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Review

Digital Twin Applications in the Water Sector: A Review

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Abstract

As cities develop and resource demands rise, the water sector faces crucial challenges to deliver reliable, sustainable, and efficient services. Digital Twins (DTs), virtual replicas of physical systems, offer a promising tool to transform how we manage water infrastructure. Originally developed in the aerospace industry, DTs are now gaining traction in the water sector, enabling real-time monitoring, simulation, and predictive control of water and wastewater treatment, collection and distribution networks, and water reclamation and reuse systems. While still emerging in the water sector, DTs have shown potential to enhance operational efficiency, reduce environmental impacts, and support smarter, more resilient water management. This review study provides a comprehensive overview of current DT applications in the water sector, highlighting successful case studies, technical challenges, and knowledge gaps. It also explores how DTs can help bridge the water–energy nexus by optimizing resources utilized across interconnected systems. By synthesizing recent advances and identifying future research directions, this paper illustrates how DTs can play a central role in building sustainable, adaptive, and digitally-enabled water infrastructure.

Keywords: digital twin; water; wastewater; process control

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1. Introduction

Increasing population and resource consumption, urbanization, industrialization, and the impacts of climate change are putting extra pressure on municipalities to move toward more sustainable and efficient infrastructure [1]. Although wastewater treatment and water reclamation provide sustainable solutions to sanitation and water scarcity, they are facing dual challenges in this regard. Providing clean water for the continuously growing population and planning under heightened uncertainty in raw-water availability on the one hand, and the energy- and carbon-intensity of water treatment, water distribution, and wastewater handling on the other hand, pose complex challenges for management and planning in the water sector [2]. In this context, employing advanced tools that combine real-time data collection, advanced data analytics, and model-based forecasts is becoming increasingly crucial for informed decision-making in the water industry. A widely discussed approach is the development of a virtual or digital representation of an actual operating system, known as a Digital Twin (DT), which satisfies the need for timely monitoring, reliable prediction, and optimized operation of water systems. This method enables more accurate simulations and predictions, leading to improved system performance and sustainability [3]. However, ongoing questions remain regarding the full integration of DTs into existing infrastructure and the challenges of scalability across water systems.

A DT is defined as the digital or virtual representation of an operating physical system [4], and has been used by the aerospace industry since the 1960s [5]. Nowadays, the concept of a DT is increasingly being adopted across a variety of industrial sectors, including manufacturing and production [6–9], smart energy systems [10], urban environment [11], residential management [12–14], and transportation [15]. In the past few years, DTs have been increasingly studied in the water sector, mainly for the design, control, and optimization of processes (e.g., collection, treatment, and distribution systems). While the implementation and application of DTs in the water sector is still a relatively new concept for researchers and municipalities, an increasing number of studies assessing different challenges associated with applying DTs in the water industry have been published in recent years. There are also a few recent studies on applying DTs in real-world water systems around the globe, in which a small number of cases have come very close to the implementation and operation of a full-scale DT.

This literature review aims to assess the key benefits, challenges, opportunities, and currently unanswered questions regarding the utilization of DTs to manage and optimize water systems. It explores how DTs are improving efficiency and sustainability in different water systems, identifies current limitations and gaps in their use, and discusses the future developments needed to enhance their integration and scalability. Following the introduction, essential DT terminology and modelling paradigms are established to provide a shared conceptual framework. The enabling system architecture is then described—covering data pipelines, sensor–actuator alignment, and between physical assets and their virtual counterparts. The analytical core synthesizes 147 peer-reviewed studies spanning the urban water cycle (review/conceptual papers, wastewater treatment, wastewater collection, water distribution, water treatment, water reclamation, and desalination). Moreover, emerging DT deployments in the real world are examined to demonstrate operational feasibility. Finally, this paper identifies research gaps and policy actions required to advance DT adoption across interconnected water- and energy-infrastructure systems, thereby situating the review's findings within a forward-looking agenda for the field.

2. Search Methodology

2.1. Scope and Search Strategy

This search supports only the quantitative synthesis reported in Section 6 and Appendix C. Other sections may cite additional peer-reviewed sources outside the 2015–2025 window for context. All counts and trend analyses in Section 6 are derived from a bounded corpus of 147 peer-reviewed studies.

The Web of Science Core Collection and Google Scholar were interrogated to maximize coverage of peer-reviewed engineering and environmental journals. Due to digital twin still being an emergent terminology in the water sector, the exact phrase "Digital Twin" was combined with the following sector-specific terminologies: "wastewater treatment", "sewer network", "wastewater management", "sewer systems", "sewer management", "sewer pipes", "wastewater system", "water distribution", "water treatment", "water resource recovery", "water reuse", and "desalination"; yielding 12 reproducible queries.

The search was restricted to publications dated 1 January 2015–1 May 2025. Records were retained if they (i) were peer-reviewed journal articles or full conference papers written in English; (ii) described, validated, or critically analyzed a DT or a DT-enabled framework applied to a real-world water infrastructure (i.e., treatment, distribution, collection, reuse, or desalination); and (iii) reported original data, models, or substantive insights. Conceptual commentaries, editorials, general modelling studies that did not include any identifiable DT element (e.g., a virtual model continuously updated with sensor data, a cyber-physical synchronization loop, or a DT-based decision-support framework), and papers outside the water domain were excluded. Review and conceptual papers inform the landscape synthesis but are not counted as implementations. The final corpus comprised 147 studies; however, domain categorizations in Section 6 allow a study to appear in more than one topical bucket when warranted; therefore, domain totals can exceed N = 147.

