







Review

Overview of Energy Management and Leakage Control Systems for Smart Water Grids and Digital Water

Carlo Giudicianni ^{1,*}, Manuel Herrera ^{2,†}, Armando di Nardo ^{1,†}, Kemi Adeyeye ^{3,†}
and Helena M. Ramos ^{4,†}

¹ Department of Engineering, Università degli Studi della Campania 'L. Vanvitelli, 81031 Aversa, Italy; armando.dinardo@unicampania.it

² Institute for Manufacturing, Department of Engineering, University of Cambridge, Cambridge CB3 0FS, UK; amh226@cam.ac.uk

³ Department of Architecture and Civil Engineering, University of Bath, Bath BA2 7AZ, UK; k.adeyeye@bath.ac.uk

⁴ CERIS, Instituto Superior Técnico, Department of Civil Engineering, Arch. and Georesources, Universidade de Lisboa, 1049-001 Lisbon, Portugal; helena.ramos@tecnico.ulisboa.pt

* Correspondence: carlo.giudicianni@unicampania.it

† These authors contributed equally to this work.

Received: 15 September 2020; Accepted: 20 October 2020; Published: 24 October 2020



Abstract: Current and future smart cities are moving towards the zero-net energy use concept. To this end, the built environment should also be designed for efficient energy use and play a significant role in the production of such energy. At present, this is achieved by focusing on energy demand in buildings and to the renewable trade-off related to smart power grids. However, urban water distribution systems constantly carry an excess of hydraulic energy that can potentially be recovered to produce electricity. This paper presents a comprehensive review of current strategies for energy production by reviewing the state-of-the-art of smart water systems. New technologies (such as cyber-physical systems, digital twins, blockchain) and new methodologies (network dynamics, geometric deep learning) associated with digital water are also discussed. The paper then focuses on modelling the installation of both micro-turbines and pumps as turbines, instead of/together with pressure reduction valves, to further demonstrate the energy-recovery methods which will enable water network partitioning into district metered areas. The associated benefits on leakage control, as a source of energy, and for contributing to overall network resilience are also highlighted. The paper concludes by presenting future research directions. Notably, digital water is proposed as the main research and operational direction for current and future Water Distribution Systems (WDS) and as a holistic, data-centred framework for the operation and management of water networks.

Keywords: water supply; energy recovery; micro-generation; pump as turbine; district metered areas; digital water; water–energy nexus; sustainability; green infrastructure

1. Introduction

Cities are stressed worldwide predominantly due to significant population growth. Global population has increased by 1500 million people in the last 20 years. The United Nations predicts that this trend will continue and it is expected that up to 6.5 billion people will live in cities by 2050. Cities are a main actor in climate change and the built environment contributes to high levels of global greenhouse gas emissions. However, the challenges for city authorities goes beyond managing growing cities, since as cities develop, their exposure to extreme weather events also increases [1].

Given these current and future scenarios, academics and industry have put in effort over the last two decades towards reducing buildings' energy use [2]. Another solution investigated in depth, and currently in development, is on the benefits of smart power grids [3]. Complimentary to this for the achievement the zero-net target is the efficient management of water distribution systems (WDSs).

The water industry is subject to changes regarding the sustainable management of urban water systems. Many external factors, including the impacts of climate change, drought and population growth in urban centres, had led to an increase in the responsibility to adopt more sustainable management of urban water resources [4]. Other challenges include income and revenue to cover operation and the monitoring and management of water resources as a public service. Additionally, the need for knowledge and understanding of the customers' demand for fair water pricing and use are some of the main challenges to resolve [5].

Over the last few years, the surge of the information and communication technology (ICT) techniques along with the application of new trends on data analytics have been shown to be essential for dealing with the challenges that a urban water infrastructure should face today. The traditional water system, then, is becoming a smart system, or smart water grid, as it can be seen as the combination of critical and digital systems into one converged, smart infrastructure. In return for such a new complexity level, water utilities now have the capability of working in an ideal smart-technology framework that supports efficient operation and management for safer and more secure water supply systems [6]. There are a number of literature reviews that can be considered an antecedent of the current overview. Mala-Jetmarova et al. [7] proposed a systematic literature review of WDS design optimisation, with a special emphasis on methodologies for the expansion and rehabilitation of already existing infrastructure. Anele et al. [8] reported an overview of methods for short-term water demand forecast, highlighting their advantages, disadvantages and future research directions. Digital water metering has been the target of two different literature reviews. Monks et al.'s [9] paper comprehends a literature review along with interviews to industry experts. The aim of such a paper was to report benefits of digital water metering that might be considered for inclusion in business cases. Rahim et al. [10] introduced a review on machine learning and data analysis techniques adapted to digital water metering. The review was complemented by a number of recommendations to improve both management and research further. Makropoulos and Savić [11] worked on a literature review paper about urban hydroinformatics where the benefits of relevant concepts such as ICT and real-time information, data analytics, and the new approach of water cycle and socio-technical system models, among others are revisited.

The paper proposed herein presents an overview of the literature on smart WDSs with respect to energy recovery and water losses due to leakage. Both challenges are strongly related. Likely procedures and models to address this typically benefit one another. Therefore, the paper starts with a review of water supply energy management in Section 2. Relevant technologies and models are introduced along with multiple key literature references. Section 3 presents a brief overview of energy loss and recovery models in WDSs. The solution of a network partitioning into district metered areas and an overview of the most successfully methodologies are presented in Section 4. Today, the traditional objective of leakage control has been expanded to also deal with energy issues and the key concept of systems resilience. Smart water grids imply efficiency in both energy management and resilience. Therefore, relevant technologies and models are introduced in all cases. Section 5 presents future research directions. Digital water is proposed as the main research and operational direction for current and future WDSs. The paper closes with a conclusions section where the main findings and challenges found in the paper are revisited.

2. Smart Water Management

Smart water management aims at the sustainable and self-sufficient management of water, at a regional or city level. A smart use of water lies in the use of innovative technologies, such as information and control technologies and monitoring [12,13]. With this approach, water management contributes

to leakage reduction, water quality assurance, improved customer experience and operational optimisation, among other key performance benefits [14–16]. The concept of “smart city”, as related to technological innovations, is relatively recent. A smart city can be defined as the city in which an investment in human and social capital is performed, by encouraging the use of “information and communication technology” as an enabler of sustainable economic growth, providing improvements in the city inhabitants’ quality of life, and consequently allowing a better management of water resources and energy. Importantly, a smart city aims to promote socioeconomic development [17,18] as ultimate objective of any associated technological advancement. Through a socioeconomic model, a city can examine its current state, and in turn, identify the areas that require further development in order to meet the necessary conditions for a smart city [14,19].

2.1. Technologies and Improvements

Smart water systems utilise advanced information technologies for system monitoring data for an efficient resource allocation. In addition, the prevention and the early detection of leaks is key for effective asset management and for efficient control of water losses.

Traditionally, water supply is essentially focused on pumping water at high pressure, enough to reach distant customers. However, a smart system uses near real-time data, variable speed pumps, dynamic control valves, and smart meters to balance the demand, minimise over-pressure in ageing pipelines and save water and energy. Therefore, water sources and systems could operate together with the same objective to maintain sustainability in water management [20]. Smart water systems, or smart water grids, are used to improve the situation of many networks, some of which are characterised by a degraded infrastructure, irregular supply, low levels of customer satisfaction or substantial deviations of the proportional bills to the real consumption. A smart water system can lead to more sustainable water services, reducing financial losses, enabling innovative business models to better serve the urban and rural population. Some of the main advantages of smart water management are an improved understanding of the water system, improved leak detection, enhanced conservation, and a constant monitoring of water quality. The implementation of smart water systems enables public services companies to build a complete database to identify areas where water losses or illegal connections occur. The advantages are economic benefits to water and energy conservation, while the efficiency of the system can improve customer service delivery. In some cases, wireless data transmission can allow clients to analyse their water consumption towards preserving and reducing their water bill [21].

2.1.1. Smart Pipe and Sensors

The prototype of a smart pipe is designed as a module unit with monitoring capacity, expandable for future available sensors [22,23]. With several smart pipes installed in critical sections of a public water system, a near real-time monitoring automatically detects flow, pressure, leaks (if any) and water quality. All these benefits come without changing the operating conditions of the hydraulic circuit. The individual sensors of smart pipes generally have the following main parts: a data collection and processing unit, transmission unit and the sensor connections. Figure 1 illustrates a general scheme for a smart pipe and a wireless sensor network.

Smart wireless sensor network is a viable solution for monitoring the state of pressure and water losses control in the system. The main advantage compared to other methods of water losses control is the continuous monitoring of the network without local operator intervention and with low energy consumption of the wireless sensor, which allows it to remain operational for long periods [24].

2.1.2. Smart Water Metering

A water meter is a device used to measure the quantity of water consumed, while a smart metering is a measuring device that can store and transmit consumption data using a certain frequency (Figure 2). To develop an efficient water management system is necessary to install sensors and/or actuators to monitor the water network. Therefore, while water meters can be read monthly or twice a month and

water bills are generated from this manual reading, the smart metering can provide consumption data over a long distance and with a higher monitoring frequency, thus, providing instantaneously access, and near real-time information from customers and from managing entities. These smart water meters are components of an advanced metering infrastructure (AMI) that water companies should install to improve the hydraulic and energy efficiency of their network, since these devices also enable the control of leakages and non-legal connections in terms of water volumes [25–27].

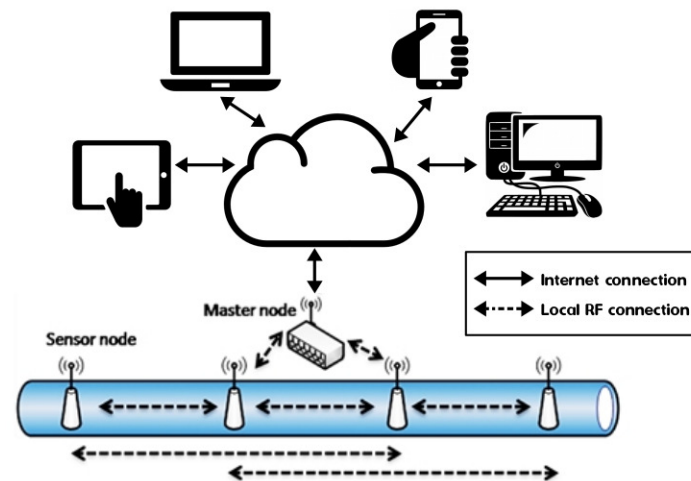


Figure 1. Scheme of a smart pipe and wireless sensor network.

