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KEY POINTS

- Unaccounted-for-water (UFW) is a key benchmarking parameter indicative of the operational and financial performance of a water utility. Maximizing the use of information and communications technology (ICT) for UFW improves the quality of service delivery to customers.
- Despite an increased application of numerical tools by water utilities (Hydraulic Modeling 1.0), the digital transformation of the water sector is lagging behind other sectors, such as energy. Cost-effective sensors combined with Internet of Things brings a paradigm shift for smart water management (Hydraulic Modeling 2.0), supported by artificial intelligence and big data analytics.
- Key areas for policy action include (i) enabling ethics in smart water utilities through regulation and public participation to secure buy-in from consumers, and to protect their personal data; (ii) issuing guidelines for a smart water road map to move water utilities toward a digital transformation; and (iii) piloting Hydraulic Modeling 2.0, first targeting the prognosis for UFW.

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Using Artificial Intelligence for Smart Water Management Systems

Hubert Jenny
Former Principal Infrastructure Finance Specialist
East Asia Department
Asian Development Bank

Yihong Wang
Senior Investment Officer
East Asia Department
Asian Development Bank

Eduardo Garcia Alonso
Consultant

Roberto Minguez
Consultant

INTRODUCTION

Data-driven "intelligent" applications have become disruptors to daily living. Innovative water utilities can benefit from this digital technology revolution to improve their performance. By harnessing the power of artificial intelligence algorithms and big data analytics, water utilities can maximize information and data available to make better decisions while enhancing service delivery and reducing costs. This brief introduces the principles of artificial intelligence for water utilities embarking on this digital transformation to improve their water distribution operation in general, and to address unaccounted-for-water problems in particular. The brief describes some of the most extended applications of big data analytics and artificial intelligence-related algorithms in water supply, discusses how water utilities can pilot artificial intelligence toward the prognosis of unaccounted-for-water, and presents recommendations for implementation and preliminary cost estimates.

ROLE OF ARTIFICIAL INTELLIGENCE IN WATER SUPPLY

Artificial intelligence (AI) comprises "a branch of computer science dealing with the simulation of intelligent behavior in computers."[1] In the context of delivering efficient water supply, AI or machine learning is mainly applied to decision-making tasks: how water utilities can maximize information and data available to make better decisions while enhancing service delivery; optimizing capital investment (CAPEX); and reducing

[1] Merriam-Webster English Dictionary. 2020. Artificial intelligence. https://www.merriam-webster.com/dictionary/artificial%20intelligence.

operating costs (OPEX), including social and environmental externalities. Water utilities are following the lead of other sectors, especially energy, sometimes without fully understanding the underlying assumptions and implications in applying information and communications technology (ICT) into their operations.

The use of AI, in general, and in water supply, in particular, has several policy implications to improve the performance of water utilities and the quality of the service delivery: **Ethics and governance** deal with the protection of personal and financial data from consumers, and technical and financial data from water utilities. **Regulation** deals with benchmarking, since unaccounted-for-water (UFW) is one of the key operational parameters to determine the efficiency of a water utility in reducing both physical losses (e.g., water leaks and pipe bursts) and commercial losses (such as illegal connection and metering errors).[2] **Technical** policies deal with line ministries and water associations to update the national and water "Code of Practice," and to guide water utilities in their digital transformation. **Financial** policies address short-term CAPEX requirements to finance smart water utilities with new financing instruments.

The digital transformation of water supply supports the Sustainable Development Goals (SDG), especially SDG 6: Ensure availability and sustainable management of water and sanitation for all; and SDG 13: Climate Action, by taking urgent actions to promote climate-related investments to combat climate change impacts. In addition, application of AI numerical tools to the water sector largely contributes to addressing key global water sector challenges, such as

(i) water assets that are aging and deteriorating, and CAPEX and OPEX limitations to control water tariff increases;
(ii) water as a growth-limiting factor in the water–food–energy nexus, both in terms of quality and scarcity, compounded by climate change impacts and increased urbanization; and
(iii) integrated water resources management, which needs to be promoted at the regional and city levels with low-impact development for sponge cities.[3]

For UFW, physical water leak detection techniques are based on combining special equipment (acoustic sensors, gas tracers, etc.) with human skills. A current trend is to incorporate AI in some of this hardware (for instance, acoustic correlators) to replace humans in interpreting the data (water leak noises). With the advances in numerical modeling of the hydraulics of water distribution networks, it is now possible to detect potential leaking pipe sectors through numerical methods, as long as the hydraulic models are fed with a sufficient amount of calibrated field data such as pressure, flow, and node consumptions.

All the hydraulic variables in a water distribution network show some type of correlation, induced by underlying hydraulic laws (mass and momentum conservation, as explained in the Bernoulli principle), which represent the foundation of any water distribution system. The numerical algorithms developed for water leak detection aim to detect certain spatial and temporal patterns and anomalies in the values of the flow and pressure parameters at different points in the water distribution network. This is to extract information about physical and commercial losses. Numerical methods require calibration with field data; when a Supervisory Control and Data Acquisition (SCADA) monitors the water distribution system, numerical methods become a cost-effective investment (see Figure).

