



Digital Water

Artificial Intelligence
Solutions for the Water Sector

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Artificial Intelligence Solutions for the Water Sector

Authors

Zoran Kapelan

Delft University of Technology, Department of Water Management, The Netherlands

Emma Weisbord

Digital Water Consultancy, Royal Haskoning DHV, The Netherlands

Vladan Babovic

National University Singapore, Department of Civil and Environmental Engineering, Singapore

Foreword



Digital technologies are penetrating every pore of our society and although digitalisation of the water sector is much discussed, it is not always fully understood. As part of the digitalisation trend, Artificial Intelligence (AI) has been often portrayed as a key technology to make a positive difference in our world.

The IWA Digital Water Programme has initiated a series of White Papers to help utilities, water professionals and all those interested in water management and stewardship issues to better understand the opportunities of digital technologies. This paper in the series focuses on AI providing several example applications and case studies of such technologies in the water industry. The intention is to offer concrete, clear examples of AI-based solutions in language that is accessible to a much wider audience.

The paper includes case studies ranging from Machine Learning-based systems to detect leaks from underground pipes, to how visualisation and AI are used to analyse CCTV video for faults in sewers, to how unconventional data sources (e.g., videos from smartphones and CCTV) can be used to monitor rainfall intensity. These examples and more demonstrate not only the power of AI, but also that water management practice is already benefiting from the developments in AI and Machine Learning.

Digital technologies have changed our everyday lives for the better and are having a similarly profound impact on water management worldwide. We must ensure we understand those technologies well and that they keep improving our lives in the future.

Professor Dragan Savic, CEO of KWR Water Research Institute
Chair – IWA Digital Water Programme Steering Committee



Digitalisation is transforming every sector of our society – from financial to education to natural resources, including how we plan our activities and how we communicate with each other. Against this wider backdrop, the water sector is increasingly embracing digitalisation in responding to customers' needs, ensuring compliance with regulations, improving performance, and ensuring efficient and reliable services.

At the same time, increasing global change pressures such as urbanisation and climate change mean the water sector will experience difficulties in efficiently managing scarcer and less reliable water resources. In order to meet these challenges, there is a need for a fundamental change in the way we manage water, based on key concepts including: interventions over the entire urban water cycle; reconsideration of the way water is used (and reused); and greater application of natural systems for water and wastewater treatment. From this perspective, digitalisation becomes a vital enabler that will allow the water sector to make this necessary and important transition. It provides the foundation for us to think and act smarter – illustrated well by the many creative digital responses that have emerged in response to the Covid-19 pandemic.

However, the uptake of digitalisation is an evolving journey. It requires changes to organizational culture coupled with the integration of digital tools that supports the progress of the water sector along the digital maturity curve, from the opportunistic deployment of digital solutions to a more transformative one. Among these, Artificial Intelligence (AI) is a key technology in the digitalisation of water utilities. It can support areas such as real time monitoring, predictive maintenance, process control, and forecasting.

IWA is actively engaging across the international water sector to support adoption of a smarter approach to water management, highlighting the advantages of digitalisation as a key enabler in the path to a smarter approach. Tapping into the expertise of our global members, the IWA can function as a catalyst for water and wastewater utilities during their journey towards the uptake of digital technologies. To support this journey, the IWA Digital Water white paper series is providing insights into core aspects of the digital space. In the case of AI, this means how it can help detect real challenges in the water sector and provide practical solutions with concrete benefits.

At IWA, we are proud to be at the front line in promoting the digitalisation of our sector and its progress along the digital maturity curve. We believe this will have a critical role in the journey towards a more sustainable and resilient future.