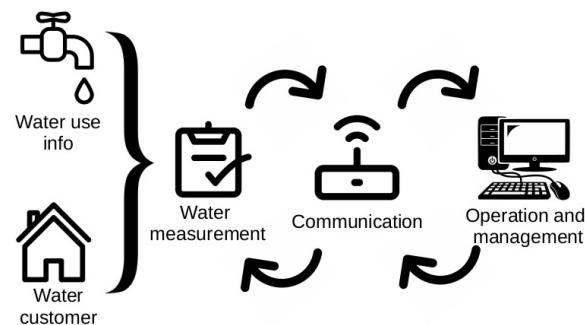


Figure 2. Scheme of a smart water metering model.

Therefore, smart water metering provides the opportunity to improve the balance between the provision of access to drinking water, the right of a managing entity to be paid for services, as well as the joint responsibility to preserve water, as a scarce resource. These systems contribute as support tools to make decisions in near real-time based on a registered database, improves network management and can help to better refine the water balance to satisfy demand and to increase the hydraulic and energy efficiency of the WDS.

2.1.3. Geographic Information System

A geographic information system (GIS) can be applied to aid smart water management in practice by providing a clearer representation of the overall system and asset location. The major advantage of a GIS is the simulation of real features, based on data systems designed to collect, store, receive, share, manipulate, analyse and present information that is geographically referenced [28]. GIS plays a strong role in smart water management, by providing a complete list of the components along the network as well as their spatial locations. Given the sophisticated network communication overlay in WDSs today, data management using GIS becomes essential. It allows for the inclusion of spatial components in an oriented model and to improve planning and management through a clear evolution of spatial constituents in the network. Figure 3 is a snapshot of the EPANET (hydraulic simulation

software [29]) extension in the the GIS open source platform QGIS [30,31]. Another piece of software to enable work in the interface between EPANET and GIS is QGISRed [32], which is an upgrade of the successful, now deprecated, GISRed [33]. QGISRed works as a QGIS plugin, while the former GISRed runs for ArcView. Commercial alternatives work with ArcGIS. This is the case of the suite InfoWater. This software is developed by the company InnoVyz[®]. InfoWater is integrated within the Esri ArcGIS environment. InfoWater software comprises other very interesting functionalities for smart water management, such as an aid for sensor placement and other options for asset management. The Pro version of InfoWater also comes with AutoCAD integration, fast modelling of large size water networks, and the management of pressure zones and district metered areas, among other interesting features. Last but not least, Bentley Systems[®] have developed the software OpenFlows WaterGEMS that also run water distribution models within ArcGIS. WaterGEMS has optimisation modules for calibration, design, pump scheduling, pipe assessment, SCADA integration, and network simplification.

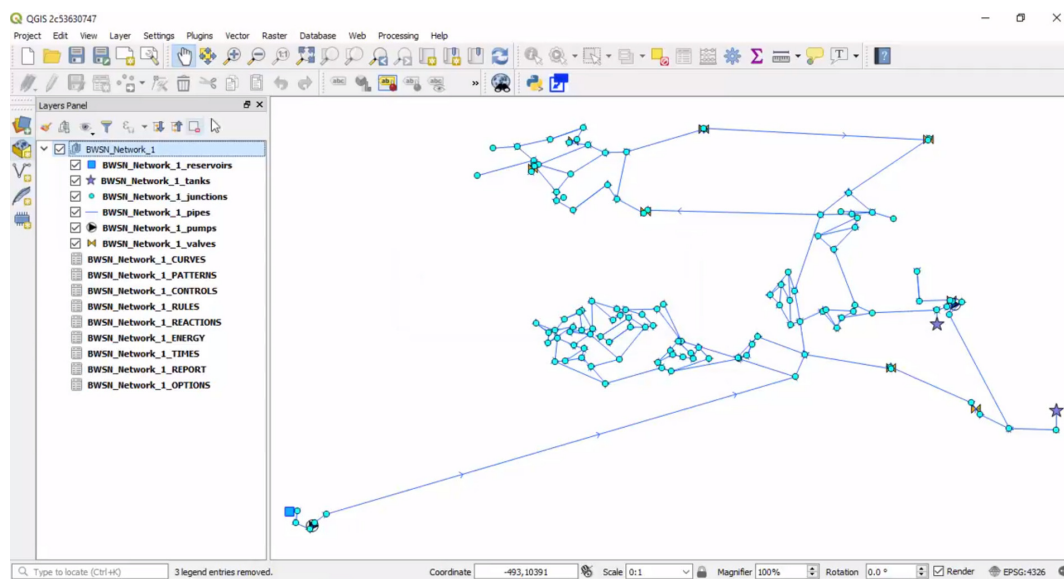


Figure 3. EPANET extension in QGIS.

2.1.4. Cloud Computing and Scada

Many public water utilities undertake the supervision, control and data management of their network through a SCADA (Supervisory Control And Data Acquisition) system [34,35]. SCADA systems typically use the collection of historical sensor readings to centrally control spatially distributed assets [36]. Overall, a SCADA system architecture comprises computers, data communications systems from sensors to human-machine interfaces (HMIs) and graphical user interfaces (GUI) for supervisory management. SCADA also counts on other peripheral devices aiding the WDS operation and management. This is the case of programmable logic controllers (PLCs) and other interfaces and devices. Figure 4 shows a scheme of a SCADA architecture.

Other critical infrastructures also use SCADA. This is the case of oil and gas pipelines, the transmission of electrical power and other public systems.

There is an open challenge for researchers and practitioners to combine SCADA capabilities with the great accessibility and programming scalability provided using data storage and computing “on the cloud”. Cloud computing is an on-demand computing resource virtually available in platforms and servers over the internet [37]. One of the main benefits of cloud computing is the ease of the scalability of such resources which can be straightforwardly reconfigured to adapt to different workloads, optimising their use. This is linked to the concept of cloud computing which refers to the use of memory and storage capacities and the calculation capacity of computers and servers shared and linked through the internet, by following the code of network computing. The storage of data is done

in servers which can be accessed from anywhere in the world, at any time, without specific physical drives for storage. Access to programs, services, and files are remote, via internet. Personal data of households and users of water-related services must, however, be sufficiently protected to avoid potential computer-driven attacks by hackers. Therefore, data protection is crucial in the development of smart water management.

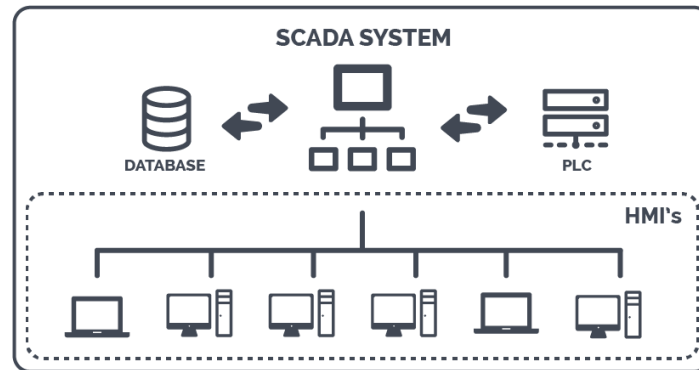


Figure 4. SCADA architecture.

2.2. Management Models and Decision Support Systems

The implementation of a common framework for measuring the water network performance based on a set of relevant indicators and data applications and interfaces helps to support the decision of the managing entities and allows for the interested parties to evaluate, create trust and confidence and monitor the improvements [38,39]. This section reviews existing models and systems to support this decision-making process.

2.2.1. Near Real-Time Models

Hydraulic models represent the most effective and viable way to predict the behaviour of the water distribution system under a wide range of conditions of demand anomalies and system failures. The knowledge of reliable short-term demand forecasting patterns is crucial to develop such models and to enable positive decisions, made in near real-time, to be implemented in smart water systems [40,41]. In addition, optimisation models of operation in near real-time allow us to extend decisions to smart water systems to improve the water network efficiency and to ensure more reliable operations, cost efficiency and environmental and social savings associated with losses.

In near real-time models, the moment the data are collected is the moment the network model is updated. Data include the characteristic parameters of pumps, valves, pressures and flows, as well as hours of operation towards the lowest operating costs. The objective is to make any operational decision almost instantly to meet the requirements for an efficient water supply [42]. Brentan et al. [43] proposed a hybrid methodology to update water demand models. To this end, an off-line procedure is used as a basis for the predictive model which is coupled with an on-line process. The proposal achieves both high accuracy and ability to adapt to new data anomalies and trends. The work also proposed an error control process to timely update the basic, off-line model cyclically, to guarantee a maximum accuracy.

2.2.2. Asset Management

Asset management is a process that water utilities use to make sure that maintenance can be conducted and capital assets (such as pumps, valves, and pipes, among others) can be repaired, replaced, or upgraded on time [44,45].

One of the main topics in asset management of a water distribution system is to prioritise the assets in rehabilitation plans. To this end, Cabral et al. [46] approached a solution involving an

economic asset performance evaluation using the infrastructure value index as a key performance indicator [47]. Other authors used a multi-criteria decision-making for rehabilitation purposes [48]. Beyond rehabilitation, asset management also deals with proactive maintenance plans driven by risk [49], resilience [50,51], or by an asset condition assessment [52].

Other central topics in asset management are of main interest for water utilities. This includes the prognosis and asset-health management in which it is key to handle the uncertainty of asset states, since utilities often have imperfect information about their assets. Another related subject to research further is about the optimal level of service (such as what to do in scarcity scenarios), asset criticality, or minimising assets' life-cycle costs.

3. Energy Recovery Systems

There are many devices that can be applied in water systems to ensure service quality. One device used to control the pressure is a pressure reducing valve (PRV) which also contributes to reduce water losses. The installation of this device usually requires the construction of a "by-pass" with the valve situated between two section valves. The set value is defined by the operator adjusting the valve opening. This valve controls and stabilises the pressure by increasing the head loss when the outlet pressure is higher than the set value [53]. This leads to an energy dissipation that can be harvested to produce electric energy.

