Digital Twins - A new paradigm for water supply and distribution networks

By Fernando Martínez Alzamora, Pilar Conejos, Mario Castro-Gama and Ina Vertommen

A digital twin (DT) is a virtual copy (a digital model) of a real system continuously fed with data to mimic the systems' past, present and future behaviour. This makes it possible to detect anomalies, test new ideas and changes in the virtual system and assess how it reacts, minimizing the risks to the real system. In this sense, the DT can be seen as a playground to explore the effects of different scenarios and to practice how to best react and operate the physical system under these circumstances. The concept of DT has been used traditionally in the industry field[1] but it can also be developed and exploited in a city management context, and in particular in Water Supply and Distribution Networks (WSDN), where it can be applied to all aspects of the system[2].

How DTs help for better management of WSDN

A DT can help to make short and long-term informed decisions in order to improve water distribution systems management. In the system design phase, it can be applied to:

- Develop masterplans by simulating the system behaviour under long-term demand projections and new scenarios. This allows for new infrastructure to be designed considering different needs for water, the most appropriate components to be added or replaced, and test the system resilience as a whole.
- Planning reengineering projects aimed at saving energy, integrating new water sources or improving the resilience of the network.
- Design the future operation of the system and determine the new infrastructure commissioning stages.
- Develop a sectorization plan for anomaly detection and gain insight into the performance of the system.
- Determine the best places where to locate the isolation, washout and purge valves for maintenance of the network with minimal disturbance to users.
- Plan the progressive implementation of Automatic Meter Reading (AMR).

For operation and maintenance, a DT can be applied to:

- Achieve a better understanding of the performance of the whole system.
- Train the operators by familiarizing them with the response of the system under different failure scenarios.
- Help operators make the best decisions in real time by simulating the effects of any operation before taking the action in the real system.
- Optimize the operation of the system, minimizing energy consumption and maximizing the quality of the service.
- Plan flushing operations to guarantee good water quality.
- Predict the behaviour of the system under short term demand forecasting.
- Detect anomalies in the system by comparing the observed values with those expected and simulated by the DT, e.g., leaks, valve failures or malfunctioning of other elements.
- Develop emergency response plans, simulating the behaviour of the system under emergency conditions.
- Develop an early warning system against possible attacks or contamination into the network.
- Improve predictive maintenance (i.e., maintenance of components before they fail) taking into account the stresses each component is submitted to and its role in ensuring service.

The components of a DT

Hydraulic model

A detailed and accurate representation of the WSDN, in the form of a hydraulic model, is the basis of a DT. The model should include all elements of the system, from pipes, junctions, demand nodes, reservoirs, pumps, valves and other minor components, to current water demands. Manually building and keeping such a hydraulic model up to date is a laborious task.

The availability and maturity of these models vary between water utilities and around the world. Nowadays, some utilities have detailed models and in general, these are updated annually, regarding water demand (average and peak demand) and new elements in the network. Models are often not updated during maintenance or repair works. This means that, for instance, valve statuses in the real system and the model differ.

The purpose of a DT imposes different requirements on the hydraulic model. For instance, for operation and anomaly detection (water quality or quantity) the hydraulic models need to be continuously updated and paired with the physical systems. In other words, a DT has to include, at every moment, changes made during maintenance/repair, variations in demands and control rules in the operation. To reproduce an isolated segment during a repair all valves must be included in the model, and if the emptying time is to be calculated then the discharge and air release valves must be also included.

Water demand

In addition to the physical elements, to accurately model the flows in the network it is important to correctly assign the demands to the nodes of the model, as well as their evolution over time. Most utilities measure water consumption for the purpose of billing. It can be measured with different levels of aggregation and frequency. In some utilities, for instance, consumption is measured directly at service connections, while in others it is measured through domestic meters. The frequency can also vary from daily, or monthly to once a year. The DT must incorporate the greatest amount of information available in this regard (at least daily, preferably hourly).