2.2. Extraction and Coding

For each included study, we extracted bibliographic metadata and structured fields: article summary, country/region, application segment, DT components present (per Appendix A), publication year, and related study-level tags. These records are available in (Supplementary Material (Table S1_Paper_Information.xlsx).

DT components were coded as present/absent (1/0) based on explicit evidence in the paper, following the definitions in Appendix A. We also applied a binary machine learning (ML) tag. A study was labeled ML = 1 if it implemented ML methods for calibration, prediction, classification, soft sensing/state estimation, control, or surrogate modeling (e.g., regularized regression, tree ensembles, gaussian processes, neural networks, reinforcement learning).

3. Definitions and Fundamentals

3.1. Model and Simulator

Modeling and simulation are fundamental components of any decision-making or management system that requires a virtual entity, such as a DT. Modeling physical, chemical, and biological processes helps acquire insights into these processes, develop control strategies, predict behavior of the system under various operational conditions, and optimize the desired outcomes [16,17]. In the context of the water industry, three primary modeling approaches are used, including mechanistic, empirical, and hybrid models.

Mechanistic modeling approaches are well-established across many industries [18]. The approach has been widely applied to wastewater treatment and water resource recovery schemes, as some important elements of urban water management, in the past decades (starting with Andrews, 1968 [19]). Mechanistic models are a representative description of a process or a set of processes (i.e., a system) that exhibit a relatively small number of state variables whose values support interpretation and comparison by subject matter experts. They are typically based on conservation laws (e.g., mass balance) combined with a community consensus to describe empirically observed relationships (e.g., alpha factor and Monod equation). Mechanistic models are typically expressed as a set of mathematical equations [20]. An example of a mechanistic model is the settling velocity function and settler model developed by Takács et al. in 1991 [21]. This model satisfies mass conservation while providing an empirical description of the settling dynamics.

In contrast, empirical models are focused on the description of empirically observed relationships and do not explicitly satisfy conservation laws. Empirical models can handle noise in measurements and identify patterns without prior knowledge of underlying processes, making them useful for predicting more complex systems such as achievable water quality in a multi-stage treatment system [22]. They are also faster and more cost-effective to develop, whereas mechanistic models require computational resources and expertise [23]. However, the structure of empirical models may be influenced by basic knowledge on the data-generating system. For example, the selection and preprocessing of measurement time series may be based on a prior qualitative understanding of the modeled process. Similarly, the physical location of a sensor (e.g., upstream or downstream of a treatment process) or basic understanding of the direction of causality may influence the allocation of the corresponding signal as a model input and output. Empirical models are used to describe, predict, and forecast patterns observed in the data.

The concept of combining mechanistic and statistical models started in the early 1990s, and it was initially used as a hybrid model in the field of chemical engineering [20]. The concept mainly emphasizes the use of both mechanistic and empirical models, highlighting the incorporation of all available knowledge (including information, data, and domain expert knowledge) into the developed model to strengthen the outputs by taking advantage of both types of models.

Computational and dynamic models developed based on mathematical equations (e.g., algebraic or partial differential equations) to describe physical or chemical phenomena involved in the process, can be integrated into simulators that enable forecasting the behavior of a system. The majority of simulators developed in the water industry are used primarily for planning infrastructure development, system optimization, and resource allocation and require significant modifications to qualify for use in real-time operational contexts [24]. For an operational DT, the underlying model should (i) represent the decision-relevant states and outputs that drive actions (e.g., effluent quality, tank levels/pressures, energy use) and map them to available sensors; (ii) include the actuation pathway and constraints (e.g., blower speed, pump variable frequency drives, valve status; physical/safety limits); (iii) represent key disturbances and boundary conditions (e.g., influent flow and load, temperature, demand), with short-range forecasts where applicable; (iv) support state/parameter synchronization via data assimilation or adaptive calibration so that the virtual state tracks the plant; and (v) quantify uncertainty and latency requirements so the model can deliver predictions/decisions within the update interval required by the use case, with validation/verification commensurate with that purpose (see Appendix A).

Currently, most simulators cannot accurately capture real-time process states at a high level of fidelity, often required for implementation of a DT [25]. Examples of simulators that are commonly used for process simulation in the water industry include *EPANET, SUMO, and BioWin.* For DTs, these simulators must be wrapped with (a) live data adapters, (b) estimation/assimilation to keep states current, (c) explicit actuator/constraint mappings for safe decision making, and (d) a runtime scheduler that meets operational latencies. Without these layers, such tools remain planning simulators or, at most, enable a digital shadow (DS) rather than a full DT.

3.2. Digital Twin and Digital Shadow

A DT system is required to have a physical entity, high-fidelity simulator, physical sensors and analyzers for the physical entity, actuators for virtual connection, physical-to-virtual connection, advanced data analysis, and interaction and services interface to serve its full practical applications. Detailed descriptions for each of these components are provided in Appendix A.

When deployed at full scale, DTs offer advantages over traditional design and decision-making methods. Unlike conventional offline models, which are typically static and rely on fixed assumptions or historical datasets, DTs remain continuously synchronized with the operational system through real-time data streams. This dynamic linkage means that design or upgrade scenarios can be evaluated not only in theory but also under conditions that reflect the system's current and evolving state [7]. By representing an operational system, DTs facilitate rapid prototyping and what-if analyses for performance prediction and risk assessment [26]. Because they maintain a high-fidelity, dynamic, self-evolving model, DTs support improved maintenance, anomaly detection, performance tuning, sensitivity analysis, auto-calibration, and overall system optimization. They also enable training and informed decision-making under unusual operating conditions, as well as remote or automated control. Altogether, these capabilities drive more sustainable and efficient operations [5].

Figure 1 shows the typical structure of a DT in the water industry, with the major components that are required to fulfill its purposes.