Literature review on UFW and nonrevenue water (NRW) shows many attempts to take advantage of both data and big data from cost-effective sensors, calibrated hydraulic modeling of the water distribution network, and advanced numerical techniques. There are two main approaches in the numerical routines used for network analysis, each one with distinct methods and underlying hypotheses:

(i) **Physically based methods** draw on the combination of statistical tools, such as state estimation techniques and pressure sensitivity analysis, with hydraulic modeling.[4] The physical methods can take full advantage of the underlying universal physical laws (conservation of mass and momentum) that govern water distribution networks. The seamless combination of data and numerical models eventually enables a "digital twin" or "digital mirror" of the physical water distribution network to test and check scenarios in real time. This approach is common to other sectors, for instance, in the operation of power distribution networks.[5]

    From the point of view of operations, physically based methods are the starting point for water utilities into their

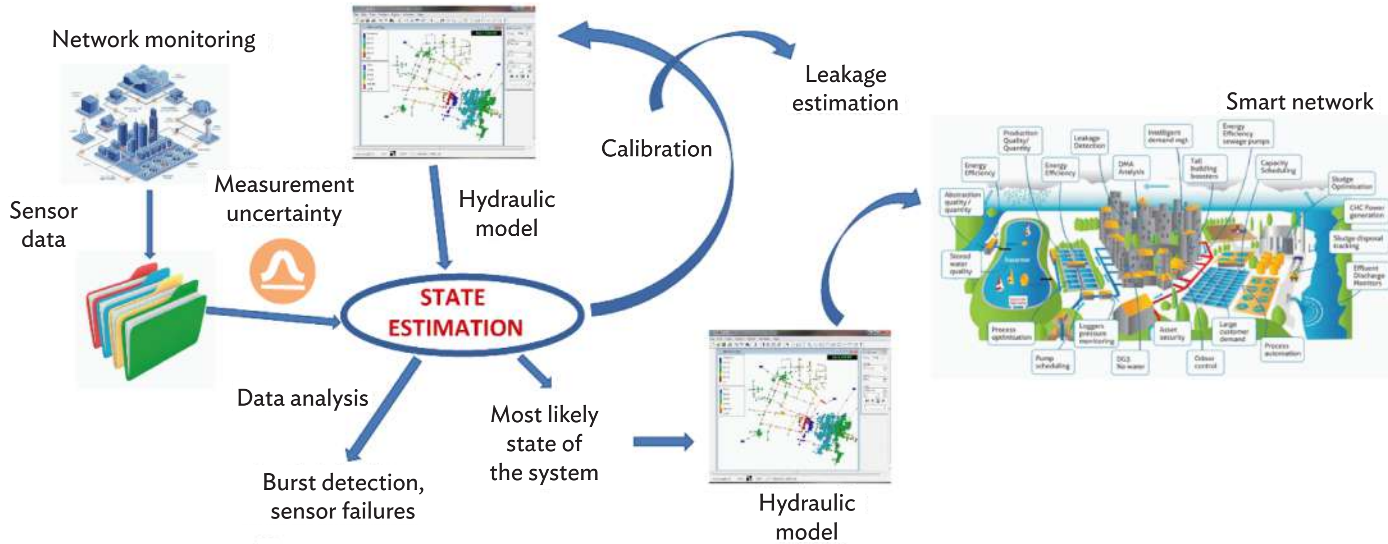
[2] The International Benchmarking Network for Water and Sanitation Utilities (funded by the World Bank Group and the International Water Association with the support of other development partners and stakeholders) promotes good benchmarking practices among water and sanitation services. See International Benchmarking Network. https://www.ib-net.org/.

[3] Low-impact development applied to sponge cities is a land planning and engineering design approach to manage stormwater as part of climate adaptation proofing of urban infrastructure. It emphasizes conservation and use of on-site-natural features to protect water quality.

[4] D. Jung and J. H. Kim. 2018. State Estimation Network Design for Water Distribution Systems. *Journal of Water Resources Planning and Management*. 144 (1); S. G. Vrachimis, D. G. Eliades, and M. M. Polycarpou. 2018. Real-time Hydraulic Interval State Estimation for Water Transport Networks: A Case Study. *Drinking Water Engineering and Science*. 11 (1). pp. 19–24; S. Díaz, J. González, and R. Mínguez. 2016. Uncertainty Evaluation for Constrained State Estimation in Water Distribution Systems. *Journal of Water Resources Planning and Management*. 142 (12); H. R. Asgari and M. F. Maghrebi. 2016. Application of Nodal Pressure Measurements in Leak Detection. *Flow Measurement and Instrumentation*. 50. pp. 128–134; and R. Pérez et al. 2011. Methodology for Leakage Isolation Using Pressure Sensitivity Analysis in Water Distribution Networks. *Control Engineering Practice*. 19 (10).