Kalanithy Vairavamoorthy

Executive Director of the International Water Association

Summary

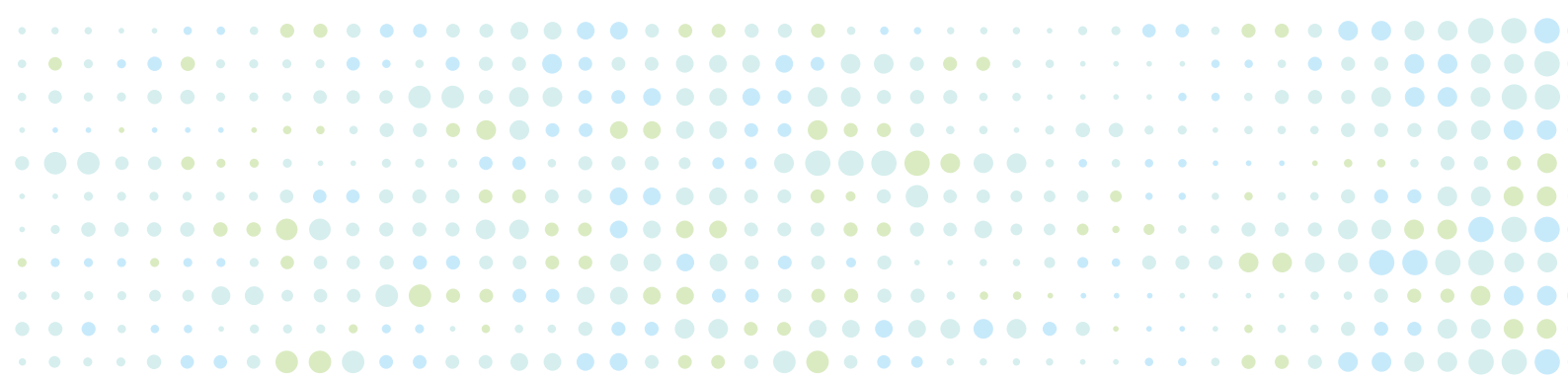
This white paper focuses on presenting Artificial Intelligence (AI) based solutions for the water sector. The aim is to introduce readers to tangible solutions (rather than technologies) that were developed to address specific challenges in real-life water systems. We hope that by using applied examples, the topic of AI and its applications in the water industry will be made clearer to a wider group of interested readers. The examples shown here were selected to demonstrate that AI-based solutions can address real challenges and provide tangible benefits to the water sector.

Introduction

A number of white and other papers have been written recently on the potential use of AI in the water sector (Sarni et al 2019). Most of these publications discuss general aspects of the AI and related *technologies*, often providing limited or no specific examples. The aim of this white paper is to fill in this gap by presenting several practical *solutions* that were developed to address specific, *actual* challenges in *real-life* water systems.

This paper is a part of a series of white paper under the IWA Digital Water Programme (IWA, 2019) which aims to generate and share knowledge on digitalisation of the water industry.

The IWA Digital Water Programme acts as a catalyst for innovation, knowledge and best practice; and provides a platform to share experiences and promote leadership in transitioning to digital water solutions. By sharing experience on the drivers and pathways to digital transformation in the water industry, the programme is consolidating lessons and guidance for water utilities to start or continue to build their journey towards digitalisation.