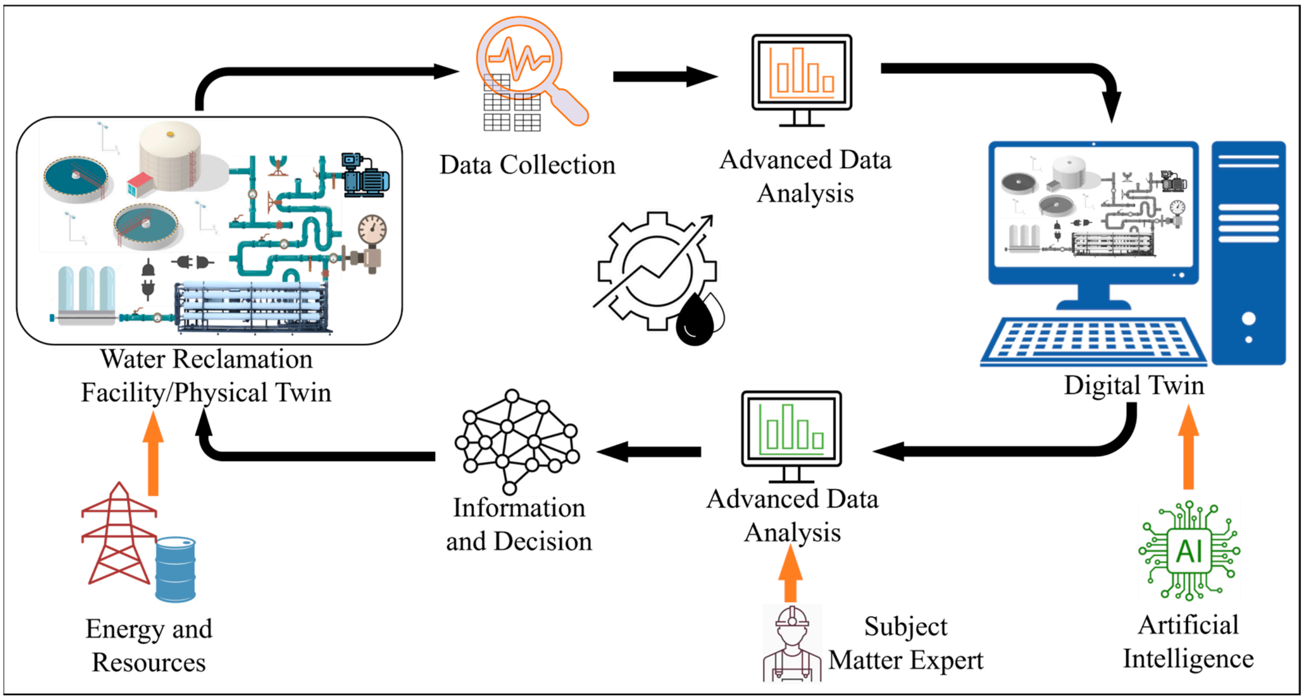

Figure 1. An illustration of the DT concept applied to a water treatment plant.

As mentioned previously, a simulator model is often used for characterization and planning purposes, mainly to minimize the costs and labor before implementation of the full-scale plan (e.g., expansion and process modifications). When integrated into advanced digital frameworks, these models can evolve into more sophisticated systems such as DSs or DTs. The key difference between DS and DT lies in data flow directionality [27]. In a DS, data from the physical asset automatically updates the digital model, but any feedback from digital to physical remains manual or absent. In contrast, a DT supports automatic, bidirectional data: real-time data from the physical object updates the virtual model, and the virtual model can autonomously trigger in the physical system [28]. Importantly, "real-time" should not be treated as a fixed latency; the acceptable update interval depends on the twin's purpose (e.g., fault detection vs. closed-loop control) and on the governing process time scales (e.g., aeration dynamics vs. sludge-age) [29]. Thus, a DT is defined by automated data ingestion and dynamic model updating, while the specific update cadence is application-dependent rather than universal.

In a DS, the virtual model's outputs require manual processing, limiting its use in strategic planning [5]. A DT, however, consists of an operational physical entity, a virtual entity that mirrors its current state and behavior, and a closed-loop, two-way data exchange (see Figure 2). The virtual entity continuously synchronizes with real-world data, enabling real-time feedback, predictive insights, and remote or automated control under varying operational conditions.

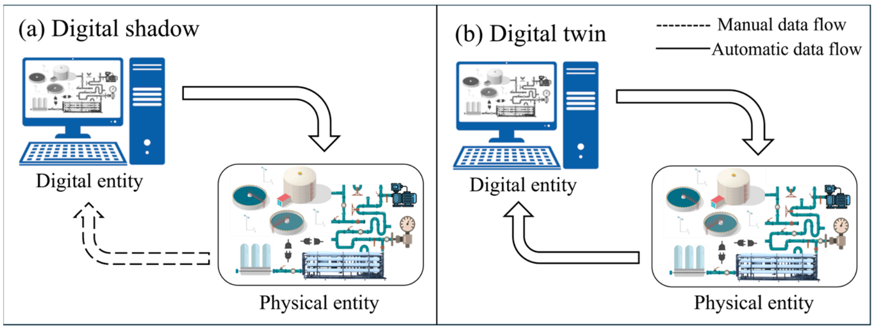

Figure 2. Data flows in (**a**) DS, and (**b**) DT.