PRV behaves in three ways: first, when the PRV is active (Figure 5 (left side)), when the pressure outlet is higher than the set value, the valve closes, increasing the head loss; second, the valve is passive open (Figure 5 (centre)), when the inlet pressure is lower than the minimum established value, and the valve opens decreasing the head loss; third, the valve is passive closed (Figure 5 (right side)) when the outlet pressure is higher than the inlet pressure and the behaviour of the PRV is akin to a check valve [54].

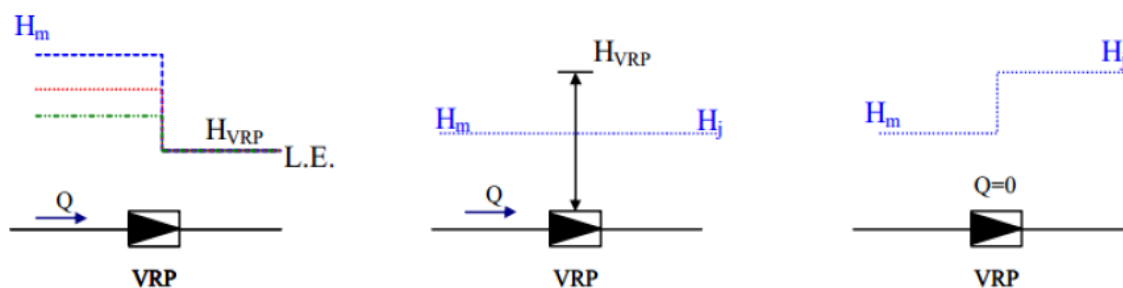


Figure 5. PRV behaviour: Active–Passive, open–passive, closed.

Using PRV in WDSs results in the creation of network discrete areas where the pressure and flow is controlled. These sectors are named district metered areas (DMAs) and they also come with the ability for a more efficient control of water losses, aiding in leakage detection and improving prevention and response. Section 4 expands the concept and discusses the methodologies and models to create DMAs.

One problem with the creation of DMAs is the PRV placement to ensure that the methodology used for network division returns optimal WDS sector areas. There are many studies for optimal valve location. Araujo et al. [55] investigated this issue in two steps: first, Genetic Algorithms are used to identify the number and the location of valves for the optimum control of pressure, and to minimise water losses; secondly, they adjusted the opening for several valves. Thus, the authors were able to define alternative scenarios for the valve location and concluded that a higher number of valves does not necessary lead to a better solution.

Principal energy converters require further study since the aim is to produce electrical energy out of urban water systems. This equipment converts pressure energy and/or kinetic energy into electric energy. The main turbines applied in water systems are divided in two groups: impulse turbines

and reaction turbines [56]. In the first group are, typically, Pelton turbines and, in a second group, Francis and Kaplan turbines. The main difference between these two groups is the flow pressure, as explained below:

- The main instance of impulse turbines is the Pelton impeller-turbine [57]. These turbines are characterised by the flow passing through, ending up at atmospheric pressure. The flow input by the injectors is shot at the bucket impeller. This makes the runner spin to create kinetic energy. The turbine can lose its efficiency if the water jet is not correctly directed to the buckets.
- Reaction turbine examples include the Francis and the Kaplan turbines. The Francis turbine is a radial-inflow hydraulic turbine that can efficiently work for a large range of head and flow values [58]. Kaplan turbines, on the other hand, are adapted for high flow rates with low heads. This type of propeller turbine has the advantage of having variable vanes that adjust to the flow [57].

The work of a turbine is defined by its characteristic curves that are related to flow, head, power and torque for a rotational speed and impeller diameter [59]. Therefore, it is possible to use these curves to trace equal efficiency lines, also known as “hill diagrams”, to operate at a better efficiency point [60].

The combination of new political and environmental policies and a high cost of energy has led to the search for new energy sources. Therefore, small hydro-systems are useful solutions for generating energy, especially in remote communities, where grid connections are not always feasible. In fact, small-scale hydroelectric power systems are emerging as a promising source of renewable energy generation [61]. In such plants, where pumps can be used in turbine mode to exploit the various advantages associated with pumps—e.g., proven technology, low initial and maintenance cost, availability for a wide range of heads and flows. The pump as turbine (PAT) method has become viable because they require low investment, maintenance and repair costs, and give reasonable efficiency. From the economic point of view, a PAT installation with power between 5–500 kW should give investment return in 2 or 3 years. The main issue of this hydraulic machine is that most suppliers do not provide the characteristic curves of pumps working as a turbine [62].

Comparative to the conventional turbines, PATs do not incorporate flow control devices. This means that it is not possible to maintain its efficiency when applied in networks with variable flow. Finding the best efficiency point (BEP) of a PAT has been the focus of many studies. Because of the losses by turbulence and friction, the BEP of a PAT when working in pumping mode is not the same when working in turbine mode. Williams et al. [63] studied water mass displacement in this context and found that 30% of the total losses are in the spiral case and 40% in the impeller.

There has been made some theoretical and experimental studies to predict PAT performance. Some are based on BEP and others on the specific speed, η_s . The relations between BEP in pumping mode and in turbine mode are presented by a correcting factor in relation to the flow and head are those represented in Equation (1),

$$h = \frac{H_t}{H_p}; \quad q = \frac{Q_t}{Q_p}, \quad (1)$$

where h is the Head correction factor and q the Flow correction factor.

The main hydraulic characteristic of a PAT comprises its hydraulic power (P_h), that is obtained by using the specific weight fluid (γ), the discharge (Q), and the net head (H). Equation (2) summarises the relationship between these variables.

$$P_h = \gamma \cdot Q_t \cdot H_u, \quad (2)$$

The mechanical power is calculated by torque (M), impeller rotational speed (ω), fluid mass density (ρ), discharge (Q), and free-vortex constants (k) are used to calculate the engine or mechanical power (P_e), by using Equation (3).

$$P_e = M \cdot \omega = \rho \cdot Q \cdot k \cdot \omega \quad (3)$$

The efficiency (η) is obtained using the electric power and the hydraulic power as it is shown in Equation (4).

$$\eta = \frac{P_e}{P_h} \quad (4)$$

The theory of the hydraulic similarity consists in three essential laws [56], summarised in Equation (5) and defined in the following bullet points:

- Geometric similarity: Dimension of the turbine cannot be reduced to a smaller scale which can induce scale effects in the prototype.
- Kinematic similarity: The triangle of velocities is equivalent in the inlet and outlet and dynamic similarity the polygon of forces must be similar both in the prototype as in the model.
- Dynamic similarity: This implies that geometric and kinematic similarities are already met. It implies a constant ratio of fluid forces, $\frac{N}{N'}$, for the flow-metering system.

$$\frac{N}{N'} = \frac{Q}{Q'}; \quad \left(\frac{N}{N'}\right)^2 = \frac{H}{H'}; \quad \left(\frac{N}{N'}\right)^3 = \frac{P_h}{P'_h} \quad (5)$$

The specific speed of a turbine gives the geometrical proportion of a similar turbine to a known turbine and it is defined by Equation (6).

$$\eta_s = \eta'_s \frac{P^{1/2}}{H^{5/4}} \quad (6)$$

With respect to a turbine performance, two characteristic curves should be defined:

- The first corresponding to $N = 0$, standstill curve, in which values of flow and head lower than this curve do not produce torque.
- Where $M = 0$, shows the values from which the torque is not transmitted to the shaft.

Figure 6 presents a graphical explanation of pump and turbine mode functioning. The main difference between is the direction of rotation. On top of this, Figure 6 points how, considering equivalent rotational speeds, the flow rate and turbine head take higher values in turbine mode at BEP than their counterparts in pump mode.

Ramos et al. [64] based on Sutter parameters proved that the right choice of PAT will always be feasible irrespective of the motor or generator used for the energy production. Ramos et al. [54] studied the hydraulic behaviour (steady and transient states) between a system with a PRV and PAT in the water network. In the steady state, the behaviours of the two devices are similar, although the transient response has some differences, such as the PRV producing higher over-pressure values. Derakhshan et al. [62] made a theoretical analysis to obtain the BEP of an industrial PAT using a method called “area ratio”. Later, they developed two equations to evaluate the PAT characteristic curves based on BEP. The authors concluded that a centrifugal pump can suitably operate as a turbine in multiple rotational speeds and a range of head and flow rates. Overall, PAT works with a higher head and flow rate than when it is in pump mode (compared at similar rotational speeds). Ramos et al. [65] identified the best points for energy production in a water network using PATs which became profitable after 5 years, depending on the production point. Recently, computational fluid dynamics (CFD) were used to predict the PAT performance [66,67], and it was found that the BEP of a PAT in turbine mode is up to 8.5% lower than the BEP in pumping mode. Carraveta et al. [68] proposed a method called “variable strategic operation” which allows for identifying the efficiency curves that maximise the PAT energy production.

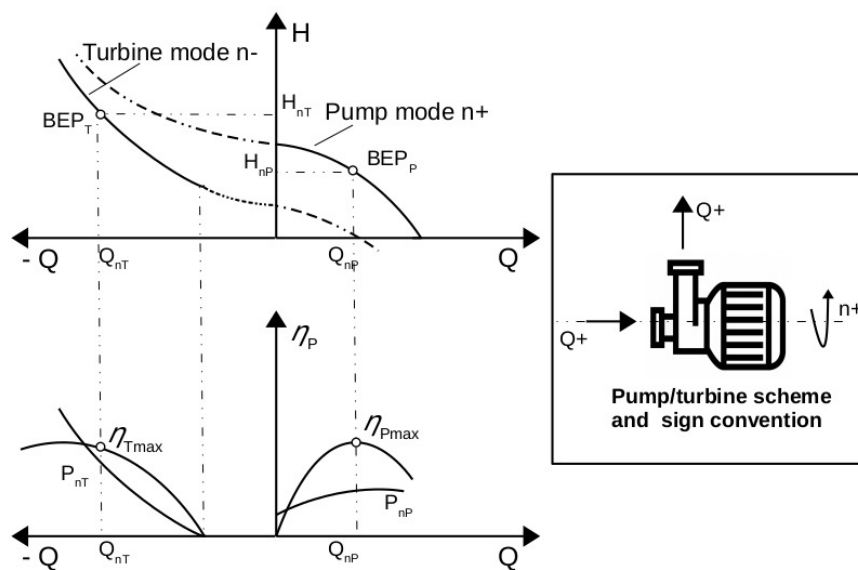


Figure 6. Pump mode vs. turbine mode. Characteristic curves and main features.