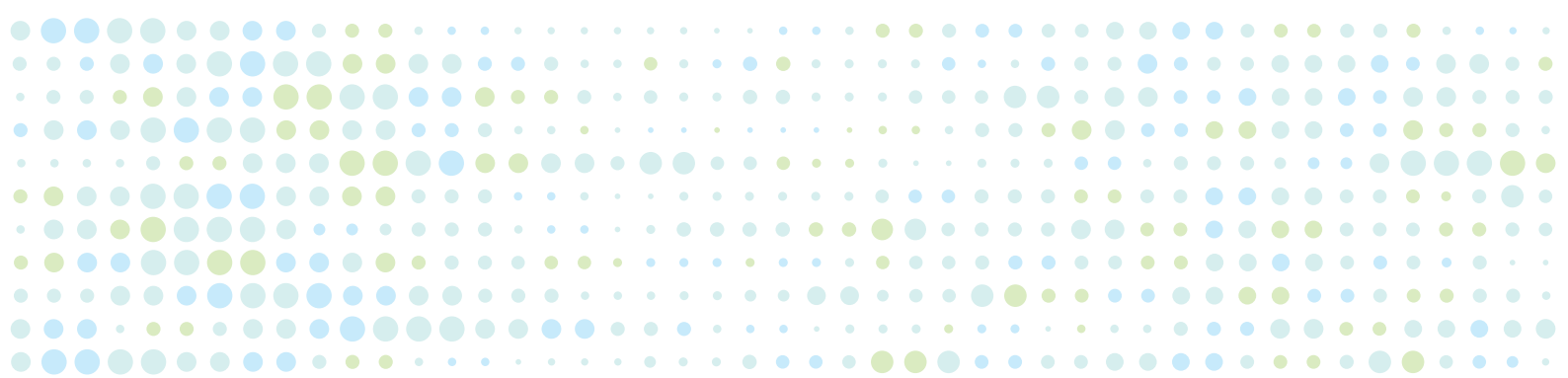


Artificial Intelligence

Artificial Intelligence is a term used to describe the theory and development of computer systems that are able to perform tasks normally requiring human intelligence. Examples of AI type systems include various expert systems, speech recognition and systems used for financial trading. Two important concepts that are frequently mentioned in the context of AI are Machine Learning and Computer Vision.

Machine Learning is the study of computer methods and algorithms that improve automatically through experience. Machine Learning typically involves building some computer model from data with the ability to make predictions later on without the need for additional software programming. One of the best-known machine learning methods is the Artificial Neural Network (ANN) that works by mimicking biological neural networks that exist in a human brain. ANNs learn from training data presented to them in order to capture the functional relationships among the data, even if the underlying relationships are not known or the physical meaning is difficult to explain. This enables the ANNs to discover patterns in data that are often unknown, even to the best experts in the field. Computer Vision denotes a set of AI-type methods that are used to train computers to essentially interpret and understand digital images and videos. Examples of computer vision applications include systems for facial recognition, medical diagnostics and driverless cars.

Many AI methods exist. It is not our attention to describe these methods in detail, including the methods mentioned in the rest of this paper. Instead, this paper focuses on the presentation of examples of AI-based solutions that make use of these methods.



Real-time Detection of Pipe Bursts in Water Distribution Networks

Leakage is a major issue in water distribution systems worldwide. This example presents an AI-based system that detects pipe bursts/leaks but also equipment and other failures in these systems. The detection system works by automatically processing pressure and flow sensor signals in near real-time to forecast the signal values in the near future (using ANN). These are then compared with incoming observations to collect different forms of evidence about the failure event taking place. The evidence collected this way is processed using Bayesian Networks to estimate the likelihood of the event occurrence and raise corresponding alarms (Romano et al 2014). The system effectively learns from historical burst and other events to predict the future ones. Elements of the detection system, developed initially as part of a research project, were built into a commercial Event Detection System (EDS).



Figure 1. EDS Screenshot with Real-Time Analysis of a Specific Alarm

EDS has been in use by a large UK water company since 2015. It processes data from over 7,000 pressure and flow sensors every 15 minutes (see Figure 1). This enables EDS to detect pipe bursts and related leaks in a timely and reliable manner, i.e., shortly after their occurrence and with high true and low false alarm rates. In addition to detection, EDS can proactively prevent burst events by detecting equipment failures that often precede these events (e.g., pressure reducing valve failures). EDS does not make use of a hydraulic or any other simulation model of the analysed water distribution network, 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 makes the EDS robust and scalable as it enables data to be processed in near real-time (i.e. within the 15 minute time window). The use of EDS has resulted in major operational cost savings to date, significantly reduced customer supply minutes lost, reduced leakage and several other benefits to the water company (full details not mentioned for commercial reasons). All this has led to a change in company business culture and improved service to over 7 million customers.

Automated Asset Condition Assessment using AI and Computer Vision

The inspection of urban drainage (i.e., sewer) systems' pipes is important as undetected structural and other faults (e.g., displaced joints, cracks, etc.) may result in severe pollution and/or flooding incidents. This inspection is done usually by recording CCTV videos and then analysing these manually. This process is time consuming (i.e., costly) and rather subjective/inconsistent in nature hence not necessarily always reliable.

The AI-based solution automates the process of analysing CCTV videos and detection of faults in pipes. It does this by using computer vision and machine learning methods (Myrans et al 2018). Image processing is conducted first to process and convert the CCTV images into suitable data. This data is used then to detect faults with a help of a Random Forest machine learning method. This method is trained before it is used on a number of pre-labelled CCTV images. The automated detection works similarly to the human face recognition system although the task of fault detection is probably more complex in sewers due to too many different types of faults that exist and that can manifest themselves in very different ways in CCTV images.