Currently, there are WSDN that have digital water meters to read daily or hourly users' demands, like in the city of Valencia (Spain). Incorporating this information into the DT makes it possible to have a more reliable hydraulic model since demands are assigned at the house connection level. In addition, demand patterns can be established depending on the type and number of users supplied, which is of great help in, for instance, locating leaks, regulating the system and managing demand in situations of scarcity.

When information from digital water meters is not available (which is currently expected to be the case for most water utilities around the world), it is necessary to find an alternative way of feeding current demands to a DT, in an accurate and dynamic way. There are several water demand models available in the literature. However, the DT requires more than a model for the average consumption of a typical user, but the actual water demand in a given area at a given moment in time. Besides understanding how consumers use water, it is necessary to know where they are at different moments. External information to grasp people movement throughout the day, like, for instance, data from traffic, use of public transport, energy consumption, and mobile phone data can be used to this end. As an example, KWR Water Research Institute in the Netherlands followed an approach wherein mobile phone data is used to capture population dynamics and couples this information to the water demand model SIMDEUM[3,4]. SIMDEUM is an end-use model that simulates stochastic residential and non-residential water demand patterns, based on statistical data on water appliances and users. In this way, the water demand is dynamically estimated over time based on the actual number of users present at each node of the network. This approach offers an additional advantage: SIMDEUM is able to estimate water demand on very short time steps (up to one second), while smart meters often provide information only at an hourly or daily basis due to battery restrictions. For some applications, such as water quality modelling, one-hour time steps are too coarse. Hence, even in cases where smart meters are available, it could be beneficial to combine both methods by using live measurements to calibrate a SIMDEUM model and then proceed to use such patterns to model demand at shorter time steps.

Real-time data

One of the most important characteristics of DTs is their continuous use of field data to reproduce the real state of the system. We refer here to those variables that change continuously and are registered by Supervisory Control And Data Acquisition (SCADA) systems and sensors in general, such as tank levels, flow meters, pressures, etc. It must be taken into account that these signals can be registered and sent at different times. Connecting them with a DT is therefore not straightforward. In addition, a data management system is necessary to filter and replace incorrect information, which can be a challenge[11].

Computerized maintenance management system (CMMS) services

One of the most outstanding features of DTs is their ability to manage the maintenance of an industrial product or an installation, by continuously monitoring its behaviour and evolution through the measurement of the most relevant variables and subsequent analysis. Unlike classic predictive maintenance systems, which are based solely on statistical data analysis, a DT provides the additional ability to reproduce past, present and future dynamic behaviour of the system as it is a virtual replica of the real system continuously updated and calibrated from a reduced number of measurements. For that, the hydraulic model must incorporate all the maintenance operations carried out since they affect the state of its elements. This is possible if the hydraulic model is linked to the CMMS. In this way, the maintenance management can be improved with the capability of incorporating predictive maintenance, based not only on the expected use of the different components, but its real behaviour as part of the system.

Additional information sources

A DT has to incorporate also complementary information that affects its behaviour or decision making, such as topography, availability and quality of water sources, type of dwellings and local facilities, types of consumers, electricity tariffs, weather forecast, and social behaviour, amongst others.

Calibrating a DT

A DT has to behave like the real system, so the calibration of the hydraulic model is crucial to achieving a reliable DT. There are different techniques and methodologies for calibrating a hydraulic model. It is useful to develop an initial pre-calibration stage, reviewing and correcting all possible errors in the information, and only afterwards calibrate the model parameters. Fortunately, with the DT many scenarios are continuously available, which allows for frequent calibration of the hydraulic model, instead of using only for single situations or days, as it has traditionally been done.