4. System Integration

As discussed above, two-way communication is an essential component of the conception of DTs in the water sector. Moreover, the need for trust and reliability of automated decisions motivates the use of mechanistic models as the basis of DTs, even if augmented with ML tools. Thus, it is critical that the states in the model are correctly paired with the corresponding actuator and sensor signals in the physical system. Additionally, since most industrial-scale systems in the water sector are one-of-a-kind, the mapping between the physical system components and the digital entity is typically established on a case-by-case basis. This tends to be a manual and tedious process for the reasons discussed below. In the present work, frequent practical issues are addressed and recent efforts that may facilitate this task are highlighted.

4.1. Variable Naming in Process Flow Diagram (PFD), Process and Instrumentation Diagram (P&ID), Data Acquisition and Control (DAC), and Model

In most pilot- and full-scale modeling projects, information that is useful for the conceptualization of a DT resides in multiple locations. Information is typically collected from a variety of isolated sources, such as flow sheets or process flow diagrams (PFDs), process and instrumentation diagrams (P&IDs), historians (time-series databases), laboratory records, and stand-alone process models, each with its own notation and level of detail. Flow diagrams provide a high-level overview of major processes and some measured variables; however, they lack standardized conventions and often require manual interpretation. P&IDs (e.g., using ISA 5.1 symbols [30]) identify actuators, sensors, and control loops with compact icons and single-letter variable codes (e.g., "F" for flow rate), yet industry standards do not consistently cover water quality variables (e.g., electrical conductivity and pH), leading to ambiguity. Historians and supervisory control and data acquisition (SCADA) systems store sensor and actuator signals as "tags" or registers and typically offer little contextual information about their physical location or signal type, making it difficult to match the tags to the processes they monitor. Laboratory data, collected, prepared, and analyzed through manual or semi-automated procedures, are essential for DT accuracy but rarely come in a standardized format listing sampled variables and locations. Finally, existing process models (not yet integrated into a DT) use proprietary shorthand to reference variables, often differing from P&ID and SCADA notations. Although efforts have been made to standardize wastewater treatment model notations [31], thus far, no single authority enforces consistency across all water sector diagrams and databases.

The current work's findings suggest that consulting all sources of information listed above is required to establish a complete list of variables, measured or not, and to identify the correspondences between the data acquisition and control system (i.e., programmable logic controller (PLC) or SCADA) and the variables represented in the model. Today, this is a manual, tedious, and possibly error-prone task. A more efficient and robust approach to identifying the correspondence is needed, especially for small-scale systems. To our knowledge, two main approaches have emerged to streamline this process. First, a simple "ground truth" method uses the P&ID as the authoritative reference: variable names in the P&ID are manually matched with SCADA tags, laboratory spreadsheets, and model notations. Once this mapping is agreed upon, all other representatives, including DT, must adhere to the ground truth. Although robust, this approach still relies on human effort for maintenance and updates. Second, computer-aided knowledge management leverages a centralized knowledge graph or ontology to consolidate information from flow diagrams, P&IDs, SCADA, and models into a single framework. Such a knowledge graph can automate validation of the DT's structure and function, an approach already demonstrated for automated model generation in manufacturing [32], and promises greater transferability of DT platforms between water sector plants, though its cost–benefit profile has not yet been fully evaluated.

4.2. Data Pipelines

In addition to the crucial matching of input and output variables in the model with actuators and sensors on the physical plant, additional meta-data will be necessary to ensure the proper design and functionality of the DT. Based on the meta-data types and recommendations listed by the International Water Association (IWA) Task Group on Meta-data Collection and Organization [33], the following is considered essential in the construction of a DT.

Every actuator and sensor signal must include its unit of measurement, converted as needed to Système International (SI) units, and a timestamp synchronized to the model's simulated time, ideally in Coordinated Universal Time (UTC). DT's ability to capture system dynamics also depends on the numeric and temporal resolution of data, the physical placement of sensors and actuators, and the mode of signal transmission (i.e., analog, digital, or manual records). Any preprocessing (such as aggregation, filtering, compression, imputation, interpolation, time synchronization, data fusion, or use of soft sensors) can further influence accuracy. Finally, metadata should document known sources of measurement error, including calibration drift, electrical glitches (outliers), and sensor fouling or scaling. Collecting this meta-data is essential to assess and ensure the DT's accuracy and fitness for its purpose. These meta-data recommendations align with practices observed in real-world deployments: full-scale DT/DS implementations integrate SCADA tags and laboratory records with hydraulic or process models (e.g., Valencia water distribution network (WDN) [3], Lushan water supply [34]), underscoring the need for consistent units, timestamps, and documented preprocessing.

4.3. Data Access Rights

A successful deployment of a DT, including a two-way information flow between the DT and the physical entity it describes, will require that the plant is equipped for real-time communication and that read and write access rights are established and implemented correctly. While this offers no technological challenge, it is often a plant-internal governance bottleneck. Here are the typical questions that must be addressed:

1. Communication infrastructure: Is the physical infrastructure ready to enable communication to, and from, the DT? For example, can the laboratory data be accessed automatically?
2. Communication configuration: What are the requirements for granting read access to the information contained in the SCADA system, present as laboratory data, or produced by the DT?
3. Write-access rights: Can the DT manipulate variables (e.g., setpoints) in the physical entity? If so, which ones, at what frequency, and within what range?

Consistent with these governance considerations, several full-scale systems in our inventory currently operate in advisory-only mode (e.g., Eindhoven water resource recovery facility (WRRF) [35], Gothenburg collection [36], Águas do Porto [37], Valencia WDN [3]), even where the communication stack exists.

4.4. Constraints for Optimization Based on a DT

A DT provides a flexible tool to test manipulations of physical entity in a virtual environment. However, to ensure the proposed control actions match what is feasible and permitted on the physical plant, it is important that the DT is equipped with all known constraints. Such constraints fall into two broad categories that are discussed here.

