for the first time the Piano Key weir [2].

A Piano Key weir is a rectangular Labyrinth weir featuring inclined aprons with cantilevered apexes, increasing crest length while reducing footprint size. This arrangement is also structurally advantageous as the cantilevered walls are shorter and steel reinforcement reduced, relative to a Labyrinth weir. The name "Piano Key weir" refers to the rectangular crest pattern and was proposed by Claude Bessière, who was involved in the development of Fusegates, a fuse system placed on a spillway crest that operates as a Labyrinth weir for a moderate range of reservoir levels and overturns at high reservoir elevation to free the supporting crest. Several types of Piano Key weirs have been defined based upon the geometry of the overhangs with the types A and B (as described by Lempérière and Ouamane in

2003) being the primary types constructed. It is interesting to note that the dams of Beni Bahdel and Bakhada, built during the 1930s in Algeria, are equipped with a weir having an inclined upstream apron similar to the type B Piano Key weir.

Following 2003, developments continued at the University of Biskra, where a specific experimental platform was built by Professor Ouamane [4]. Additional advancements at LNH were provided by Mr Cicero but also at IIT Roorkee, IWHR Laboratory (China) and at Ho Chi Minh and Hanoi Hydraulic Laboratories (Vietnam). Subsequent research contributions and design advancements were provided by Ecole Polytechnique Fédérale de Lausanne (Switzerland), University of Liege (Belgium) and Utah State University (USA). The next crucial step in Piano Key weir development was reached with the design and construction of the first prototype structures. Electricité de France with Mr Laugier applied the concept to increase the discharge capacity of existing dams in France (Figure 2), while it has been used by the Vietnamese National Committee on Large Dams with the advices of Mr Ho Ta Khanh to avoid more expensive and less safe surface gates on new structures in Vietnam (Figure 3). As for traditional Labyrinths, the collaboration between research, consultancy and industry was a key element in the Piano Key weirs development success. Of particular note is the early organization of several specific international workshops and conferences that facilitated the connection of all these actors, forming an international nonlinear weir community. At these special events, an open and friendly environment was established where knowledge from practice and research was freely exchanged; these events also resulted in the publication of multiple reference books on these two weir types (https://www.pkw.uliege.be).

Since the 2006 Goulours dam Piano Key weir commissioning in France, more than 35 Piano Key weirs have been build worldwide, consistent with the number of traditional Labyrinth weirs built during that same period [1]. Research continues throughout the globe, with an average of 15 contributions in scientific journals every year since 2010. This prompt and fast development shows that the Piano Key weir solution fills a gap in hydraulic structures engineering, in particular in the current period of climate evolution, limited resources and continually increasing water related issues.

Labyrinth and Piano Key weirs, both very efficient free surface flow weir solutions, have a huge potential of development and application worldwide. This potential has been well used for the first type in the US, while for the latter it has mainly been exploited for existing dams in France and new structures in Vietnam. It is the authors' belief that the fast development of these nonlinear weir solutions will continue into the future, with a wish that the same level of enthusiasm, collaborative spirit and competency with which it began persists. ■

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**Figure 3. Van Phong dam spillway with a 5 m high type-A Piano Key weir in Vietnam (commissioned in April 2015). Photo courtesy of VNCOLD.**


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# Prince Sultan Bin Abdulaziz International Prize for Water

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**1) The team of Dr. Benjamin S. Hsiao (Stony Brook University, New York, USA)**
for the development of adsorbents, coagulants and membrane materials from sustainable, biomass-sourced nanocellulose fibres along with numerous practical applications that promise to provide effective water purification for off-grid communities of the developing world. (The team also includes Dr. Priyanka Sharma, research scientist at Stony Brook University).

Dr. Sherif El-Safty

**2) The team of Dr. Sherif El-Safty (National Institute for Materials Science, Japan)**
for developing novel nano-materials in hierarchal and micrometric monoliths to achieve a nano-filtration/capture/detection process that quantitatively detects and selectively removes a wide range of water contaminants in a single step. A diverse range of these materials, which are conducive to mass-scale production, provides nano-filtration membranes and filters for water management applications, including purification, remediation, and the monitoring of hazard levels of various water sources.

## Surface Water Prize

Dr. Zbigniew Kundzewicz

**Dr. Zbigniew Kundzewicz (Polish Academy of Sciences, Poznan)**
for advancing our understanding of the relationship between flood risk, river flow, and climate change.

## Groundwater Prize

Dr. J. Jaime Gómez-Hernández

**Dr. J. Jaime Gómez-Hernández (Universitat Politècnica de València, Spain)**
for pioneering work on solving the "inverse problem" in hydrogeology.

## Alternative Water Resources Prize

Dr. Peng Wang

**Dr. Peng Wang (King Abdullah University of Science and Technology, Thuwal, Saudi Arabia)**
for work at the forefront of solar-evaporation water production technology.

## Water Management and Protection Prize

Dr. Jay R. Lund

**Dr. Jay R. Lund (University of California Davis, USA)**
for the development of the CALVIN water supply optimization model that couples traditional water-supply criteria with economic considerations.

Nominations are open for the 10th Award. Nominations can be made online until 31 December 2021.

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