One of the aspects which is commonly challenging for model calibration is the demand allocation. In cases where smart water meters are available, such as in Valencia (Spain), these data can be used to calibrate the model. Internal pipe diameters and roughness coefficients are the most relevant parameters bound to uncertainty. In other countries, such as in the Netherlands, the calibration of water distribution network models is an iterative process of updating of assets, demands and operation criteria. For most utilities, these updates are scheduled at an annual or bi-annual basis. Almost all systems in the Netherlands are operated as a single zone, for that reason most data are known at the booster stations, and only a few flow meters and pressure loggers are located within the network. While industrial and 'large' users, such as sports facilities, carwashes and hospitals, are monitored using digital water meters, this is not the norm at the household level, introducing a serious challenge to model calibration.

The existence of a large number of valves in the distribution system poses an additional challenge for modelling. Although most valve manipulations are registered, it is estimated that at least 2-3% of the valves are not properly displayed or their status is changed (i.e., partially opened). This requires a large amount of effort as these mis-registrations are not easy to detect until additional operations in the surroundings are performed. Likewise, the presence of numerous regulation elements can significantly complicate the calibration of the model [5].

DTs, Decision Support Systems and Artificial Intelligence

One of the most important reasons that justify the development and maintenance of a DT is to use a replica of reality as Decision Support System (DSS). The concept of DSS has usually been linked to optimization techniques, aimed at minimizing one or more objectives, whether technical or economical, by modifying the values of the decision variables subject to certain restrictions; sometimes some of these restrictions can be relaxed by being incorporated as additional objectives. Among the most important applications of DSS in the field of the WSDN that can be cited are those used to determine the adjustment parameters in a calibration process, for optimal sizing of pipes and control elements, for optimal location of valves and other accessories to facilitate the network maintenance, for optimal identification of Demand Metered Areas (DMA's) in a sectorization plan, for optimal sensor location to identify leaks or for the early detection of contaminant intrusion, for optimal operation of the system to reduce energy consumption or the associated cost, to design optimal strategies to renew water in stagnant areas or to reduce the retention time in tanks, to plan preventive maintenance operations, to plan investments in asset management, etc. Methods used by optimizers to achieve these goals range from classical Linear Programing (LP), Mixed-Integer Linear Programming (MILP) and Non-linear programming (NLP) to the most advanced Evolutionary Algorithms (EA), depending on the nature and complexity of the problem, and the type of variables involved. For some of these applications a simplified model of the network may be sufficient, but in others cases it is very important to take into account each and every one of the elements that make up the real network as per a DT, for example in asset management, maintenance issues, network sectorization, etc. When simplified models are enough, they can also be derived from a DT.

Another field in which DTs can play a relevant role is to exploit the capabilities offered by modern advanced analytics techniques and Artificial Intelligence (AI) [6]. Optimization should not be confused with them. They are fundamentally based on the data observation of a large number of real situations and on learning about the system behavior from these data, which usually come from field sensors but not limited to them. In its application to WSDN management, the signals will come from the SCADA system, from the maintenance management system or from the remote readings of consumption. But if we have a well-calibrated DT, the training variables can also be synthesized from the results provided by the DT under certain scenarios, with the advantage of its low acquisition cost and the high quality of the data, in contrast to the data taken from the actual operation of the system. AI uses Machine Learning (ML) algorithms to achieve its purposes. In a first instance, they can be arranged in supervised, unsupervised, mixed, or reinforced, being the latter the most promising for future.

In supervised learning, sets of paired values for the input and output variables are given. The algorithm must be able to reproduce the outputs from the inputs with the minimum error. Actually, the classical regression techniques would fall in this group, but in the last decades other much more powerful methods have been developed to tackle more complex problems having a high number of input/output variables with strongly non-linear relationships, such as k-Nearest Neighbors, Logistic Regression, Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF) and particularly Artificial Neural Networks (ANN), initially developed around the concept of the Multilayer Perceptron (MLP). In recent years ANN have been developed greatly with the introduction of new architectures under the concept of Deep Learning, like the Convolutional Neural Networks (CNN) and the Recurrent Neural Networks (RNN), with results as astonishing as facial or speech recognition.