[5] E. Caro, R. Mínguez, and A. J. Conejo. 2013. Robust WLS Estimator Using Reweighting Techniques for Electric Energy Systems. *Electric Power Systems Research*. 104. pp. 9–17.

Figure: Main Components of a Network Analysis System, Including Hydraulic Modeling 2.0 Functionalities



Source: Asian Development Bank.

digital transformation. The initial stage, called Hydraulic Modeling 1.0, does not require advanced big data analytics. All water utilities should have a standard hydraulic model that can reproduce with sufficient accuracy the typical working conditions of the water distribution network, using deterministic (fixed) parameters and consumption laws. Only when such a model is in place is it advisable to move toward a more advanced method that incorporates the probabilistic, time-varying nature of the different inputs and parameters.

(ii) **Data-driven methods** are based on the application of AI or machine learning algorithms as artificial neural networks (with their many variations generally known as deep learning methods), as well as support vector machines, classification trees, adaptive neuro-fuzzy inference systems, etc. These techniques, after being properly trained with large data sets, can extract information and detect patterns without use of network equations.[6] Several data-driven approaches for pipe burst detection in water systems are summarized in the literature.[7]

Data-driven methods are not the natural approach for the hydraulic analysis of water networks (water leaks, pipe bursts, UFW, etc.), due to a number of reasons. Among these are that historical databases are usually too small to train the algorithms and detect new abnormal events not previously measured. There are also some factors involved in a hydraulic model that are complex and not subject to universal governing equations; hence, not suitable for physically based methods. Among these, aggregate human behavior, affected by exogenous variables such as climate and socioeconomic factors, dictates water consumption patterns, illegal connections, social response to service incidences, etc. Meanwhile, water leaks, pipe bursts, and roughness depend on complex physicochemical interactions between soil, water, pipes, and external loads. Several phenomena such as pipe cracking, joint wearing, corrosion, biofilming, etc. are not yet fully understood and cannot be accurately modeled. It is when these factors come into play that data-driven methods can bring further benefits for the operations and management of the water utilities.

Eventually, both physically based and data-driven methods need to be combined into a "hybrid methodology" that tries to integrate the best of both worlds—Hydraulic Modeling 2.0—the natural evolution of standard water network analysis meeting big data and AI algorithms to breed a new generation of tools.

[6] S. R. Mounce et al. 2015. Cloud-Based Machine Learning Approaches for Leakage Assessment and Management in Smart Water Networks. *Procedia Engineering*. 119; and W. P. Cantos, I. Juran, and S. Tinelli. 2020. Machine-Learning–Based Risk Assessment Method for Leak Detection and Geolocation in a Water Distribution System. *Journal of Infrastructure Systems*. 26 (1).

[7] R. Li et al. 2015. A Review of Methods for Burst/Leakage Detection and Location in Water Distribution Systems. *Water Science and Technology: Water Supply*. 15 (3). pp. 429–441; and Y. Wu and S. Liu. 2017. A Review of Data-Driven Approaches for Burst Detection in Water Distribution Systems. *Urban Water Journal*. 14 (9). pp. 972–983.

(iii) The first task for water utilities embarking on the road of digital transformation is to analyze the existing monitoring systems of the water distribution network in terms of quantity, quality, and availability of data (in digital format or not). The initial analysis would confirm the need for additional measuring points, or if the existing sensors provide a reasonable representation of the water distribution system. For water utilities with a SCADA in operation, the potential operational improvement will depend on the distribution, density, and characteristics of the deployed sensors. Water utilities should approach the challenge of their digital transition from the end of the value chain (what are the most urgent operational challenges and what data is required?). This is to drive the scope and phasing of ICT investments (sensors, SCADA, and analysis tools), including soft investment in capacity building and business processes. The infrastructure for ICT, digital platforms, and AI numerical methods are powerful tools to integrate data for processing and to solve specific and practical operational issues.

For a medium-size water utility (less than 100,000 connections) with little experience in smart water, the initial operational assessment would identify where digital transformation brings the largest benefits ("low-hanging fruits"), and then draft a smart water road map. A typical starter digital transformation package would look into

(i) defining operational targets and key performance indicators (KPIs);
(ii) integrating network analysis tools that provide the diagnosis and the decision support to achieve the KPIs;
(iii) developing an optimal monitoring network to obtain the maximum amount of information based on a minimum number of strategically placed sensors with the lowest ratio of flowmeters versus pressure gauges to minimize costs;[8] and
(iv) implementing a SCADA basic solution for the distribution network.