First, physical constraints define equipment limits. For instance, a valve's opening setpoint must lie between fully closed and fully open. Second, safety or regulatory constraints restrict operations to protect the environment, equipment, and personnel, even if equipment could physically exceed these bounds. Many SCADA systems and PLCs impose such constraints automatically so that safety is guaranteed, even if the DT does not account for them. For example, a valve, while physically enabling a complete closing, may only be allowed to close down to 10%. To ensure that (a) the DT accurately reflects the behavior of the plant (monitoring and live updating) and (b) that the optimized control actions provided by the DT can be realized practically, it is important that they are accounted for during optimization.

A practical challenge is that constraint logic often resides within proprietary PLC or SCADA programming, such as variable-frequency drive controllers or third-party custom code, that utility staff may not have direct access to. Because these hidden control loops govern permissible setpoints and safety limits, failing to represent them in the DT can lead to proposed actions that cannot be executed or that violate safety requirements. Despite this, few systematic methods currently exist to extract and encode both physical and safety constraints from the plant's control infrastructure into the DT, making it difficult to guarantee that model-based recommendations can be implemented in practice.

5. Digital Twin Applications

Several review studies have explored DT development and requirements across industries. For instance, Lim et al. (2019) [38] reviewed DT programming, applications, and benefits, with an emphasis on the manufacturing field. Similarly, Tao et al. (2018) [7] reviewed the history of DT in the real world and in the literature. They focused on several major areas where DTs are used: product design, production, prognostics, health management (the most popular area), and service. They identified two promising areas for DTs that include dispatching optimization and operational control. And finally, Rasheed et al. (2020) [39] provided a general overview of what DTs are, and what the values, challenges, and enablers of implementing and operating a DT from a modeling perspective are. Although the study was not directly related to one specific industry, some of the findings can be applied to any corresponding field, including the water industry. Compared with broad industrial reviews, water-sector applications emphasize plant-wide process control and energy optimization at WRRFs (e.g., Changi water reclamation plant [29]; EWE Cuxhaven [40]) and district-scale hydraulics for flood risk and leakage in collection/distribution systems (e.g., Gothenburg [36]; Valencia [3]). These emphases shape model choices (hybrid/mechanistic + ML) and data orchestration across SCADA and smart-meter infrastructures.

According to the abovementioned studies, although a full-scale DT, when all the required components and elements are implemented in the design, provides all the benefits and advantages of having a virtual representation of an operational physical system, some

DTs are designed to serve a specific purpose. Accordingly, a DT can fall into one specific category, including Monitoring DT (MDT) [41], Optimizing DT (ODT) [42], Forecasting DT (FDT) [43], Sensitivity DT (SDT) [44], or a Wrapper for process safety [45], which are discussed in detail in Appendix B. While these categorizations offer a focused application of DT technology, it is important to recognize that they may not fully align with the holistic definition of DTs that integrates all key functions into a unified system. In this review, MDT/ODT/FDT/SDT/Wrapper are used as functional roles (not mutually exclusive) that a deployment may emphasize; they do not redefine what a DT is. As DTs are ideally intended to be comprehensive digital counterparts of physical entities, categorization of them into specific types may limit the scope of their application and potentially restrict their full potential. For instance, in the concept of MDT, Wang et al. (2020) [41] utilized a DT for real-time monitoring of a system; however, the capability for data transmission or modification from the digital dashboard back to the physical system was not implemented. This approach, therefore, aligns more closely with the concept of a DS, as it lacks the bidirectional communication characteristics essential to a comprehensive DT.

The segmentation into singular-purpose DTs, while valuable for specific operational goals, might miss the opportunity to leverage the full range of interconnected capabilities that a DT can provide when implemented as an all-encompassing system. Therefore, although these specific types of DTs contribute significantly to the advancement and specialization of technology, it is essential to acknowledge that a more integrated approach might offer a richer and more accurate representation of what DTs are fundamentally designed to achieve. This perspective encourages further exploration into ways these different functionalities could be brought together into a more comprehensive DT model.

6. Digital Twins in the Water Industry

A review of 147 studies published between January 2015 and May 2025 highlights the growing maturity of DT applications in the water sector (see Figure 3). Research has expanded from a single publication in 2015 to 41 in 2024. These studies are grouped into seven topical categories that are most applicable to the water industry: (1) review and conceptual studies, (2) wastewater treatment, (3) wastewater collection systems, (4) water distribution networks, (5) drinking water treatment, (6) water reclamation, and (7) water desalination. Most studies focus on water distribution networks (a total of 47 studies), wastewater treatment (a total of 41 studies), and drinking water treatment plants (a total of 25 studies). Additional topics include reviews and conceptual frameworks (a total of 38 studies), wastewater collection (a total of 17 studies), water reclamation (a total of 17 studies), and desalination (a total of 4 studies). Coverage remains uneven across domains. Desalination is scarcely represented (4 studies), with water reclamation and wastewater collection also underexplored (17 each); these areas merit focused DT research and deployment, consistent with the identified gaps in membrane-based systems. Because several studies spanned more than one domain, multi-label classification was used and each study assigned to all applicable categories; consequently, category totals reflect 189 assignments across 147 unique studies. While the scope of the topic is expanding, key gaps remain, particularly in membrane-based systems and applications in low- and middle-income regions.

The coded corpus is geographically concentrated in higher-income regions. Based on the country/region tags compiled in our screening sheet (see Section 2.2 and Supplementary Material Table S1_Paper_Information.xlsx), China and the United States contribute the largest shares (n = 18 each), followed by the United Kingdom and Italy (n = 6 each), with Singapore and Canada close behind (n = 5 each). Representation from low- and middle-income regions is comparatively limited, which likely reflects differences in sensing/IT infrastructure, metadata discipline, and governance around control authority. This imbalance should be considered when generalizing results; it also motivates future work pairing lower-cost sensing and open data stacks with staged automation tailored to utilities operating under tighter resource constraints.