The above solution was successfully tested and validated on unseen real CCTV data from several water companies in the UK, Finland and Australia. It has a high true detection rate accompanied with low false alarms rate. This technology is currently being commercialised in collaboration with the UK water company.

Predictive Wastewater Treatment Plant Control

Royal Haskoning DHV's Aquasuite® software (<https://aquasuite.ai/en/>) was deployed at PUB Singapore's Integrated Validation Plant at Ulu Pandan Water Reclamation Plant in March 2019. It was introduced to provide operators and managers with predictive insights while improving plant performance. Aquasuite PURE collects real-time data on the plant's flows and qualitative measurements, including those for ammonia, nitrates,



Figure 2. Dashboard view of Aquasuite Pure

oxygen, phosphates and dry solids and builds a historical database. The software then makes use of advanced analytics and Machine Learning algorithms to predict the plant's wastewater flows and loads, oxygen needs, chemical dosing needs, and other requirements (see Figure 2). The system controls key treatment processes, automatically optimising them in real-time based on its predictions and the plant's historical performance. It further detects anomalies in the plant's processes through quantile regression techniques based on multiple measurements. Prediction accuracy of the influent flow increases over time as the software is learning, reaching a prediction accuracy of 88% after just one month.

Connecting to the plant's Supervisory Control and Data Acquisition (SCADA) system to gather data and control key processes, data is sent to the Aquasuite cloud solution. With the data collected in near real-time in the cloud, the software tracks the actual performance of the on-premise solution through a digital twin, a digital replica of a physical system. More advanced analytics are made available to operators through the cloud, while the on-premise part keeps optimising real-time performance. Machine learning is used to understand the efficiency of each process, the learnt relationship is then used with the prediction of the influent load to decide the most optimal efficient set-points for treatment. Results show that Aquasuite learns and predicts operations several days ahead and it can function as an autopilot, able to perform unattended operation. Preliminary results show a reduced aeration flow of up to 15% with predictive control, resulting in corresponding energy savings.

Smart Alarms for Proactive Wastewater Network Management

Aquasuite FLOW is an AI powered predictive analytics tool for wastewater networks that enables prediction and early warning of critically high-water levels in sewers, potential pollution events, and detection of anomalous levels that could indicate blockages in the network (see Figure 3).



Figure 3. Dashboard view of flow levels and predicted outcomes

Water utilities are most at risk for blockages during rainfall events, in part because of sewer flooding, capacity limitations, and foreign objects. Aquasuite uses AI to detect when high level flows in sewers exceed critical levels or are not consistent with the expected flows. The system identifies these as anomalies through a customisable smart alarm notification system. Using AI in this context drastically reduces false alarms and prioritises the remaining alarms to accurately and efficiently manage blockages through early detection and real-time response, preventing further problems like fatbergs. Monitors located strategically around the catchment collect flow and level data. That data is transmitted to a secure, reliable Aquasuite cloud platform that displays the information in easy to use dashboards and reports for analysis. Using smart algorithms, real time data, historical data sets and information from other sources such as rainfall, data are translated into actionable insights for operators.

The AI model is built on two multi-layer perceptron ANNs that work together to support operators. A regressive ANN predicts flow levels for the next 48 hours and a heuristic ANN identifies event anomalies like blockages. Integrating machine learning allows the anomaly detection to continually improve over time. Aquasuite data technicians review the data alongside the predictive analytics software to verify the alarm protocols. The additional human intervention helps detect any existing or temporary anomalies, seasonal variations and external influences. Prediction of a high sewer level enables water utilities to proactively inform their customers of potential sewer flooding, and, in critical environmental regions, to actively prevent spills. Anomaly detection enables the utilities to detect and clear blockages before they cause sewer overflows.