The SCADA and the monitoring network track the specific KPIs set by the water utility with a high level of customization to reduce CAPEX and OPEX. The AI algorithms increase the value of each data collected because monitoring points are carefully selected (where, what, and how) to avoid redundancy and maximize the total information content. For typical smart water applications (leak detection, NRW reduction, and energy saving), AI algorithms will prioritize a minimum number of affordable and low-impact sensors (pressure gauges, water levels at reservoirs, and smart meters at top consumers). Pressure and level gauges are low-cost, but smart meters are expensive (about $200 per unit excluding installation and data collection). As such, they cannot be mainstreamed into the operation of most water utilities. However, AI algorithms include classification tools that can divide customers into groups based on similar consumption patterns. The number of smart meters can then be drastically reduced and strategically placed to be statistically representative of the customers consumption patterns.

ARTIFICIAL INTELLIGENCE FOR OPTIMIZATION AND DECISION SUPPORT TOOLS IN WATER SUPPLY

Hydraulic models are used for several purposes:

(i) **explanation and prediction tools**, for what happened in one location at one time in the water distribution network without any instrumental and sensor data;
(ii) **forecasting tools**, for the "what if" scenario for planning and operation of the water distribution network; and
(iii) **prescriptive tools**, for decision support platforms, which are becoming popular by advising on the best options available to solve a particular problem or constraint and, in some cases, automate the decision.

In its most simple version, decision making involves optimization techniques to find the combination of factors that maximize or minimize a numerical objective function. From the onset of hydraulic modeling, optimization techniques have been applied to water distribution networks. With the ascent of fast processors and cost-effective sensors resulting in cheaper computer power, optimization techniques are now mainstreamed into the operation of most water utilities. One way is via **observability analysis**, or optimization of the location of a limited number of sensors to provide the maximum amount of information about the water supply system. Another is through **operational analysis**, involving real-time and optimized control of certain parts of the water distribution network, especially pumping stations and pressure or flow control valves,[9] to reduce energy consumption or monitor water quality.[10]

In addition to the increased computer and graphics processing powers, big data generated by social media, mobile phones, and the Internet of Things (IoT) directly feed into AI, creating a big data ecosystem. The term AI refers to any algorithm that can process data and learn, increasing its performance over time as it becomes better trained. Many statistical models like decision trees, nonhierarchical classification methods, and Bayesian networks have become the backbone of machine learning tools, fed by big data.

[8] Optimal refers to the least-cost deployment of sensors and remote terminal units that can provide the information strictly needed to feed the network analysis tools.

[9] O. Piller and J. E. van Zyl. 2014. Modeling Control Valves in Water Distribution Systems Using a Continuous State Formulation. *Journal of Hydraulic Engineering*. 140 (11).; and Ž. Vasilić et al. 2017. Network Sectorisation through Aggregation of Strong Connected Components. *Procedia Engineering*. 186. pp. 244–251.

[10] J. García-Alba et al. 2019. Artificial Neural Networks as Emulators of Process-based Models to Analyse Bathing Water Quality in Estuaries. *Water Research*. 150. pp. 283–295; and K. P. Singh and S. Gupta. 2012. Artificial Intelligence-Based Modeling for Predicting the Disinfection By-products in Water. *Chemometrics and Intelligent Laboratory Systems*. 114. pp. 122–131.

One set of algorithms, called multilayered artificial neural networks or "deep learning", have recently produced remarkable results for many well-known applications, such as image classification, voice recognition, and autonomous vehicles. It is unclear yet if deep learning will revolutionize water network analysis in the same way it is upending customer relations and business processes. Currently, deep learning and other data-driven techniques do not seem to be a viable alternative to physically based models for network analysis, although it is true that AI-based algorithms for water demand forecasting are becoming more powerful than the standard ones. On this basis, a "hybrid" approach, encapsulated in Hydraulic Modeling 2.0, is the preferred strategy.

With access to big data, AI algorithms provide the following functionalities:

(i) **Optimal design of monitoring and control networks.** Monitoring and control networks are the digital counterpart of the physical pipes, allowing the transition of water utilities to the digital information era. The AI algorithms provide objective information-based criteria to define the location of a given number of sensors in a particular network, in order to extract the maximum amount of information about the whole system with the lowest CAPEX. This implies not only minimizing the number of control points, but also prioritizing the installation of pressure gauges instead of expensive flowmeters. This quantitative approach to network instrumentation also creates a direct link between ICT investments and the operational gains to be expected, setting a realistic framework for a cost–benefit analysis, which is often missing.

(ii) **Numerical detection of physical and apparent water losses.** Using state estimation and stochastic optimization techniques, AI algorithms can provide spatial information on the amount and type of water losses. The AI algorithms then try to find the most likely status of the network after assigning a certain degree of uncertainty to the existing data. They essentially perform a continuous and probabilistic calibration of the network (instead of the standard one-time, deterministic calibration), which allows analyzing the structure of the errors (difference between the measurements and the model predictions) at each control point, and extracting information from the error patterns. The distinction among different types of water losses (for instance, pipe leaks versus unauthorized consumption) is possible, depending on the density and frequency of measurement in each sector of the network. This numerical location of losses cannot replace pinpointing of water leaks or connections with field equipment; however, it saves time and money from deploying leak detection teams, optimizing the distribution networks' sectorization;[11] and prioritizing pipe replacement programs.[12] In addition, it would also be possible to detect abnormal measurements, such as equipment failure, etc. The probabilistic calibration improves the hydraulic model representation by computing the most likely pipe roughness coefficients.