4. Water Network Partitioning and Leakage Control

Leakage detection and location has been an important challenge over the years for urban water management [69]. In the last two decades, significant efforts have been towards efficient leakage management techniques in water distribution systems [70]. Smart data analysis and techniques have also played an important role to address it [71,72]. Poulakis et al. [73] developed a Bayesian approach for leakage detection in water supply systems. The importance of this research lies in the uncertainty models for the imperfect information management often related to pipe bursts and leakages. Izquierdo et al. [74] proposed a procedure for estimating anomalous pipe states based on neuro-fuzzy theory. Years later, Candelieri et al. [75] used a combination of SCADA, GIS, and customer information systems, to better address leakage control. This work has multiple extensions by approaching leakage using big data [76] or by optimal procedures for sensor placement [77].

4.1. Water Network Partitioning

Today, multiple methodologies and procedures for a water distribution system partitioned into district metered areas (DMAs) have been developed as a consequence of an adaptation process from heuristics models and machine learning techniques [78]. Water network partitioning (WNP) is the process of dividing the water system into independent DMAs [79], formed by placing gate valves and flow meters along boundary pipes to connect one DMA to another. Figure 7 shows a scheme of a WNP into DMAs. The closure of a number of pipes provides an overall head drop, which leads to a reduction in water losses. In addition, leakage can be more easily quantified in each DMA by measuring minimum night flows. Burst detection is simplified, critical areas can be identified, and consequently, the interventions can be prioritised with an economic benefit and time reduction.

The methodologies enumerated below are the most widely used in research so far. A common point for all is to consider a water distribution system represented by a graph over which may run methodologies related to complex network analysis. Water sources and consumption points are, then, represented by nodes of a network, while pipes and valves are the links connecting such nodes to each other.

- Graph clustering and graph spectral clustering: Graph clustering finds groups in a graph based on different areas of connectivity between nodes. A similarity measure of nodes based on algorithms such as the shortest paths is applied often. There are relevant examples of graph clustering application in the urban water literature [80–82]. Spectral clustering has its basis on the Laplacian

matrix of the graph representing the water network. The physical properties of the graph Laplacian spectrum, in terms of network connectivity, are further considered to apply traditional clustering algorithms to the subset of eigenvectors associated with the top eigenvalues [83–87].

- Breadth and depth first search: Breadth-first search is a widely used algorithm for traversing a graph, starting from a randomly chosen node of the graph, the procedure then checks its neighbouring nodes (those nodes linked to the initial node) and points to the shorter distance nodes to continue the checking process. A counter of the accumulated distance travelled is recorded if notes are found. A backtrack, depth-first process allows one to return to previous nodes in the path to double check that the route is following the shortest path in this endeavour. This algorithm has been adapted to find groups in networks and is used in urban water studies for network partitioning purposes [88,89].
- Community detection: Community detection algorithms in water networks are based on similarities on such a water network to a social network. Clustering algorithms in social networks are based on detection of areas in which individuals are strongly related (linked) and information is easily spread. This is the fundamental idea, as that adopted in water networks considers consumption points for information sharing [90,91].
- Agent-based systems: Agent-based modelling can model and simulate the evolution of a dynamic, complex system from a distributed approach. That is, by decomposing the system into a collection of autonomous decision-making entities, called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules which allow them to reach individual and common objectives. To this end, the agents evolve themselves, interacting with the environment and with other agents via coordination, cooperation and competition, among other actions. To divide a water network into DMAs, agents are considered the consumption nodes and have varying properties (demand, pressure, cluster membership, etc.). Agents communicate/negotiate with others by links representing pipes and valves to finally find a distributed notion of similarity and distance that make the higher similarity and/or lower distance network nodes to form clusters [92,93].

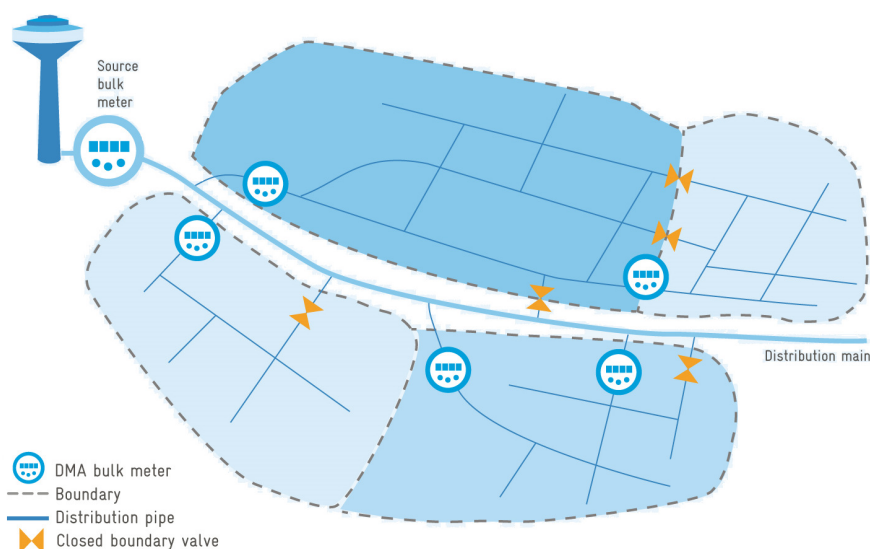


Figure 7. Scheme example of a WDS partitioned into DMAs.

Figure 8 shows a general process followed by any WNP procedure using any of the above methodologies or others.

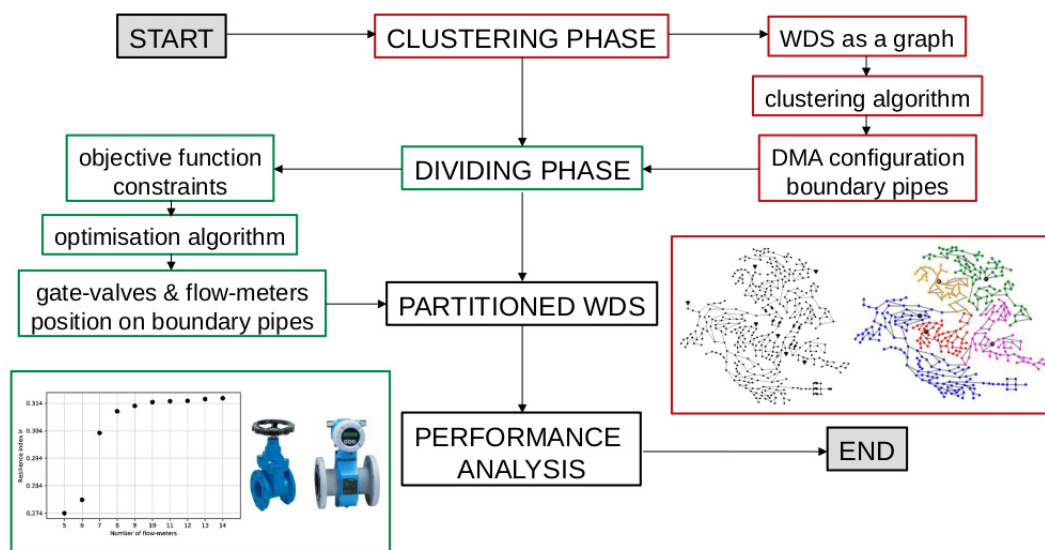


Figure 8. Scheme for a WNP process.

The last frontier for a DMA management strategy is represented by an adaptive/dynamic reconfiguration of the districts according to the variability of the functioning conditions [94]. This allows us to find an optimal trade-off by maximising the benefits of an open WDS configuration (i.e. pressure, water quality, and energy efficiency) while still getting the advantages of managing and control a partitioned layout.

4.2. “Less Is More” in Hydraulic Resilience through Wnp

A water network partitioning into DMAs can also be used for other operational and management issues in WDSs. Some of them include a multi-objective approach for such a partitioning [95]. Still, the system must continue to be resilient after partitioning [96–99]. Considering a classical definition of energy resilience in Hydraulic Engineering (e.g., resilience index of Todini [100]), WNP unequivocally produces a head pressure drop and, consequently, a resilience reduction, due to the closure of a number of boundary pipes. Although important, this represents a WNP resilience assessment through just one single approach. In this sense, the approach of resilience of the Multidisciplinary Center for Earthquake Engineering Research (MCEER) [101] provides a deeper framework. According to MCEER: “Resilient systems reduce the probabilities of failure; the consequences of failure, and the time for recovery”. MCEER investigators developed the so-called R4 framework highlighting the multiple paths to resilience. The following bullet-points show the benefits of WNP in terms of resilience under such an R4 framework.

- **Robustness:** Ability of the system and system elements, to withstand disaster-induced damage and disruption without significant degradation or loss of performance. WNP allows one to divide the system in areas of a similar hydraulic head, uniformly all over the system, and limiting the oscillations between night and day. This leads to a significant reduction in stress on pipes and devices that consequently preserves, for a longer period, their mechanical performance.
- **Redundancy:** Extent to which system elements are replaceable, or equivalently, extent to which alternative paths and modes can be employed if some elements lose function. Due to the closure of some boundary pipes, WNP leads to a loss in both topological and energy redundancy, since some alternative paths are precluded. However, the possibility to isolate districts from the rest of the system during an abnormal event (e.g., pipe breakage, contamination) allows one to isolate the problem as well as guarantee normal functioning.
- **Resourcefulness:** Ability to diagnose and prioritise problems and to initiate solutions by identifying and mobilising material, monetary, informational, technological, and human resources.

By splitting the system in monitored sub-areas, WNP allows one to separately manage them. Thus, efficiency is increased by the prioritisation of interventions.

- **Rapidity:** Capacity to restore functionality in a timely way, containing losses and avoiding disruptions. WNP's inherent division of the system in smaller areas, allows to focus each to operate in a more efficient way and adapt rapidly to any problem in corresponding districts.