Unsupervised learning instead tries either to group the set of data (observed or synthetic) into differentiated classes using cluster analysis techniques, to reduce the size of the problem, or to discover behavior laws among the data set, in an attempt in all cases to abstract the information and synthesize it, which constitutes one of the pillars of the development of human intelligence. Compared with the classical statistical techniques used for this purpose such as k-Means, Hierarchical Cluster Analysis (HCA), Expectation Minimization (EM) or Principal Component Analysis (PCA), the ANNs, and in particular the architectures associated with Deep Learning such as the Autoencoders and the Reinforced Learning (RL), seem very promising.

To finish this brief description of the state of the art of AI, it should be noted that in any application it is necessary to differentiate whether the variables managed are continuous or discrete, if the data set is static or dynamic (real-time systems), and in the latter case, if the goal of the algorithm is to properly reproduce the recent past or to forecast the future.

All these techniques have applications to WSDN management, although most of them are still incipient compared to other areas such as image recognition, marketing or business. The first applications have been aimed at characterizing and classifying demand patterns, by differentiating the type of consumers or the effect of exogenous factors such as the day of the week, the season or the temperature. Past data and unsupervised methods are used for this purpose. These patterns could be used later to detect deviations from the expected values, due to the occurrence of a leak for example, and to issue the corresponding warnings.

Other applications try to directly predict the demand in the coming hours, either at consumer or sector level, based on past and recent data. In contrast to the classic Box-Jenkins techniques, which assume a linear behavior of the time series, Recurrent Neural Networks (RNN), and in particular Long Short Term Memory (LSTM) networks characterized by progressively reducing the weight of the oldest readings, have provided so far the best results. The RNN is fed in this case with continuous and dynamic data to carry out a supervised training.

AI techniques can also be used to detect sudden anomalies, such as a pipe break, a sensor failure, or a contaminant intrusion into the network. Supervised methods fed by synthetic data provided by DT can be used to train convolutional ANNs for this purpose. However, when the nature of the anomaly is not anticipated, unsupervised methods would be more appropriate.

Regarding predictive maintenance, the use of AI techniques can lead also to significant advances to improve WSDN management. Supervised training techniques such as Decision Trees (DT) or Random Forest (RF) have been mainly applied for this purpose, but using the Gradient Boosting, a variant of RF more suitable when the number of leaves on the tree is reduced, or the LSTM already discussed above, are more promising in the future. The source of data in this case must be real data because it is very difficult to physically model a fault. In WSDN is common to have a lack of recorded data concerning faults and maintenance operations, so a greater sensorization is needed in the future to take full advantage of these techniques. One of the most important applications along this line would be the capability to anticipate new leaks.

By considering the power of AI, new applications for improving WSDN management are constantly arising. For example, AI can be used to fast respond in emergency situations, to reduce the daily energy consumption, to manage the pressure in DMAs in order to reduce leaks or to control demand, to manage DMAs in case of unforeseen incidents, and to detect incipient leaks by observing the drift of certain signals in a zone. All these applications require huge data for training the AI algorithms, but fortunately DTs working upon well calibrated models can produce such data automatically at low cost, by subjecting them to multiple randomly generated scenarios. A training data set can be built just with the results of the simulations or with the outcomes of a subsequent optimization process looking for the best solution for each scenario, thus combining optimization with AI techniques. In the future it is possible that, thanks to the power of Reinforced Learning (RL) algorithms, ANNs can reach by themselves the optimal solution to each situation posed thanks to a previous self-training process aid by DTs, just as AlphaGO Zero learned to play GO on his own, defeating the world champion in 2017, without the need for a prior supervised training.

Viewers and User Interface

For a DT to be used by water utilities, it is necessary to build a user-friendly and intuitive graphical user interface. The interface has to be interactive and fine-tuned to its use (daily operation or long-term design for instance).