Real-Time Forecasting of Sea Currents

Over the past few decades ANNs have evolved in a popular approximation and forecasting tool, frequently used in a range of problems and application areas (ASCE Task Force, 2000). In this solution, a recurrent ANN is used to create a real-time hybrid data assimilation system resulting in extremely accurate forecasts of sea surface currents. This solution was developed to support the construction of Øresund Link connecting Danish capital Copenhagen and City of Malmö in Sweden (Babovic et al, 2001). The combined roadway and rail line bridge run nearly 8 km where it then transitions into an underwater tunnel for the remaining 3.5 km. Due to the material of the seafloor, a tunnel was not possible. Instead, engineers chose to sink and connect 20 prefabricated reinforced concrete segments – the largest in the world at 55,000 tonnes each – and interconnect them in a trench dug at the seabed. The elements were prefabricated in a special-purpose build facility North of Copenhagen, sealed shut and using a specially designed barge along with 7 tugboats, lowered into place at required accuracy of alignment of 2.5 cm. The towing operation for each element could be conducted within a “window of opportunity” of 36 hours during which sea surface currents had to be guaranteed to be less than 0.75 m/s. Despite extremely challenging conditions, all 20 elements

of the Øresund link's tunnel were successfully placed at their positions between August 11, 1997, and January 6, 1999 - 20 towing operations in 17 months! It is alleged that the accurate ANN-based forecasting of sea surface currents was one of the key factors in this achievement. The Øresund Strait Link was opened to the public on July 1, 2000.

Bayesian Networks for Proactive Asset Management

The economic and social costs associated with pipe bursts and leakage in modern water supply systems are rising to unacceptably high levels. The challenge for the decision maker is to determine what pipes in the network to rehabilitate, by which rehabilitation method and at what time within the planning horizon. Advanced AI, machine learning and statistical methods are used in order to establish risks of pipe bursts (Economou et al 2014). For example, analysis of the database of already occurred burst events can be used to learn a risk model as a function of associated characteristics of bursting pipe (its age, diameter, material of which it is built, etc.), soil type in which a pipe is laid, climatological factors (such as temperature), traffic loading, etc. In this context, a machine learning model based on Bayesian Network is used to predict which pipes are most vulnerable to failure including a metric for failure probability (Babovic et al, 2002). Bayesian networks are a probabilistic graphical model that use Bayesian inference for probability computations. The approach models conditional dependence and, therefore, causation. Through these relationships, one can efficiently conduct inference on the variables in the graph exemplifying pipe failure mechanism. Pilot projects using the approach have been conducted in Stockholm, Singapore, UK and Denmark.

Computer Vision for Opportunistic Rainfall Monitoring

The quantity and quality of precipitation data are crucial in meteorological and water resource management applications. Rain gauges are a classic approach to measuring rainfall. However, as we enter the age of the Internet of Things in which “anything may become data” so-called opportunistic sensing using unconventional data sources offer a promise to enhance the spatiotemporal representation of existing observation networks. One particular area attracting attention is the estimation of quantitative and analytical rainfall intensity from video feeds acquired by smart phones or CCTV surveillance cameras. Technological advances in image processing and computer vision enable extraction of diverse features, including identification of rain streaks enabling estimation of the instantaneous rainfall intensity (Allamano et al, 2015). Recent AI and machine learning approaches rely on the use of autoencoders, deep learning and convolutional neural networks to address the problems. Companies such as WaterView (Italy), Hydroinformatics Institute (Singapore), as well as universities (Southern University of Science and Technology China, Shenzhen) have proposed and implemented practical approaches to weather hazards in energy, automotive and smart cities application domains (Jiant et al, 2019).

Conclusion

This white paper presented a number of Artificial Intelligence (AI) based solutions for the water sector. The focus was on presenting actual solutions (rather than technologies) that were developed to address specific, real challenges in real-life water systems.

Despite the limited number of examples shown, it can be concluded that AI-based solutions have a lot to offer to the water sector, i.e., that these solutions can effectively address real challenges in these systems whilst providing tangible benefits.

For further information about the AI-based solutions presented in this paper please contact Prof. Zoran Kapelan (z.kapelan@delft.nl).

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INTERNATIONAL WATER ASSOCIATION

Alliance House • 12 Caxton Street
London SW1H 0QS United Kingdom
Tel: +44 (0)20 7654 5500
Fax: +44 (0)20 7654 5555
E-mail: water@iwahq.org

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