Overall, working by DMAs improves the capacity of the system to respond and recover from both normal and extreme events, allowing for better reorganisation and a smarter management of the water network, even if leads to a general reduction in energy (that we can identify as part of providing the Redundancy specified in the 4R resilience framework). Therefore, WNP can be a key element for designing an optimal preparedness for the absorptive phase of resilience in water networks [102,103].

5. Emergent Paradigm of Digital Water and Future Research Directions

Water utilities face unprecedented pressures and complexity in their decision-making as a result population growth and challenges related to climate change such as heavy rainfall and drought periods. Further, an increasingly automated and interconnected world creates new sources of vulnerability, such as cyber-attacks to their automated system management [104,105] or the increasing likelihood of failure propagation through multiple, urban infrastructures [106]. However, digitalisation and interconnectivity also bring solutions to the challenges faced by a water utility today.

The concept of “digital water” is a novel, holistic approach for urban water operation and management [107,108]. Water systems need to be understood as smart water grids, since they actually are a cyber-physical system made by sensors, processors, and actuators continuously communicating with each other, and integrated into any monitor and control management layer, to achieve optimal decision-making in a near real-time. In addition, water infrastructure is not only aimed at providing clean water at an appropriate pressure. As discussed in this paper, the energy moving the water flow can be recovered and further used to provide energy [109]. Thus, digital water is a paradigm with a basis in a new generation of urban hydroinformatics [11] that will revolutionise urban water systems in multiple ways.

The International Water Association's (IWA) report on digital water [107], highlighted that even if the transformation is not always easy (due to ageing infrastructure, inadequate investment, changing climate and demographics) digital water is seen not as an “option” but as an “imperative”. Therefore, water utilities are at the centre of a greater, more complex and interconnected ecosystem (Figure 9) that includes stakeholders from across the water and wastewater spectrum, such as private and public utility peers, governmental bodies, technology solution providers, academic institutions, consultancies, industry associations and technology accelerators.



Figure 9. Digital water ecosystem. Figure adapted from [107], under Creative Commons license.

Overall, digital water encompasses the following main features:

- Distributed systems management as an efficient methodology to deal with big data streams coming at near real-time from the cyber-physical structure controlling and monitoring the smart water grid.
- Innovative and necessary data analysis methodologies for increasing the efficiency and benefit of the decision-making processes. These methodologies can be found within the subjects of machine learning and artificial intelligence, big data, complexity science, and robotics.
- Water companies are an important, active stakeholder in digital water. This brings to the overall process the need of a business reconfiguration, implying a multiscale thinking in which individual assets play an important role in the global physical and digital infrastructure. Along with their interrelationship to other utilities and the society network as a customer.
- There is a disruption of new markets and business models around the digital water management. Data again plays a pivotal role in this and new technologies, such as blockchain, allow for secure data sharing and decision making in case multiple companies and stakeholders can be involved in the overall approach.

5.1. Future Technologies for Smart Water Grids

There are several technologies that play a relevant role in the future of smart water grids and digital water. Cyber-physical systems (CPSs) and digital twins (DTs) will aid general operation and management. Blockchain will be determinant to changing the business model of water utilities. The following bullet points further introduce and provide key references for each of these technologies:

- Cyber-physical systems: The concept of a smart water grid is directly related to a CPS [110]. In the case of a water distribution system, these are the set of sensors, smart monitors, and actuators distributed along the physical infrastructure. Internet of Things (IoT) is the main vehicle for communication in a CPS and for endowing the system with an optimal decision-making capability both in a hierarchical and a distributed manner [111]. Directly related to SCADA and a near real-time water operation and management [112], the benefits of a CPS expand to an online knowledge of the hydraulic state of a water distribution system [113], safety and security [114,115], contamination detection in a water distribution system [116], and optimal performance [117], among others.
- Digital twins: The paradigm of the digital twin is closely related to digital water. DT models map near real-time data and updated models from the assets of the CPS to a high resolution digital system reproduction. The aim for digital twins' models of water distribution systems is to reproduce disruption scenarios for resilience assessment purposes, to validate beforehand new solutions for network configurations, and to analyse asset prognosis and health-status to determine proactive maintenance models. DTs are still a paradigm to explore further in urban water. Conejos et al. [118] presented one of the first scientific articles in this regard, as more of the development so far in DTs for urban water is directly approached by innovation teams within water utilities. DTs have been an enormous development in the last years by the deployment of twins. The challenge for water utilities and urban water researchers is to consider the complexity of dealing with a network of assets, along with their interaction models and data sharing and management.
- Blockchain technologies: Blockchain can be considered a decentralised database with the records partitioned into blocks forming a chain configuration. The information at each block is only a partial view of the data. Therefore, the partition of the records into blocks guarantees a safe and secure access to information, when it is shared by multiple stakeholders. This is a step-forward to address data security issues associated with the new business of digital water. The blocks of information can be considered as network nodes and the operations between them are network links. This complex network approach to blockchain technologies generates new paradigms about

the database synchronisation and control [119] and the further use of machine learning models for an optimal database management and representation [120].

5.2. Future Model Analytics for Smart Water Grids

A smart water grid can be seen as the blending of water resources management strategies, Information Communication Technology (ICT), data analysis and conscious participation of users (see Figure 10). Smart water grids and digital water need to count on the support of innovative models and analysis techniques. In this regard, the use of machine learning and artificial intelligence is foreseen as a basis of their development. The current paper further foresees the great importance of network dynamics. The recent advances and future research in this topic will be of great importance for near real-time models and big size networks analysis, along with addressing main operational and management issues, such as sensor placement and contaminant early detection. Network dynamics research can be expanded and/or complemented with the investigation of geometric deep learning solutions to undertake even more ambitious challenges, such as, among others, leakage detection. The following bullet points are a brief introduction both for network dynamics and geometric deep learning.

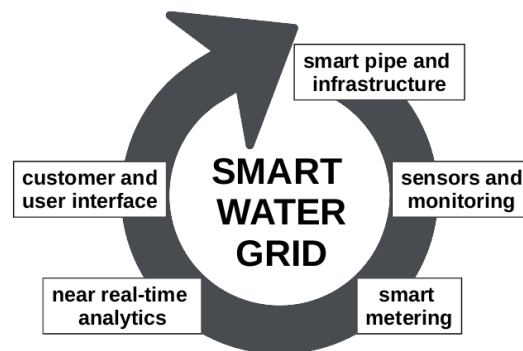


Figure 10. Smart water grid paradigm.

- Network dynamics: Now to consider the difference between “dynamic of networks” (as a variation on time of configuration; network topology—and number of the nodes and links of a network) and “dynamics on networks” as a variation on time of nodes and links weights or values; likely depending on the network flow and node demand. Multilayer networks can be defined as multiple interconnected networks, each can represent another network or a variation of the original network (regarding its topology or element status) [121]. In the latter, through a snapshot of the network at each time and per individual network layer. Considering network dynamics within the formal framework of multilayer networks is, therefore, an open research avenue for researchers and practitioners in smart water grids, where complex network analysis already plays a pivotal role. The challenge of time series processes in networks can be extended to other statistical and machine learning methods approached on networks [122].
- Geometric deep learning: It is a new emergent topic in which convolutional neural networks (CNN), mainly focused so far on image analysis, are used for manifolds and graph-structured databases [123]; having inherited the name for the latest of graph-CNN or directly graph neural networks (GNN). During an image analysis, a series of convolutional filters and pooling CNN layers extract relevant features and patterns in an image. The operations are of similar nature in geometric deep learning but approached over the adjacency or the Laplacian matrix of the graph representing, in this case, the smart water grid. The main characteristic to adopt and adapt CNNs to complex networks is to consider those matrices representing such networks that preserve spatial meaning of that, along with another properties of interest. Problems related to a smart

water grid monitor and control can be approached through geometric deep learning in addition to a number of other important applications [124].

6. Conclusions

In recent years, the water sector have faced significant challenges, in particular with the effort to develop a smart water system to improve the efficiency and sustainability performance (e.g., social, technical, and environmental) of water networks. Through the technological innovations, smart cities can reduce costs, increase the quality of service (in quantity, quality, and costs) and optimise the operation of the system. The policy of smart water grids is different for each system, as is the degree of efficiency. Therefore, the selected techniques and actions will depend on the required objectives and restrictions of each system, the available capital, and techniques for investment. Besides, strategies must be associated with a worldwide awareness of the society to facilitate the sustainable management and use of the available resources.

This paper presented an overview of technologies, models, and strategies for smart water grids. The following bullet points better describe these items:

- **Technologies:** smart pipe and sensors, smart water metering, GIS and SCADA have been introduced in this manuscript as key technologies to accomplish the paradigm of a smart water grid. Cyber-physical systems, digital twins, and blockchain have been identified as future breakthrough technologies.
- **Models:** The importance of counting on near real-time models has also been highlighted in the document, showing how they may lead to an improved water efficiency and more reliable operations. In this regard, the role of asset management models in smart water grids have also been discussed. Complex networks (dynamics) and geometric deep learning were foreseen as key basis for any future model development in smart water grids.
- **Strategies:** A main part of the document is dedicated to describe and propose the use of strategies for energy recovery and water network partitioning. Both points have the common objective of improving the water network efficiency.

The document placed specific emphasis on energy recovery systems, since they play an essential role both for smart water grids and for smart and resilient cities. Energy recovery systems development is, therefore, key for future net zero energy management towards not only a smart but also green infrastructure. Furthermore, water network partitioning was shown to be pivotal for energy recovery and leakage control. This paper also revisited the cutting-edge methodologies for approaching such a partition into the so called district metered areas. The review goes from the more traditional procedures aimed at leakage control and pressure management to those methods with more innovative objectives, such optimising network resilience and energy dissipation. The procedure on how to optimally design dynamic DMAs was also revisited.