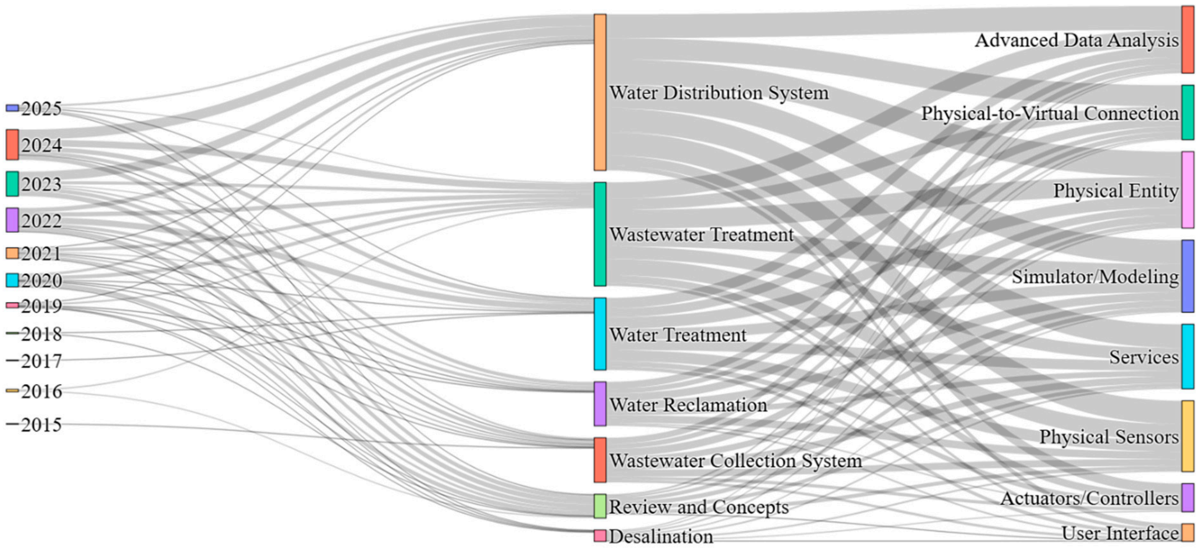

Figure 3. Sankey diagram illustrating the distribution of 147 peer-reviewed studies from 1 January 2015 to 1 May 2025 across six application areas in the water sector, along with review and conceptual works. Each flow represents the linkage between the application domain and key DT components. An interactive version of this Sankey chart is available as Supplementary Material (Supplementary File S1_Sankey_Chart.html). Note: Counts are multi-label category assignments (some studies appear in more than one category), so totals exceed the 147 unique studies.

Most DT prototypes described in the literature implement only part of the eight components defined in Appendix A. Early work (2015–2018) primarily focused on detecting anomalies and developing soft sensors. Since 2019, studies increasingly combine live control-system data with calibrated simulations. By 2023, a few utilities had begun to implement full model-predictive control systems. When a study applied supervised/unsupervised ML, deep learning, reinforcement learning, or hybrid physics–ML approaches, it was labeled as an ML study; routine statistical fitting or purely mechanistic calibration without a learning algorithm was not labeled ML. 58 of 147 studies (40%) apply ML methods, indicating growing adoption of hybrid modeling. However, only eight studies contain all the defined components essential for a fully implemented DT, which will be discussed in the next section along with other full-scale DTs implemented in the water industries. A comprehensive review was conducted for these research studies and additional information is provided in Appendix C.

Conceptual and review studies have systematically mapped the landscape of DTs in the water sector, identifying the core functions, architectures, and challenges for practical implementation. Early surveys catalogued available open-source tools and framed DTs as enablers of carbon-aware operations [2], while broader reviews highlight transferable strategies from manufacturing and energy systems [10]. Foundational works by Grieves and Vickers [46] and Moser et al. [47] defined essential DT characteristics such as dynamic synchronization, bidirectional feedback, and modular and mechanistic models, laying the groundwork for water-sector adaptations. More recent studies have proposed service-oriented architectures (referred to as Digital Water Services) that federate asset-level twins via standardized Application Programming Interfaces (APIs) [48], and cyber-physical testbeds that integrate artificial intelligence (AI), soft sensors, and threat modeling for drinking-water systems [49].

In wastewater treatment, research has progressed from standalone soft sensors and anomaly detection to integrated, model-predictive control systems. Initial efforts applied Long Short-Term Memory (LSTM) and deep-belief networks to estimate influent quality and energy use [50,51], while hybrid frameworks coupling mechanistic activated-sludge simulators with Convolutional Neural Networks (CNNs) have achieved real-time forecasting with high interpretability [52]. Pilot-scale implementations demonstrate energy-aware control: Heo et al. [53] reduced blower energy by 17% under nitrogen-ratio constraints, and Chen et al. [54] achieved <5% mean absolute percentage error in three-hour effluent forecasts with automated dosing adjustments. Modular BIM-enabled (building information modeling) approaches for pump maintenance [55,56] and federated "digital water services" architectures [48] point toward full-plant DTs that encompass design, operation, and asset management.