As a DT manages a significant amount of information of different nature and origin it can be useful to use a combination of different products and interfaces, such as Application Programming Interfaces (APIs), web services, map-based interfaces, GIS integration, dashboards, and web interfaces.

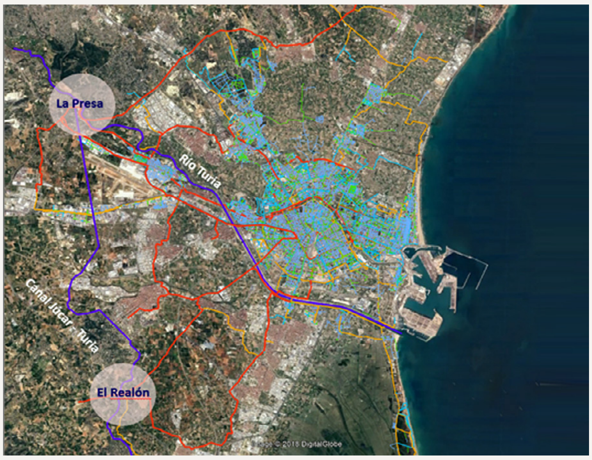
Applications

In this section, two application cases (at different maturity levels) are presented to illustrate the possibilities, benefits and challenges of DTs applied to WSDN. These cases refer to the DTs of Valencia, Spain and Eindhoven, The Netherlands (**Figure 1**).

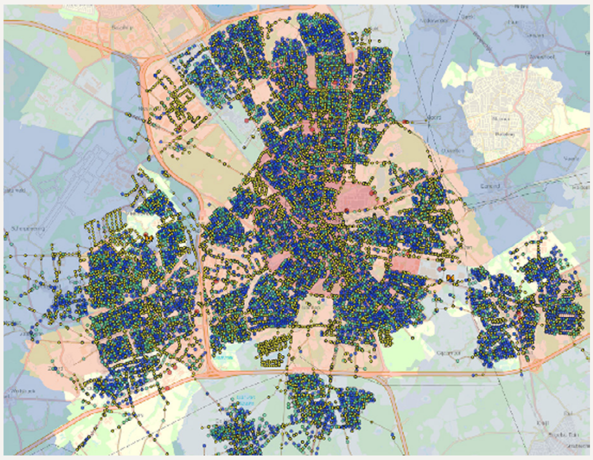
The DT of Valencia

Today Global Omnium (GO) operates a DT for the water distribution network of Valencia Metropolitan Area. The DT works upon a hydraulic model connected with the main sources of the information provided by the physical system. The addition of advanced analytics like AI starts to exploit the potential of the DT, particularly to identify demand patterns, to forecast demands and to detect anomalies in the hydraulic variables. In a near future much more applications are envisaged.

The first strategic model of the city of Valencia was created in 1993 in collaboration between GO and the Universitat Politècnica de València (UPV) and since then, significant progress has been made. In 2007 the hydraulic model was connected to SCADA for the first time[7] in order to run live simulations and help the operators make decisions in the Network Control Center. The AMR implementation in Valencia opened up new opportunities, so in 2016 GO and UPV began the ambitious project of building a full DT for the system by connecting the hydraulic model with all information sources: SCADA, sensors, GIS, CMMS, AMR, etc. The DT had to be interoperable with new IT platforms and be scalable to any size of the supply system. The result was the Digital Twin developed with GoAigua, a smart water platform by Idrica, a Spanish company that provides technological services. It is now fully operational and in use in the Control Room of the water supply system of Valencia and its metropolitan area. The model is connected in real time with 600 sensors and replicates the real behaviour of the network with a 95% accuracy for flows and 98% for pressures[5]. It is now a vital tool in support of decision-making for both daily operations and planning tasks[8].