Smart water grids are closely related to the emergent trend of digital water, and is currently positioned to revolutionise the urban water industry and research. The paper introduces digital water along with its associated technologies, methodologies, and models. Among the future technologies having a strong relationship to digital water, it highlighted cyber-physical systems in a water network, such as one with sensors, smart-meters, and actuators, to automatise the operation, monitoring and control of the infrastructure. Digital twins open the possibility to enhance anomaly detection models and asset management plans. A third proposal for digital water is the blockchain technology. This will be key to new business models towards the collaboration of multiple companies. As a digital water approach is data-centred, blockchain provides a framework for effective and trustworthy data sharing among the different business actors. With respect to future model analytics and methodologies, it is foreseen that machine learning and artificial intelligence tools will underpin future approaches in digital water and smart water grids. Beyond hydraulic considerations, this paper establishes network of dynamics and geometric deep learning as pivotal topics for future digital water and smart water grid

models. Both topics are the basis of cutting-edge research on machine learning models and predictive analytics over a graph structure that could be adapted to smart water grids. That is, modelling the information of a WDS, considering the multiple spatial/structural, temporal (flow and topological modifications) and infrastructure dimensions (inter-infrastructure approaches). Beyond any doubt, these approaches comprise an essential add-on to the future research in smart water grids.

Author Contributions: All authors contributed equally to the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Herrera, M.; Ferreira, A.A.; Coley, D.A.; de Aquino, R.R. SAX-quantile based multiresolution approach for finding heatwave events in summer temperature time series. *AI Commun.* **2016**, *29*, 725–732. [[CrossRef](#)]
- Hernandez, P.; Kenny, P. From net energy to zero energy buildings: Defining life cycle zero energy buildings (LC-ZEB). *Energy Build.* **2010**, *42*, 815–821. [[CrossRef](#)]
- Keyhani, A. Smart power grids. In *Smart Power Grids 2011*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 1–25.
- Sachidananda, M.; Webb, D.P.; Rahimifard, S. A concept of water usage efficiency to support water reduction in manufacturing industry. *Sustainability* **2016**, *8*, 1222. [[CrossRef](#)]
- Boyle, T.; Giurco, D.; Mukheibir, P.; Liu, A.; Moy, C.; White, S.; Stewart, R. Intelligent metering for urban water: A review. *Water* **2013**, *5*, 1052–1081. [[CrossRef](#)]
- Butler, D.; Farmani, R.; Fu, G.; Ward, S.; Diao, K.; Astaraie-Imani, M. A new approach to urban water management: Safe and sure. *Procedia Eng.* **2014**, 347–354. [[CrossRef](#)]
- Mala-Jetmarova, H.; Sultanova, N.; Savic, D. Lost in optimisation of water distribution systems? A literature review of system design. *Water* **2018**, *10*, 307. [[CrossRef](#)]
- Anele, A.O.; Hamam, Y.; Abu-Mahfouz, A.M.; Todini, E. Overview, comparative assessment and recommendations of forecasting models for short-term water demand prediction. *Water* **2017**, *9*, 887. [[CrossRef](#)]
- Monks, I.; Stewart, R.A.; Sahin, O.; Keller, R. Revealing unreported benefits of digital water metering: Literature review and expert opinions. *Water* **2019**, *11*, 838. [[CrossRef](#)]
- Rahim, M.S.; Nguyen, K.A.; Stewart, R.A.; Giurco, D.; Blumenstein, M. Machine Learning and Data Analytic Techniques in Digital Water Metering: A Review. *Water* **2020**, *12*, 294. [[CrossRef](#)]
- Makropoulos, C.; Savić, D. Urban hydroinformatics: Past, present and future. *Water* **2019**, *11*, 1959. [[CrossRef](#)]
- Onishi, M.; Kageyama, K. Smart Water Management and Usage Systems for Society and Environment. *Hitachi Rev.* **2011**, *60*, 165.
- Ramos, H.M.; Carravetta, A.; Nabola, A.M. New Challenges in Water Systems. *Water* **2020**, *12*, 2340. [[CrossRef](#)]
- Howell, S.; Rezgui, Y.; Beach, T. Integrating building and urban semantics to empower smart water solutions. *Autom. Constr.* **2017**, *81*, 434–448. [[CrossRef](#)]
- Mounce, S.; Pedraza, C.; Jackson, T.; Linford, P.; Boxall, J. Cloud based machine learning approaches for leakage assessment and management in smart water networks. *Procedia Eng.* **2015**, *119*, 43–52. [[CrossRef](#)]
- Di Nardo, A.; Di Natale, M.; Giudicianni, C.; Santonastaso, G.; Savic, D. Simplified approach to water distribution system management via identification of a primary network. *J. Water Resour. Plan. Manag.* **2018**, *144*, 04017089. [[CrossRef](#)]
- Lombardi, P.; Giordano, S.; Farouh, H.; Yousef, W. Modelling the smart city performance. *Innov. Eur. J. Soc. Sci. Res.* **2012**, *25*, 137–149. [[CrossRef](#)]
- Colldahl, C.; Frey, S.; Kelemen, J.E. *Smart Cities: Strategic Sustainable Development for an Urban World*; School of Engineering, Blekinge Institute of Technology: Karlskrona, Sweden, 2013.
- Nam, T.; Pardo, T.A. Conceptualizing smart city with dimensions of technology, people, and institutions. In *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times*, College Park, MD, USA, 12–15 June 2011; pp. 282–291.

20. Dobbie, M.F.; Brown, R.R.; Farrelly, M.A. Risk governance in the water sensitive city: Practitioner perspectives on ownership, management and trust. *Environ. Sci. Policy* **2016**, *55*, 218–227. [[CrossRef](#)]
21. Hellström, D.; Jeppsson, U.; Kärrman, E. A framework for systems analysis of sustainable urban water management. *Environ. Impact Assess. Rev.* **2000**, *20*, 311–321. [[CrossRef](#)]
22. Lin, Y.F.; Liu, C.; Whisler, J. Smart pipe—Nanosensors for monitoring water quantity and quality in public water systems. In Proceedings of the World Environmental and Water Resources Congress 2009, Great Rivers, Kansas City, MO, USA, 17–21 May 2009; pp. 1–8.
23. Sadeghioon, A.M.; Metje, N.; Chapman, D.N.; Anthony, C.J. SmartPipes: Smart wireless sensor networks for leak detection in water pipelines. *J. Sens. Actuator Netw.* **2014**, *3*, 64–78. [[CrossRef](#)]
24. Maas, C.; McClenaghan, T.; Pleasance, G. *The Water-Energy Nexus. Linking Water and Energy in Ontario Policy*; Policy Report; About the Water Conservation Alliance: Ottawa, ON, Canada, 2010.
25. Ntuli, N.; Abu-Mahfouz, A. A simple security architecture for smart water management system. *Procedia Comput. Sci.* **2016**, *83*, 1164–1169. [[CrossRef](#)]
26. Britton, T.C.; Stewart, R.A.; O'Halloran, K.R. Smart metering: Enabler for rapid and effective post meter leakage identification and water loss management. *J. Clean. Prod.* **2013**, *54*, 166–176. [[CrossRef](#)]
27. Hall, J.; Szabo, J.; Panguluri, S.; Meiners, G. Distribution System Water Quality Monitoring: Sensor Technology Evaluation Methodology and Results. In *A Guide for Sensor Manufacturers and Water Utilities*; Technical Report; Environmental Protection Agency: Washington, DC, USA, 2009.
28. Sharvelle, S.; Dozier, A.; Arabi, M.; Reichel, B. A geospatially-enabled web tool for urban water demand forecasting and assessment of alternative urban water management strategies. *Environ. Model. Softw.* **2017**, *97*, 213–228. [[CrossRef](#)]
29. Rossman, L.A. *EPANET 2: Users Manual*; Technical Report; US Environmental Protection Agency Office of Research and Development: Cincinnati, OH, USA, 2000.
30. Kyriakou, M.; Eliades, D. ImportEpanetInpFiles. In *Import/Export Epanet INP Files*; KIOS, Research and Innovation Center of Excellence: Nicosia, Cyprus, 2016. Available online: <https://github.com/KIOS-Research/ImportEpanetInpFiles> (accessed on 23 October 2020).
31. Menapace, A.; Pisaturo, G.R.; De Luca, A.; Gerola, D.; Righetti, M. EPANET in QGIS framework: The QEPANET plugin. *J. Water Supply Res. Technol. AQUA* **2020**, *69*, 1–5. [[CrossRef](#)]
32. Martínez Alzamora, F.; Lerma, N.; Bartolin, H.; Vegas Niño, O. Upgrade of the GISRed application for the free analysis of WDN under GIS environment. In Proceedings of the 17th International Computing & Control for the Water Industry Conference, CCWI, Exeter, UK, 1–4 September 2019; pp. 1–3.
33. Martínez, F.; Bartolín, H.; Sancho, H.; Ayza, M. GISRed v1.0: Una herramienta SIG de ayuda para la confección de modelos y Planes Directores de redes de distribución del agua. *Tecnología del Agua* **2004**, *250*, 32–41.
34. Boyer, S.A. *SCADA: Supervisory Control and Data Acquisition*; International Society of Automation: Research Triangle Park, NC, USA, 2009.
35. Ottenburger, S.; Airaksinen, M.; Pinto-Seppä, I.; Raskob, W. Enhancing urban resilience via a real-time decision support system for smart cities. In Proceedings of the 2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC), Funchal, Portugal, 27–29 June 2017; pp. 836–844.
36. Marti-Puig, P.; Martí-Sarri, A.; Serra-Serra, M. Different approaches to SCADA data completion in water networks. *Water* **2019**, *11*, 1023. [[CrossRef](#)]
37. Furht, B.; Escalante, A. *Handbook of Cloud Computing*; Springer: Boston, MA, USA, 2010.
38. Boulos, P.F.; Wiley, A.N. Can We make Water systems smarter? *Opflow* **2013**, *39*, 20–22. [[CrossRef](#)]
39. Gurung, T.R.; Stewart, R.A.; Beal, C.D.; Sharma, A.K. Smart meter enabled water end-use demand data: Platform for the enhanced infrastructure planning of contemporary urban water supply networks. *J. Clean. Prod.* **2015**, *87*, 642–654. [[CrossRef](#)]
40. Romano, M.; Kapelan, Z. Adaptive water demand forecasting for near real-time management of smart water distribution systems. *Environ. Model. Softw.* **2014**, *60*, 265–276. [[CrossRef](#)]
41. Herrera, M.; Izquierdo, J.; Pérez-García, R.; Ayala-Cabrera, D. On-line learning of predictive kernel models for urban water demand in a smart city. *Procedia Eng.* **2014**, *70*, 791–799. [[CrossRef](#)]
42. Creaco, E.; Campisano, A.; Fontana, N.; Marini, G.; Page, P.; Walski, T. Real time control of water distribution networks: A state-of-the-art review. *Water Res.* **2019**, *161*, 517–530. [[CrossRef](#)]