Sewer network DTs tackle the twin imperatives of overflow mitigation and structural health monitoring. Early empirical diagnostics used stacked autoencoders for pump-failure detection [57] and deep-reinforcement learning for energy-efficient pumping [58]. Stormwater twins integrating storm water management model and data-assimilation filters supported flood forecasting [59,60], while VandCenter Syd's "living" DT concept distinguished real-time operational twins from offline prototypes [61]. Advanced sensing and modeling—physics-informed neural networks for heat-transfer estimation [62] and rapid LiDAR-to-3D-model workflows [63]—enable continuous structural updates. Gothenburg's 140 km combined sewer overflow (CSO) control system and Germany's KaSyTwin robotics initiative showcases fully cloud-hosted, predictive-maintenance DTs in action [36,64].

Water distribution DTs emphasize leak detection and energy optimization across large urban networks. Pioneering frameworks in Valencia combined EPANET hydraulic models with geographic information system (GIS) and telemetry for scenario analysis [3,65]. Lab-scale studies achieved >97% leak-classification accuracy using CNN–VAE (Convolutional Neural Network- Variational Autoencoder) architectures [66], while mixed-integer nonlinear programming models explored turbine-based energy recovery [67]. Real-time calibration routines adjust demand patterns via pressure feedback [68], and temporal graph–convolutional controllers optimize pump speeds in EPANET–WNTR environments [69]. Roadmaps for staged DT maturation outline the path from static models to self-updating, value-tracking systems [70], and service-oriented "Digital Water Service" platforms promise seamless integration across distribution, treatment, and asset management.

Drinking water treatment DTs have evolved from anomaly-detection proofs of concept to plant-wide, self-adapting control systems. Unsupervised models for cyber-physical anomaly detection [71] and BiLSTM-based (Bidirectional Long Short-Term Memory) quality alarms [72] led to predictive-maintenance twins for pumps and valves [73] and coverage-based online model updating in treatment plants [74,75]. Utility-scale frameworks combining BIM and asset management [76] and service-oriented "Digital Water Service" architectures [48,77] laid the data-governance groundwork. Recent demonstrations coupled multi-scale process twins with edge micro-services, reinforcement-learning dose controllers, virtual reality cyber-security training, and energy-optimal pump scheduling [78–82]. The latest hybrids dynamically switch between first-principles and LSTM surrogates, keeping turbidity prediction errors < 0.2 NTU across variable raw-water conditions [83], signaling a shift from isolated algorithms to resilient, policy-aligned decision-support twins for safe and energy-efficient drinking-water delivery.

Water-reclamation DTs address the dual complexity of advanced treatment and reclaimed-water distribution. Conceptual studies framed twins as next-generation tools for multi-barrier purification [84], while adaptive grey-box observers [85] and hybrid mechanistic/ML models [20,29] proved the value of empirical calibration. Supporting modules emerged for influent synthesis [86] and cyber-resilience assessment [87,88]. Governance roadmaps and asset-twin federation schemes preceded plant-wide, real-time twins: a hybrid neural/Activated Sludge Model (ASM) model cutting nitrate-prediction error to ≈2% [89], a two-hour-look-ahead operational twin at Eindhoven WRRF [35], and soft-sensor pipelines delivering sub-minute latency [90]. Greenhouse gas emission-aware (GHG-aware) prediction engines [91,92] and industrial-reuse salinity twins [93] broaden the focus from process reliability to sustainability metrics, pushing WRRF DTs toward integrated, emissions-conscious decision support.

Desalination DTs concentrate on energy, fouling, and cost optimization in Reverse Osmosis (RO) systems. A model-predictive controller prototype for a Peruvian pilot plant [94] and simulation reviews of RO optimization strategies [95] set the stage. Operational twins now predict specific energy consumption at full-scale [96] and support condition-based membrane cleaning and replacement during algal blooms at the Carlsbad plant [97]. These studies illustrate how real-time soft sensors, energy/fouling trade-off analytics, and decision-support dashboards are converging into near-complete, plant-wide DTs that drive higher recovery, lower specific energy, and smarter maintenance scheduling in energy-intensive desalination facilities.

7. Digital Twin Implementation in Real-World Systems

As discussed previously, only a small subset of the 147 reviewed studies included all the components required for a true DT. In this section, we examine those studies alongside additional full- and pilot-scale implementations, drawn from global projects that have not been formally published, in detail. Although many of these efforts claim to be complete DTs, they function more like DSs due to lack of bidirectional, real-time connectivity between the physical asset and its virtual counterpart. Their digital models serve only as advisory tools and cannot autonomously adjust the actual system. From this analysis, nine full-scale (see Table 1) and seven pilot-scale (see Table 2) implementations emerged as genuine DT candidates. These projects are discussed in the following sections.

Table 1. Full-scale implementation of DT and DS in a Water System.

Facility Name	Location	Facility Type	Implementation	Reference
Changi Water Reclamation Plant	Singapore	Water Reclamation	DT: Operated in the advisory-only mode, but it has capability of bidirectional communication	[29]
Eindhoven Water Resource Recovery	Netherlands	Water Resource Recovery	DS: Advisory only	[35]
Bresso-Niguarda Water Resource Recovery	Italy	Water Resource Recovery	DS: Advisory only	[98]
Gothenburg Regional Sewage System	Sweden	Wastewater Collection	DS: Advisory only	[36]
EWE WASSER GmbH	Germany	Wastewater Treatment	DS: Advisory only	[40]
Águas do Porto	Portugal	Integrated Urban Water Cycle Management	DS: Advisory only	[37]
Lushan Water Supply Company	China	Water Supply System	DT: Advisory and process control	[34]
Water Distribution Network of Valencia	Spain	Water Supply System	DS: Advisory only	[3]
Strongford Wastewater Treatment Plant	United Kingdom	Wastewater Treatment	N/A *	[99]

Note: * N/A: not enough information.