Valencia
1,700,000 inhabitants | 101,300 junctions | 113,267 pipes | 46,801 manual valves



Eindhoven
223,300 inhabitants[1] | 29,444 junctions | 57,194 pipes | 13,828 manual valves

Figure 1 | Characteristics of the WSDN of Valencia and Eindhoven.

How the DT is built and maintained: detailed and strategic models

The Valencia DT uses the GoAigua platform to integrate information from various sources. From there a set of algorithms configuring the application GO2HydNet, builds automatically from scratch and by querying different sources for the required information, an EPANET-based detailed model for the whole network or a selected area, which reproduces with accuracy its behaviour for a certain time period. This detailed model includes all the pipes, operating elements and auxiliary elements that affect water flows, and is connected with the SCADA information to make live simulations. Hence, it can be used as an assistant to test and make real-time decisions. Building the detailed 24-hour model of Valencia, including service connections with their corresponding consumption pattern when available, to reach a complete model of 325,000 nodes takes about 1 minute of computation time on a standard PC i7-3.2 GHz (the time required for data pre-processing is not included). Thus, as data sources are updated, the model is also updated. However, depending on the use, a strategic model containing only the main elements is more useful to have a general view of the systems' behaviour. For this reason, the Control Center works with a 10,000 nodes strategic model—a simplified model obtained from the detailed model, and always connected to it. This strategy makes it possible to perform every operation with either the detailed or the strategic model, in such a way that, both models together constitute the DT of Global Omnium (**Figure 2**).

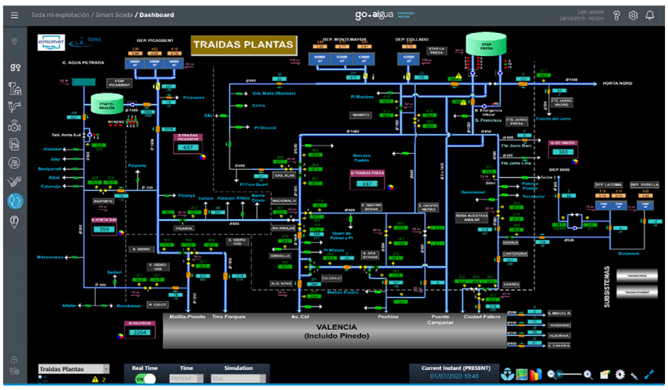


Figure 2 | The DT of Valencia WSDN connected in real time with field data. Real-time data are compared with simulated ones next to each box. The proposed actions can be simulated before carrying them out in the real system.

Use cases

GoAigua's DT is used in GO for planning, design and management of the daily operations in the Valencia Metropolitan Area since it provides a complete overview of the network in real time, along with informative and actionable dashboards 24/7. Valencia's DT provides operational teams with:

- Simulation of past, present and future scenarios under all kinds of operating conditions.
- On-the-fly analysis of what-if situations for both present and the future, facilitating support decision-making on the best time for network maintenance and other operations.
- Anomaly detection: the DT calculates in real time pressures and flows at all nodes and pipes of the strategic model, providing a great understanding of the performance of the system and allowing the fast detection of incidents (**Figure 3**).
- Forecast of the network behaviour in the next 24 hours, which facilitates the prediction of potential events.
- A playground for training new staff in network operations.

Valencia's DT is also used for planning tasks such as:

- Development of contingency plans for emergencies.
- Designing the new infrastructure required according to the network needs.
- Defining, in advance, the operation of the new infrastructure and determine the network commissioning stages.
- Planning long-term actions, including investments to optimize Capex and risk levels.