43. Brentan, B.M.; Luvizotto, E., Jr.; Herrera, M.; Izquierdo, J.; Pérez-García, R. Hybrid regression model for near real-time urban water demand forecasting. *J. Comput. Appl. Math.* **2017**, *309*, 532–541. [[CrossRef](#)]
44. Berg, S.V. *Best Practices in Regulating State-Owned and Municipal Water Utilities*; Technical Report; Economic Commission for Latin America and the Caribbean (ECLAC), United Nations: Santiago, Chile, 2013.
45. Pollard, S. *Risk Management for Water and Wastewater Utilities*; IWA Publishing: London, UK, 2016.
46. Cabral, M.; Loureiro, D.; Covas, D. Using economic asset valuation to meet rehabilitation priority needs in the water sector. *Urban Water J.* **2019**, *16*, 205–214. [[CrossRef](#)]
47. Alegre, H.; Baptista, J.M.; Cabrera, E., Jr.; Cubillo, F.; Duarte, P.; Hirner, W.; Merkel, W.; Parena, R. *Performance Indicators for Water Supply Services*; IWA Publishing: London, UK, 2016.
48. Carriço, N.; Covas, D.; Almeida, M.C.; Leitão, J.; Alegre, H. Prioritization of rehabilitation interventions for urban water assets using multiple criteria decision-aid methods. *Water Sci. Technol.* **2012**, *66*, 1007–1014. [[CrossRef](#)] [[PubMed](#)]
49. Salehi, S.; Tabesh, M.; Jalili Ghazizadeh, M. HRDM method for rehabilitation of pipes in water distribution networks with inaccurate operational-failure data. *J. Water Resour. Plan. Manag.* **2018**, *144*, 04018053. [[CrossRef](#)]
50. Rasoulkhani, K.; Mostafavi, A.; Cole, J.; Sharvelle, S. Resilience-based infrastructure planning and asset management: Study of dual and singular water distribution infrastructure performance using a simulation approach. *Sustain. Cities Soc.* **2019**, *48*, 101577. [[CrossRef](#)]
51. Izadi, A.; Yazdandoost, F.; Ranjbar, R. Asset-Based Assessment of Resiliency in Water Distribution Networks. *Water Resour. Manag.* **2020**, *34*, 1407–1422. [[CrossRef](#)]
52. Kumar, G.; Jain, V.; Gandhi, O. Availability analysis of mechanical systems with condition-based maintenance using semi-Markov and evaluation of optimal condition monitoring interval. *J. Ind. Eng. Int.* **2018**, *14*, 119–131. [[CrossRef](#)]
53. Fecarotta, O.; Aricò, C.; Carravetta, A.; Martino, R.; Ramos, H.M. Hydropower potential in water distribution networks: Pressure control by PATs. *Water Resour. Manag.* **2015**, *29*, 699–714. [[CrossRef](#)]
54. Ramos, H.; Covas, D.; Araujo, L.; Mello, M. Available energy assessment in water supply systems. In Proceedings of the 31th International Association for Hydro-Environment Engineering and Research (IAHR) Congress, Seoul, Korea, 11–16 September 2005; pp. 11–16.
55. Araujo, L.; Ramos, H.; Coelho, S. Pressure control for leakage minimisation in water distribution systems management. *Water Resour. Manag.* **2006**, *20*, 133–149. [[CrossRef](#)]
56. Quintela, A.D.C. *Hidráulica*, 10th ed.; Fundação Calouste Gulbenkian: Lisbon, Portugal, 2007.
57. Dixon, S.; Hall, C. Chapter 9—Hydraulic Turbines. In *Fluid Mechanics and Thermodynamics of Turbomachinery*, 6th ed.; Dixon, S., Hall, C., Eds.; Butterworth-Heinemann: Boston, MA, USA, 2010; pp. 303–355.
58. Bortoni, E.; Souza, Z.D.; Viana, A.; Villa-Nova, H.; Rezek, Â.; Pinto, L.; Siniscalchi, R.; Bragança, R.; Bernardes, J. The Benefits of Variable Speed Operation in Hydropower Plants Driven by Francis Turbines. *Energies* **2019**, *12*, 3719. [[CrossRef](#)]
59. Menarin, H.A.; Costa, H.A.; Fredo, G.L.M.; Gosmann, R.P.; Finardi, E.C.; Weiss, L.A. Dynamic modeling of Kaplan turbines including flow rate and efficiency static characteristics. *IEEE Trans. Power Syst.* **2019**, *34*, 3026–3034. [[CrossRef](#)]
60. Valavi, M.; Nysveen, A. Variable-speed operation of hydropower plants: Past, present, and future. In Proceedings of the 2016 XXII International Conference on Electrical Machines (ICEM), Lausanne, Switzerland, 4–7 September 2016; pp. 640–646.
61. Jain, S.V.; Patel, R.N. Investigations on pump running in turbine mode: A review of the state-of-the-art. *Renew. Sustain. Energy Rev.* **2014**, *30*, 841–868. [[CrossRef](#)]
62. Derakhshan, S.; Nourbakhsh, A. Experimental study of characteristic curves of centrifugal pumps working as turbines in different specific speeds. *Exp. Therm. Fluid Sci.* **2008**, *32*, 800–807. [[CrossRef](#)]
63. Williams, A.; Rodrigues, A.; Singh, P.; Nestmann, F.; Lai, E. Hydraulic Analysis of a Pump as a Turbine with CFD and Experimental Data. In Proceedings of the IMechE Seminar, Computational Fluid Dynamics for Fluid Machinery, London, UK, 18 November 2003; Technical Report.
64. Ramos, H.; Borga, A. Pumps yielding power. *Dam Eng. Water Power Dam Constr.* **2000**, *10*, 197–217.
65. Ramos, H.; Covas, D.; Gonçalves, F.; Soares, A. *Geração de Energia Sustentável em Sistemas de Abastecimento de água—Análise Econômica e Proposta de Optimização*; IST/CEHIDRO: Lisbon, Portugal, 2008.

66. Simão, M.; Ramos, H.M. Hydrodynamic and performance of low power turbines: Conception, modelling and experimental tests. *Int. J. Energy Environ.* **2010**, *1*, 431–444.
67. Nautiyal, H.; Varun, V.; Kumar, A.; Yadav, S.Y.S. Experimental investigation of centrifugal pump working as turbine for small hydropower systems. *Energy Sci. Technol.* **2011**, *1*, 79–86.
68. Carravetta, A.; Del Giudice, G.; Fecarotta, O.; Ramos, H.M. Energy production in water distribution networks: A PAT design strategy. *Water Resour. Manag.* **2012**, *26*, 3947–3959. [[CrossRef](#)]
69. Puust, R.; Kapelan, Z.; Savic, D.; Koppel, T. A review of methods for leakage management in pipe networks. *Urban Water J.* **2010**, *7*, 25–45. [[CrossRef](#)]
70. Gupta, A.; Kulat, K. A selective literature review on leak management techniques for water distribution system. *Water Resour. Manag.* **2018**, *32*, 3247–3269. [[CrossRef](#)]
71. Li, R.; Huang, H.; Xin, K.; Tao, T. A review of methods for burst/leakage detection and location in water distribution systems. *Water Sci. Technol. Water Supply* **2015**, *15*, 429–441. [[CrossRef](#)]
72. Chan, T.K.; Chin, C.S.; Zhong, X. Review of current technologies and proposed intelligent methodologies for water distributed network leakage detection. *IEEE Access* **2018**, *6*, 78846–78867. [[CrossRef](#)]
73. Poulakis, Z.; Valougeorgis, D.; Papadimitriou, C. Leakage detection in water pipe networks using a Bayesian probabilistic framework. *Probabilistic Eng. Mech.* **2003**, *18*, 315–327. [[CrossRef](#)]
74. Izquierdo, J.; López, P.; Martínez, F.; Pérez, R. Fault detection in water supply systems using hybrid (theory and data-driven) modelling. *Math. Comput. Model.* **2007**, *46*, 341–350. [[CrossRef](#)]
75. Candelieri, A.; Archetti, F.; Messina, E. Improving leakage management in urban water distribution networks through data analytics and hydraulic simulation. *WIT Trans. Ecol. Environ.* **2013**, *171*, 107–117.
76. Candelieri, A.; Archetti, F. Smart water in urban distribution networks: Limited financial capacity and Big Data analytics. *WIT Trans. Built Environ.* **2014**, *139*, 11.
77. Candelieri, A.; Soldi, D.; Archetti, F. Cost-effective sensors placement and leak localization—the Neptun pilot of the ICeWater project. *J. Water Supply Res. Technol. AQUA* **2015**, *64*, 567–582. [[CrossRef](#)]
78. Khoa Bui, X.; S Marlim, M.; Kang, D. Water Network Partitioning into District Metered Areas: A State-Of-The-Art Review. *Water* **2020**, *12*, 1002. [[CrossRef](#)]
79. UK Water Industry Research Limited. *A Manual of DMA Practice*; UK Water Industry Research Limited: London, UK, 1999.
80. Di Nardo, A.; Di Natale, M. A heuristic design support methodology based on graph theory for district metering of water supply networks. *Eng. Optim.* **2011**, *43*, 193–211. [[CrossRef](#)]
81. Perelman, L.; Ostfeld, A. Topological clustering for water distribution systems analysis. *Environ. Model. Softw.* **2011**, *26*, 969–972. [[CrossRef](#)]
82. Scarpa, F.; Lobba, A.; Becciu, G. Elementary DMA design of looped water distribution networks with multiple sources. *J. Water Resour. Plan. Manag.* **2016**, *142*, 04016011. [[CrossRef](#)]
83. Herrera, M.; Canu, S.; Karatzoglou, A.; Pérez-García, R.; Izquierdo, J. An approach to water supply clusters by semi-supervised learning. In Proceedings of the 5th International Congress on Environmental Modelling and Software, San Sebastian, Spain, 23–25 June 2010; pp. 315–322.
84. Herrera, M.; Izquierdo, J.; Pérez-García, R.; Montalvo, I. Multi-agent adaptive boosting on semi-supervised water supply clusters. *Adv. Eng. Softw.* **2012**, *50*, 131–136. [[CrossRef](#)]
85. Candelieri, A.; Giordani, I.; Archetti, F. Automatic configuration of Kernel-based clustering: An optimization approach. In Proceedings of the International Conference on Learning and Intelligent Optimization, Nizhny Novgorod, Russia, 19–21 June 2017; Springer International Publishing: Cham, Switzerland, 2017; pp. 34–49.
86. Di Nardo, A.; Di Natale, M.; Giudicianni, C.; Greco, R.; Santonastaso, G.F. Weighted spectral clustering for water distribution network partitioning. *Appl. Netw. Sci.* **2017**, *2*, 19. [[CrossRef](#)] [[PubMed](#)]
87. Di Nardo, A.; Giudicianni, C.; Greco, R.; Herrera, M.; Santonastaso, G.F. Applications of graph spectral techniques to water distribution network management. *Water* **2018**, *10*, 45. [[CrossRef](#)]
88. Deuerlein, J.W. Decomposition model of a general water supply network graph. *J. Hydraul. Eng.* **2008**, *134*, 822–832. [[CrossRef](#)]
89. Di Nardo, A.; Di Natale, M.; Santonastaso, G.F.; Tzatchkov, V.G.; Alcocer-Yamanaka, V.H. Water network sectorization based on graph theory and energy performance indices. *J. Water Resour. Plan. Manag.* **2014**, *140*, 620–629. [[CrossRef](#)]