(iii) **Energy savings.** The AI algorithms can guide energy savings in network operations using stochastic optimization techniques with two different approaches: first, by defining the most efficient operating procedures complying with minimum service levels given a predetermined configuration of pumping facilities, storage tanks, and energy tariffs; and second, identifying the most cost-efficient investment in a given system (pump replacement, increased storage capacity, change of energy contract, etc.) for energy savings.

(iv) **Definition of contingency plans and protocols.** Water utilities prepare to cope with emergencies and minimize the impacts on the customers. In addition, abnormal situations may arise from pipe bursts, breakdown, energy blackouts, water scarcity, and contamination events. The AI algorithms assist to optimize a response based on the level of risks (from service interruptions to health threats). Such contingency protocols can be predefined (for example algal blooms in reservoirs) or determined in real time (what valves to close to minimize the impact of a pipe burst to the consumers).

(v) **Classification of consumption patterns and demand forecasting.** Based on historical data and advanced statistical tools, the AI algorithms learn and improve as more data become available to forecast water demand at a node or a group of nodes. Forecasts can be produced in real time for the next 24 hours or for the longer term (years) to assist with capacity expansion plans. All forecasts include the level of uncertainty based on the amount of historical information available to calibrate the hydraulic model. Long-term predictions are linked to future climatic and socioeconomic scenarios (user-defined).

(vi) **Network expansion design with optimal configuration.** Advanced AI optimization tools give insight on the most efficient configurations based on cost minimization (CAPEX plus discounted OPEX) or any other selected target. Dedicated AI algorithms can identify optimal alternatives for network expansions. They take into consideration the uncertainty of some design parameters, such as population forecast and spatial urban growth to support a more robust approach to decision making.

(vii) **Active asset management programs.** Most water utilities have a clear strategy to combine maintenance and replacement to support optimal service levels and minimize costs. Active asset management is about acting first, rather than reacting to external random events. Algorithms help to define optimal schedules for monitoring and replacing assets based on the statistical definition of their useful life, criticality, and other variables.

[11] Sectorization refers to the physical division of the water distribution network into sectors along pressure zones.

[12] E. H. Y. Beh et al. 2017. Robust Optimization of Water Infrastructure Planning Under Deep Uncertainty Using Metamodels. *Environmental Modelling & Software*. 93. pp. 92–105; and D. Jung, S. Lee, and J. H. Kim. 2019. Robustness and Water Distribution System: State-of-the-Art Review. *Water*. 11 (5). p. 974.

ARTIFICIAL INTELLIGENCE FOR BUSINESS PROCESSES

Water utilities, as highly specialized organizations, gather data through benchmarking from their competitive environment and their customers to make strategic decisions and deliver a better service. As such, many of the existing business tools can be adopted in the water sector.

Business Intelligence

Business intelligence is the modern discipline of navigating the era of big data at management level. Business intelligence tools include a combination of the following features related to data:

(i) **Integration.** This involves consolidation of different types of data coming from various sources (operations, customers, financial, marketing, competitors, market, etc.), within and outside the water utility. As result of this integration, business intelligence tools are useful to track the trends of KPIs.
(ii) **Smart visualization.** A picture is worth a thousand words. Business intelligence tools are specifically designed and customized to create the most useful graphs and dashboards for operation staff, as well as decision makers.
(iii) **Trend forecasting.** Data analysis identifies relationships and trends between variables. Through dedicated spatial analysis based on location and time variables, business intelligence tools can forecast the evolution of the water distribution system under certain scenarios.
(iv) **Advanced trend forecasting (AI platform).** Advanced business intelligence tools use machine learning algorithms to detect internal patterns and identify hidden relationships among data.[13] Using explanatory variables, such as calendar events, socioeconomic development, climatological variables, etc. external to the water utility, the AI platform can predict the evolution of its operations way beyond trend analysis.

Knowledge Management

The data revolution is ultimately based on knowledge to be preserved, distributed, and further enriched. Knowledge, together with corporate image, values, and organizational culture, are key competitive advantages for any company since they can hardly be replicated. Therefore, the ultimate protection from competition for water utilities, and a way to maintain a competitive edge in the sector, is to build knowledge management at the core of their operations.