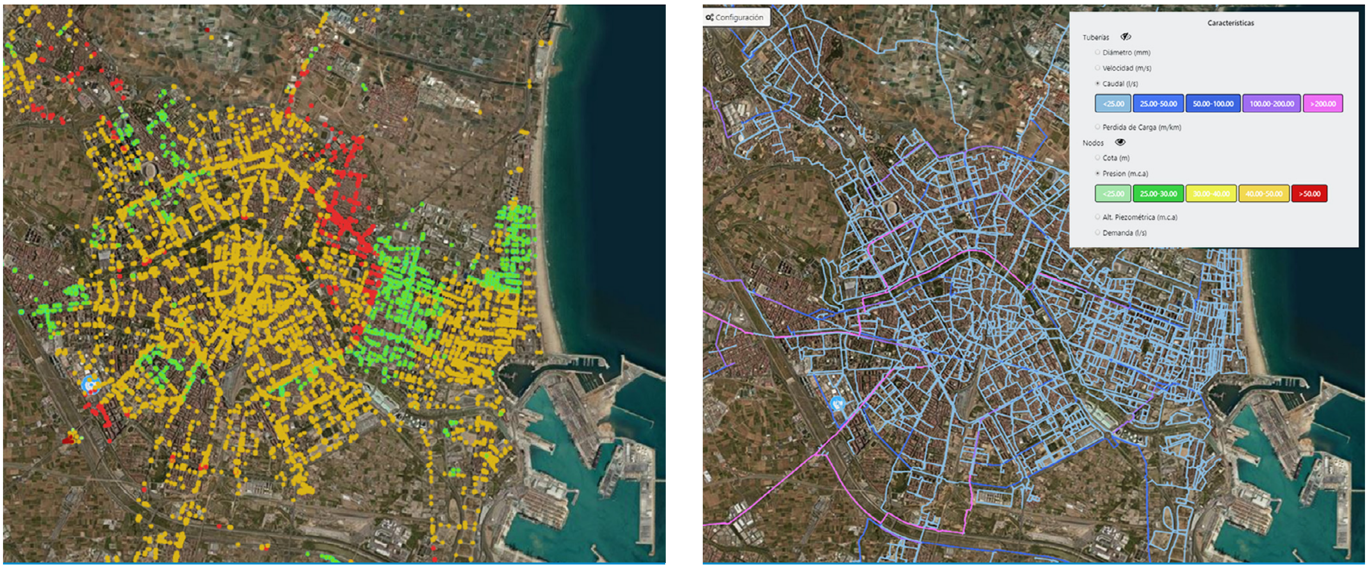


Figure 3 | With 600 measurements (pressures, flows and levels), it is possible to know in real time all flows (right) and pressures (left) of a 10,000 nodes strategic model.

The DT of Eindhoven

Recently KWR took the first steps in building a DT of the WSDN serving the city of Eindhoven with about 223,300 inhabitants[9]. The WSDN, operated by Brabant Water, is fed by a total of five pumping stations. One of the aspects to consider is that the topography of the city is reasonably flat. For that reason, this network is operated as a single pressure management zone. This means that no sectors, like district or pressure metered areas, are implemented, and the available flow measurements regard the total area. The assets registration is in general of excellent quality and continuously updated by the Brabant Water operators. The network model is coupled to different data sources, in particular, data from mobile phones (i.e. how many mobile phones present in a given area at a given moment in time) are used to capture population dynamics, and together with weather, land use and population data (ranging from numbers of inhabitants to household size and composition), which feed the water demand model SIMDEUM. Maintenance and repair activities, as well as unplanned events such as leakages, offer additional relevant information. By linking all the aforementioned data, the DT was used to model water demand, pressure and flow in the WSDN of Eindhoven, at three different times in the year: a regular week, a week with warm temperatures and a week during the vacation period. From the obtained results it is clear there is a correlation between the number of users in an area (estimated with the mobile phones) and the water consumption measured in the same period.