90. Diao, K.; Zhou, Y.; Rauch, W. Automated creation of district metered area boundaries in water distribution systems. *J. Water Resour. Plan. Manag.* **2013**, *139*, 184–190. [[CrossRef](#)]
91. Brentan, B.M.; Campbell, E.; Goulart, T.; Manzi, D.; Meirelles, G.; Herrera, M.; Izquierdo, J.; Luvizotto, E. Social network community detection and hybrid optimization for dividing water supply into district metered areas. *J. Water Resour. Plan. Manag.* **2018**, *144*, 04018020-1. [[CrossRef](#)]
92. Izquierdo, J.; Herrera, M.; Montalvo, I.; Pérez-García, R. Division of water supply systems into district metered areas using a multi-agent based approach. In Proceedings of the International Conference on Software and Data Technologies, Sofia, Bulgaria, 26–29 July 2009; Springer: Berlin/Heidelberg, Germany, 2009; pp. 167–180.
93. Hajebi, S.; Barrett, S.; Clarke, A.; Clarke, S. Multi-agent simulation to support water distribution network partitioning. In Proceedings of the 27th European Simulation and Modelling Conference-ESM'2013, Lancaster, UK, 23–25 October 2013; pp. 1–6.
94. Giudicianni, C.; Herrera, M.; Di Nardo, A.; Adeyeye, K. Automatic multiscale approach for water networks partitioning into dynamic district metered areas. *Water Resour. Manag.* **2020**, *34*, 835–848. [[CrossRef](#)]
95. Zhang, K.; Yan, H.; Zeng, H.; Xin, K.; Tao, T. A practical multi-objective optimization sectorization method for water distribution network. *Sci. Total Environ.* **2019**, *656*, 1401–1412. [[CrossRef](#)]
96. Gomez, P.; Cubillo, F.; Martín, F. Comprehensive and efficient sectorization of distribution networks. *Procedia Eng.* **2014**, *70*, 753–762. [[CrossRef](#)]
97. Perelman, L.S.; Abbas, W.; Koutsoukos, X.; Amin, S. Sensor placement for fault location identification in water networks: A minimum test cover approach. *Automatica* **2016**, *72*, 166–176. [[CrossRef](#)]
98. Herrera, M.; Abraham, E.; Stoianov, I. A graph-theoretic framework for assessing the resilience of sectorised water distribution networks. *Water Resour. Manag.* **2016**, *30*, 1685–1699. [[CrossRef](#)]
99. Ciaponi, C.; Murari, E.; Todeschini, S. Modularity-based procedure for partitioning water distribution systems into independent districts. *Water Resour. Manag.* **2016**, *30*, 2021–2036. [[CrossRef](#)]
100. Todini, E. Looped water distribution networks design using a resilience index based heuristic approach. *Urban Water* **2000**, *2*, 115–122. [[CrossRef](#)]
101. Tierney, K.; Bruneau, M. Conceptualizing and measuring resilience: A key to disaster loss reduction. *TR News* **2007**, *250*, 14–15, 17.
102. Ayala-Cabrera, D.; Piller, O.; Deuerlein, J.; Herrera, M. Key performance indicators to enhance water distribution network resilience in three-stages. *Water Util. J.* **2018**, *19*, 79–90.
103. Ayala-Cabrera, D.; Piller, O.; Herrera, M.; Gilbert, D.; Deuerlein, J. Absorptive Resilience Phase Assessment Based on Criticality Performance Indicators for Water Distribution Networks. *J. Water Resour. Plan. Manag.* **2019**, *145*, 04019037. [[CrossRef](#)]
104. Taormina, R.; Galelli, S.; Tippenhauer, N.O.; Salomons, E.; Ostfeld, A.; Eliades, D.G.; Aghashahi, M.; Sundararajan, R.; Pourahmadi, M.; Banks, M.K.; et al. Battle of the attack detection algorithms: Disclosing cyber attacks on water distribution networks. *J. Water Resour. Plan. Manag.* **2018**, *144*, 04018048. [[CrossRef](#)]
105. Hassanzadeh, A.; Rasekh, A.; Galelli, S.; Aghashahi, M.; Taormina, R.; Ostfeld, A.; Banks, M.K. A review of cybersecurity incidents in the water sector. *J. Environ. Eng.* **2020**, *146*, 03120003. [[CrossRef](#)]
106. Lu, L.; Wang, X.; Ouyang, Y.; Roningen, J.; Myers, N.; Calfas, G. Vulnerability of interdependent urban infrastructure networks: Equilibrium after failure propagation and cascading impacts. *Comput.-Aided Civ. Infrastruct. Eng.* **2018**, *33*, 300–315. [[CrossRef](#)]
107. Sarni, W.; White, C.; Webb, R.; Cross, K.; Glotzbach, R. *Digital Water: Industry Leaders Chart the Transformation Journey*; Technical Report; IWA Publishing: London, UK, 2019.
108. Kapelan, Z. Digital Water Approach for Smarter Water Management in Cities with Interconnected Infrastructure. In Proceedings of the EGU General Assembly Conference Abstracts, Online, 4–8 May 2020; p. 7259.
109. Giudicianni, C.; Herrera, M.; di Nardo, A.; Carravetta, A.; Ramos, H.M.; Adeyeye, K. Zero-net energy management for the monitoring and control of dynamically-partitioned smart water systems. *J. Clean. Prod.* **2020**, *252*, 119745. [[CrossRef](#)]
110. Tsakalides, P.; Panousopoulou, A.; Tsagkatakis, G.; Montestruque, L. *Smart Water Grids: A Cyber-Physical Systems Approach*; CRC Press: Boca Raton, FL, USA, 2018.

111. Robles, T.; Alcarria, R.; Martín, D.; Morales, A.; Navarro, M.; Calero, R.; Iglesias, S.; López, M. An internet of things-based model for smart water management. In Proceedings of the 2014 28th International Conference on Advanced Information Networking and Applications Workshops, Victoria, BC, Canada, 13–16 May 2014; pp. 821–826.
112. Saravanan, K.; Anusuya, E.; Kumar, R. Real-time water quality monitoring using Internet of Things in SCADA. *Environ. Monit. Assess.* **2018**, *190*, 556. [[CrossRef](#)]
113. Vrachimis, S.G.; Timotheou, S.; Eliades, D.G.; Polycarpou, M.M. Iterative Hydraulic Interval State Estimation for Water Distribution Networks. *J. Water Resour. Plan. Manag.* **2019**, *145*, 04018087. [[CrossRef](#)]
114. Wolf, M.; Serpanos, D. Safety and security in cyber-physical systems and internet-of-things systems. *Proc. IEEE* **2017**, *106*, 9–20. [[CrossRef](#)]
115. Barrère, M.; Hankin, C.; Nicolaou, N.; Eliades, D.G.; Parisini, T. Measuring cyber-physical security in industrial control systems via minimum-effort attack strategies. *J. Inf. Secur. Appl.* **2020**, *52*, 102471.
116. Vrachimis, S.G.; Lifshitz, R.; Eliades, D.G.; Polycarpou, M.M.; Ostfeld, A. Active contamination detection in water-distribution systems. *J. Water Resour. Plan. Manag.* **2020**, *146*, 04020014. [[CrossRef](#)]
117. Leitão, P.; Colombo, A.W.; Karnouskos, S. Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges. *Comput. Ind.* **2016**, *81*, 11–25. [[CrossRef](#)]
118. Conejos Fuertes, P.; Martínez Alzamora, F.; Hervás Carot, M.; Alonso Campos, J. Building and exploiting a Digital Twin for the management of drinking water distribution networks. *Urban Water J.* **2020**. [[CrossRef](#)]
119. Crosby, M.; Nachiappan; Pattanayak, P.; Verma, S.; Kalyanaraman, V. Blockchain technology: Beyond bitcoin. *Appl. Innov.* **2016**, *2*, 71.
120. Salah, K.; Rehman, M.H.U.; Nizamuddin, N.; Al-Fuqaha, A. Blockchain for AI: Review and open research challenges. *IEEE Access* **2019**, *7*, 10127–10149. [[CrossRef](#)]
121. Bianconi, G. *Multilayer Networks: Structure and Function*; Oxford University Press: Oxford, UK, 2018.
122. Porto, S.; Quiles, M.G. Clustering Data Streams: A Complex Network Approach. In Proceedings of the International Conference on Computational Science and Its Applications, Saint Petersburg, Russia, 1–4 July 2019; pp. 52–65.
123. Zhang, S.; Tong, H.; Xu, J.; Maciejewski, R. Graph convolutional networks: A comprehensive review. *Comput. Soc. Netw.* **2019**, *6*, 11. [[CrossRef](#)]
124. Manessi, F.; Rozza, A.; Manzo, M. Dynamic graph convolutional networks. *Pattern Recognit.* **2020**, *97*, 107000. [[CrossRef](#)]

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).