Knowledge is an abstract concept. Knowledge tools are trending topics in the corporate world promoting teamwork, continuous training, and information exchange with increased productivity resulting from enhanced staff engagement, creation of company culture and strengthened company values. Several standard business activities directly linked to knowledge management are being deeply transformed by new technologies:

(i) **Human resources management.** The AI algorithms can detect cognitive and emotional traits or automate the hiring process. These AI tools do not replace human resources employees (just yet), but can match behavioral patterns in successful staff specific to a position with potential candidates.
(ii) **Collaborative and knowledge-sharing platforms.** Any internal company communication system is a potential vehicle for knowledge. Specific applications cater to collaborative teamwork platforms, including enhanced messaging tools and research and development-oriented tools.
(iii) **E-learning platforms.** Instead of maintaining expensive training centers, water utilities, water associations, and regulators can use cost-effective e-learning platforms and web applications from massive online open courses and customized online solutions for training their staff and the customers.

Some of the applications of AI raise ethical concerns, particularly the issue of agency (who is liable for AI errors resulting in consequential damages?). However, water utilities will probably apply these new technologies after they have been widely tested (and possibly regulated) in other fields and industries. Increasing the scope of cybersecurity and the use of blockchains can protect personal and commercial data.

Corporate Image

Water utilities are customer-oriented companies and maximize knowledge obtained by phone and surveys, internet, and social media as competitive advantage, even in the monopolistic environment of the water sector. As water becomes a limiting factor for growth and customers demand higher level of service, water utilities enhance conventional customer service centers with virtual centers to promote access to information and seek a larger number of customer views with AI algorithms detecting and classifying messages, photos, and videos.

In addition, many water utilities use social media to maintain an official institutional profile in pursuit of certain objectives. One is to gather, filter, and store real-time data about incidences and emergencies, wherein customer calls or notices on water shortages, low pressures, or turbidity excess can be used as qualitative information in an early warning system. It is common to have the network control center (where the SCADA is operated) next to the technical support of the customer management system. (However, inquiries regarding billing are not related with real-time operations

[13] J. C. Preciado et al. 2019. A High-Frequency Data-Driven Machine Learning Approach for Demand Forecasting in Smart Cities. *Scientific Programming*. pp. 1–16; M. Firat, M. E. Turan, and M. A. Yurdusev. 2010. Comparative Analysis of Neural Network Techniques for Predicting Water Consumption Time Series. *Journal of Hydrology*. 384 (1–2). pp. 46–51; and S. Patabendige et al. 2018. Detection and Interpretation of Anomalous Water Use for Nonresidential Customers. *Environmental Modelling & Software*. 100. pp. 291–301.

and must be redirected to another department.) Another objective is to gain insight about the social perception of some water or environmental problem to adjust a public response. Still another objective is to enhance the water utility's social corporate responsibility image, for the execution and dissemination of an agenda of social, cultural, and educational activities.

Cybersecurity

All ICT systems, including AI platforms and AI tools, require active and up-to-date protection measures against external attacks. Cybersecurity is of particular concern in water supply because water is a critical asset with a high public health risk; and because water utilities manage customer databases with confidential and private information, from financial data to water consumption patterns. Without appropriate measures, smart water increases the risk of cyberattacks, with IoT providing a paradise for computer hackers. Artificial intelligence is taking cybersecurity to new levels, using deep learning algorithms applied to behavioral analytics to detect abnormal actions and robo-hunters (AI tools constantly looking for and learning from threats). Blockchain technology is a disruptor in cybersecurity in general, and customer data management in particular, by safeguarding information and data.[14]

ARTIFICIAL INTELLIGENCE AND HYDRAULIC MODELING 2.0

Hydraulic Modeling 2.0 is the way forward for water utilities to embrace AI at the core of their planning and operations. Hydraulic Modeling 2.0 represents a qualitative step forward compared to the conventional Hydraulic Modeling 1.0 currently used by the water utilities. The key differences are summarized in the table.

The new paradigm for water distribution network analysis reflected in Hydraulic Modeling 2.0 draws on the same physical laws and principles in the conventional Hydraulic Modeling 1.0 models. Therefore, water utilities are expected to move toward the more advanced Hydraulic Modeling 2.0 based on the experience gained with conventional hydraulic models. Water utilities considering advanced and high-level hydraulic modeling should first master the deterministic version of their hydraulic model and clearly identify its limitations as a constraint in their operations before moving toward Hydraulic Modeling 2.0.

According to Global Water Intelligence, a think tank for the water sector, the potential savings from adopting smart water

Hydraulic Modeling 1.0 (Conventional)	Hydraulic Modeling 2.0 (High-Level Technology)
Deterministic System represented by average values of the state variables (flows and pressures).	**Probabilistic** All variables treated as probabilistic with their density functions and cross-correlations.
One-off calibration Hydraulic model calibrated once a year (at best) based on aggregate error functions. Model parameters are usually fixed.	**Continuous learning** Hydraulic model real-time learning with new data generated: calibration constantly updated with past and current data.
Limited data Hydraulic model set up with limited data without the need for real-time data, except to update water consumption. More data does not imply better model.	**Big data** Hydraulic model maximizes all data available (the more data, the better): well suited to a data-rich and real-time environment.
Simplification Uncertainty in water demand at the nodes not quantified and not considered.	**Uncertainties** Water demand reflects the uncertainty from the meters' errors and the aggregation of nodes when no meter is available.
Shortcut Measurements' errors for flows and pressures not considered.	**Holistic** Measurement errors from sensors introduced into the model with a non-negligible impact on the results.
Anomalies Anomalies mostly not detected or if so, not characterized, nor classified.	**Classification and sorting** The algorithm analyzes the residuals values (differences between field data and model results) and classifies them into categories: illegal connections, water leaks, pipe bursts, malfunctioning sensors, abnormal water consumption patterns, etc.