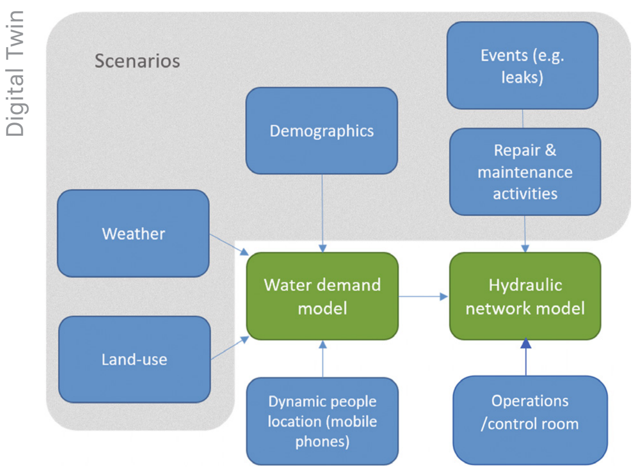


Figure 4 | Conceptual design of DT using different data sources in the Netherlands. Demographics and land use are based on large governmental databases (Kadaster, CBS). Weather data is available from the meteorological organization (KNMI). Dynamic population information is obtained using mobile phone data (third-party vendor). The water demand model is fed with this information using a stochastic demand simulator (SIMDEUM®), while the hydraulic network model is obtained from the water utility (Brabant Water). Several scenarios can be simulated based on this information.

Moreover, it was possible to model the effects of leakages and wrongly registered valve statuses on the network performance, for both regular, warm and vacation periods, identifying for instance areas with lower pressures. This information is valuable for water utilities to help them identify sensitive areas and to anticipate how to best operate the network when facing particular conditions.

The conceptual design of the DT (Figure 4) is suitable for both (near) real-time modelling and scenario analysis. The use of mobile data as input for consumer demands suggests that aspects of population dynamics can be integrated into a DT. However, at the time being, mobile phone data are not (yet) available on a real-time basis in the Netherlands, making the proposed approach more suitable for scenario studies. Once the data of mobile phones can be fetched in a timely manner, the DT could be used for real-time modelling as well.

The conducted research shows the potential of DTs for the Dutch drinking water industry. In the Dutch context, DTs can be developed in the short-term, as water utilities have good network models, and multiple data sources are already available. In the upcoming months, the Eindhoven DT will be further developed to include additional data, such as traffic information, and to better model non-household water demand. Dutch water utilities want to use DTs to understand the effects of the lockdown and other governmental measures imposed in control the spread of Covid 19 in combination with the drought.

1 | For privacy reasons the smallest area for which data is available is the 4-number postcode used in the Netherlands (more detailed postcodes include 4 numbers and 2 letters). If less than 10 mobile phones are available in the area, the data is not shared. Only the number/amount of mobile phones is shared, data about the mobile phones such as the number/owner is not. Data treatment takes 2 weeks' time.

Conclusions

The introduction of DTs in the reality of water utilities requires a paradigm shift in the way of managing WSDN. The current capabilities of computers to simulate the behaviour of networks in real-time is beyond debate, even using a standard PC. The main challenges lie in sensor deployment of the networks and the collection and treatment of a large amount of data, ranging from SCADA signals to consumption data and maintenance operation. The potential results of this complex effort are considerable in improving the service provided to customers, as has been shown in the case of the DT of Valencia. While sensor data is not widely available (the shift towards smart water metering, for instance, can take years), one can think of alternative data sources and modelling approaches, such as those used in the Netherlands taking advantage of mobile phone data in combination with SIMDEUM to better model water demand. The cost of mobile phone data is lower than that for large-scale implementation of digital water metering. However, a complete analysis of the relationship between mobile phone data and water consumption during different seasons must be performed in order to reduce the uncertainty of their use within DTs.

The current coronavirus pandemic imposes new short-term challenges to water utilities as consumers change their habits. In combination with other factors such as drought and ageing infrastructure, DTs are a powerful tool to provide insight into network behaviour under new circumstances and into how to best operate it in the long and short term. For many operators, a WSDN is a black box. DTs are a key step in unravelling it.

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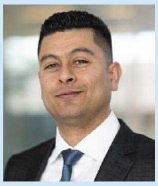

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