Source: Asian Development Bank.

[14] A. Arnold. 2019. 4 Promising Use Cases of Blockchain In Cybersecurity. https://www.forbes.com/sites/andrewarnold/2019/01/30/4-promising-use-cases-of-blockchain-in-cybersecurity/#1a3721f73ac3.

technologies in the next decade can amount to around 11% of the total annual expenditures (CAPEX+OPEX) of an average water utility.[15] A 2019 white paper shows that smart water technologies could reduce a water utility's total cost by 7.4% (baseline costs).[16] Most of the savings would come from better and more efficient CAPEX utilization (12.5% reduction) and improved UFW reduction (3.5%). Although the AI algorithms' contribution is not broken down, we can assume that most of the gains come from data processing and analysis, since sensors and data on their own provide little direct benefit.

PILOTING ARTIFICIAL INTELLIGENCE INTO UNACCOUNTED-FOR-WATER

National water sector policies need to be updated to support water utilities in this digital transformation with a new set of technical guidelines and road map for an efficient and cost-effective use of AI numerical tools. Any water utility using Hydraulic Modeling 1.0 with access to data in digital form can take advantage of the recent advances in AI and big data to improve its operations and customer service. Piloting the concept of AI and Hydraulic Modeling 2.0 for UFW would demonstrate how advanced network analysis algorithms improve operational efficiency and service delivery; and will provide the water utility with a competitive edge by harnessing the power of AI combined with big data sourced from the SCADA system, as fed from the various sensors on the water distribution network.

An AI pilot analyzes numerical UFW and pipe burst detection as well as sensor failure routines on the primary water distribution network (pipe diameter over 200 millimeters). The AI algorithms are tested on one water distribution network sector or a small water distribution system selected in association with the water utility based on the following criteria:

(i) the length of the water distribution network should be up to 800 kilometers, and linear pipe length and characteristics (pipe size, location, and material) must be available in digital format (Geographic Information System or Hydraulic Modelling 1.0) with sufficient accuracy;
(ii) the water distribution network should have a minimum density of sensors (pressure gauges, macro-meters, and customer meters) with at least 2 years of historical time series of pressure and flows, and status of pumps and valves in digital format. A good starting point would be that part of the distribution network with a water balance for UFW estimation; and
(iii) the availability of a conventional hydraulic model, which would be a plus, but is not strictly required.

The AI pilot starts with an off-line demonstration making a hindcast based on historical records collected by the water utility on the selected portion of the water distribution system.[17] This off-line approach in the first phase of the AI pilot demonstrates the benefits of using the AI algorithms to the water utility with the following advantages:

(i) AI removes the complexities of connecting in real time to the water utility's digital systems;
(ii) AI assesses the performance of the water distribution network with a larger set of data than could be generated in real time, considering the limited time span for the pilot;
(iii) AI algorithms confirm the methodology to detect past events, such as pipe burst or sensor disruptions; and
(iv) AI allows simultaneous comparison among UFW estimations produced with conventional methods and the prognosis from the AI algorithms.

A typical pilot project (phase 1) would consist of several sequential tasks over 9–12 months:

(i) **Task 1**: selection and validation of the pilot site in agreement with the water utility's representatives (1 month);
(ii) **Task 2**: initial analysis of the pilot site and data provided by the water utility to check for inconsistencies, data gaps, and other issues (1–2 months);
(iii) **Task 3**: setting up and localization of the AI algorithms (3–4 months); and
(iv) **Task 4**: exploitation of AI algorithms using historical data in a hindcast mode (4–6 months).

After completing the off-line testing of the AI algorithms, phase 2 can start using the AI algorithms in real-time operation, including for the prognosis of UFW. The need to integrate the numerical results with the current operation and the development of complementary algorithms suggests another 18 months to implementation for phase 2. Based on the real-time results and experience, the AI pilot can be upscaled to the entire water distribution system.

Implementation costs for consulting services are estimated at around $100,000 (phase I) and $200,000 (phase II). These costs do not include hardware (servers, network equipment, and sensors) and software (algorithms and hydraulic model). These can fluctuate depending on the length, characteristics of the pilot network, and functionalities of the system. For a water utility with less than 25,000 connections, corresponding to a city of 100,000 inhabitants, the cost of implementing a smart water project with an AI pilot would be around $1.5 million (<$15/person or <$1.5 per month per customer), which will finance

15 Global Water Intelligence. 2019. Water's Digital Future. London. https://www.globalwaterintel.com/products-and-services/market-research-reports/waters-digital-future.
16 Sensus. 2020. Improving Utility Performance Through Analytics: Market Research Report. *White Paper*. https://sensus.com/resources/white-papers/improving-utility-performance-through-analytics-market-research-report/.
17 Hindcast (also known as back-testing) involves testing using a mathematical model. Known or closely estimated inputs for past events are entered into the model and compared with output against known results.

(i) initial assessment;
(ii) basic monitoring network (about 200 pressure gauges, 500 smart meters, and 10 macro-meters and special valves);
(iii) cloud-based SCADA and network analysis with AI algorithms (including licensing); and
(iv) training and reporting.

A new set of financing instruments for the water sector in general, and UFW in particular, are also needed by the water utilities to finance the short-term CAPEX requirement of this digital transformation. Development partners can support line ministries and water associations in developing technical guidelines and strengthening regulations, governance, and ethics resulting from the introduction of powerful AI numerical tools. The financing requirements of smart water utilities can also be supported by customizing the energy savings business model (with energy savings companies) through funding based on a digital and smart water road map and payback, and secured through operational improvements guaranteed by water tariff increases resulting from the enhanced service delivery to customers.

For any water utility, the first step to move from Hydraulic Modeling 1.0 to 2.0 is to start an ICT project using AI algorithms to optimize the number and location of the sensors. The second step is to start building historical data in digital format using SCADA, Network Operations Center, and hydraulic modeling. The first application detailed in this paper is to address one of the KPIs of UFW for NRW reduction. The broader scope of using AI algorithms in water supply is to enhance the overall performance of the operations of the water utility, such as asset management system and maintenance, energy efficiency, and reducing carbon and water footprint, etc., thereby improving service delivery both in terms of quality and cost. Artificial intelligence contributes to building the resilience of the water utility to implement water conservation plans, water safety plans, disaster risk management plans, sponge cities, and integrated water resources management.

CONCLUSION

Water utilities worldwide are undergoing a digital transformation, driven by the internet, big data, and AI algorithms. To remain competitive and improve customer service delivery, water utilities need to shift from an "old school" operation, as a result of operating a monopoly with little external pressure, or Hydraulic Modeling 1.0, to a new era of efficiency and accountability, or Hydraulic Modeling 2.0. The availability of affordable big data from sensors, customers, and staff drives this transformation. Access to information is not knowledge, as big data needs to be processed further for operational and planning decisions. Artificial intelligence algorithms help the water utility to become more data-efficient by transforming information into a leaner operation, boosting data-driven decision making through a combination of AI numerical tools and human operational skills. Such digital transformation to become a "smart" water utility goes beyond the technical challenge of integrating data, but also requires a new organization structure, and new sets of operational procedures with buy-in from the staff and the consumers. A new set of national and sector policies is needed to support this digital transformation of the water sector; specifically, to improve governance resulting from the organizational restructuring and enhanced regulation for cost-effective implementation.

Most water utilities start their digital transition with a SCADA linked to a network control center; then figure out how to turn these ICT investments into real benefits. As a result, the digital capacities of many water utilities, particularly in developing countries, are not so useful for day-to-day operations and do not bring a clear benefit to the customers. The digital transition of water utilities should be progressive, pragmatic, and target-oriented.

This brief presented the current trends in application of advanced technologies and techniques, especially AI algorithms, in water supply in general and for the prognosis of UFW in particular. Even though there are many AI tools for many different applications, the most promising ones for water distribution network analysis and UFW estimation are those based on a combination of physically based and data-driven models. Physically based methods are the way forward for water utilities to start their digital transformation into smart water. The integration of data from SCADA with advanced hydraulic modeling tools—comprising AI in water supply—through data-driven approaches supplements the physically based methods with powerful optimization and decision support tools, business intelligence, and knowledge management. Hydraulic Modeling 2.0 is a new network analysis approach that encompasses the joint application of several methods to provide a dynamic, probabilistic representation of water distribution networks, allowing the numerical detection of UFW.

Water utilities can test the potential benefits of the AI techniques by embarking on low-risk, low-scale pilot projects that can also be used to assess their technological capacities and define a realistic ICT road map. Big data and AI algorithms are promising tools for water utilities and should be piloted in current operations of ADB. The same should be piloted in the Climate Resilience and Smart Urban Water Infrastructure Project currently under preparation and due for approval in 2020.[18]

[18] A joint project between ADB's East Asia Department and Private Sector Operations Department with the Shenzhen Water Group, Shenzhen, People's Republic of China.

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Asian Development Bank
6 ADB Avenue, Mandaluyong City
1550 Metro Manila, Philippines
Tel +63 2 8632 4444
Fax +63 2 8636 2444

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