Table 2. Pilot-scale implementation of DT and DS in a Water System.

Authors	Location	System Type	Implementation	Reference
Bartos & Kerkez	USA	Surface Water Systems	DS: Advisory only	[60]
Komulainen & Johansen	Norway	Wastewater Treatment	DS: Advisory only	[100]
Lian et al.	Various communities China and Australia	Pilot plants for desalination	DS (2) * + DT (2)	[88]
Zekri et al.	Oman	Water distribution	DT: Advisory and process control	[101]
Gomez-Coronel et al.	Mexico	Water distribution	DT: Advisory and process control	[102]
Lumley et al.	Sweden (7) + Norway	Wastewater Collection	DS: Advisory only	[103]
Lumley et al.	Denmark (4) + Netherlands + Italy	Water Treatment	DS: Advisory only	[103]

Note: * Numbers in parentheses indicate the number of individual pilot plants.

7.1. Full-Scale Implementation

Changi Water Reclamation Plant [29]. Jacobs partnered with Singapore Public Utilities Board to develop a DT for the Changi Water Reclamation Plant using the Replica™ platform. This DT integrates approximately 1200 data tags in real time from the SCADA system for dynamic modeling of the entire plant process. It is a hybrid model and uses both mechanistic and empirical models that are automatically calibrated through SCADA and laboratory data. It is implemented in advisory-only mode and has three primary uses: (1) evaluation of DT vs. measured results to highlight areas of attention for operational staff, (2) simulating scenarios for informed operational planning, and (3) forecasting significant process events up to 5 days in advance.

Eindhoven Water Resource Recovery Facility [35]. The Eindhoven WRRF in Netherlands utilizes a DT for dynamic plant-wide process monitoring, scenario analysis, and forecasting. The continuous data pipeline developed for the DT uses the plant's SCADA system to collect and store raw data in an iHistorian database. Every 2 h, the data is automatically filtered and converted into various data formats for modeling. The plant-wide model aggregates the three physical parallel treatment trains into one treatment lane with the combined volume and flow rate. An important aspect of the DT involves refining the compartmentalized model of the aeration tank to better account for non-ideal mixing, which is a well-documented challenge in such systems. While DT has led to increased accuracy of predicted dissolved oxygen and air flow rate profiles, nitrate and mixed liquor suspended solids are especially susceptible to prediction inaccuracies in wet weather conditions.

Bresso-Niguarda WRRF [98]. Gruppo CAP, the integrated water service provider of the Metropolitan City of Milan, implemented the Twin Plant DT system developed by the Danish Hydraulic Institute (DHI A/S) at the Bresso-Niguarda wastewater treatment plant (WWTP) in Milan, Italy. This system automatically acquires online information from over 60 sensors, including 18 energy meters, and uses the Wastewater Treatment Plant Expert Simulation Tool (WEST) developed by DHI A/S to forecast plant performance with a 24-h horizon. Using these predictions, operators, process engineers, and energy management personnel can evaluate various operational strategies and identify optimal operational settings.

Gothenburg Regional Sewage System [36]. Gothenburg's central treatment facility, the Rya WRRF in Sweden, experiences large variations in influent flow due to heavy rainfall and 25% of the sewers being combined. As a result, the city faces the risk of flooding and discharge of untreated wastewater during heavy rain events. The DT includes a detailed hydrodynamic model of the collection system and its 250 km^2 catchment. This allows for real-time prognosis, forecasting, and scenario training.

EWE Wasser GmbH [40]. German utility EWE Wasser GmbH partnered with Xylem to deploy a DT at the Cuxhaven treatment plant. The DT is connected to the plant's SCADA system which provides real-time data as well as several virtual sensors which provide estimations of incoming constituent loading. In particular, the DT utilizes carbon, nitrogen and phosphorous loading estimations coupled with ML to predict carbon, nitrogen, and phosphorous removal in real time. These dynamic estimations of biological oxygen demand (BOD) and nutrient removal enable the tuning of aeration setpoints to minimize power consumption. Since implementation, the Cuxhaven treatment plant has been able to decrease aeration by 30% while maintaining effluent quality standards. This has resulted in an annual power saving of 1.2 million kWh.

Águas do Porto [37]. Águas do Porto, the municipal water utility of Porto in Portugal, implemented H2PORTO, a real-time integrated management platform that functions as a DT for the entire urban water cycle, covering water supply, wastewater, stormwater, and coastal systems. The system integrates data from 22 different sources, including SCADA systems, meteorological inputs, and historical records. H2PORTO uses the Bentley Systems OpenFlows Suite, including WaterGEMS for water distribution modeling, SewerGEMS for wastewater network simulation, and FLOOD for urban flood modeling. These tools provide hydraulic and hydrological modeling capabilities within DT. This DT enables real-time system monitoring, predictive analytics (e.g., for flood risks and water quality), and supports operational decision-making, emergency response, and preventive maintenance planning.

Lushan Water Supply Company [34]. Lushan Water Supply Company in China upgraded its water supply infrastructure in Guling using a DT developed in a partnership with Siemens. The system is powered by SIMATIC PCS neo, Siemens' web-based distributed control system platform. Real-time operational data including flow rates, water pressure, and water quality metrics are collected through a network of sensors and processed via SCADA integration. The DT uses hydraulic simulation models to represent the behavior of the water distribution system. These simulations support operational forecasting, performance optimization, and asset management.

Water Distribution Network of Valencia (Spain) and its Metropolitan Area [3]. Global Omnium, the operator of Valencia's water system, deployed GoAigua, a centralized smart water platform that acts as the DT for the city and its metropolitan water distribution network. The system collects and combines data from more than 20,000 readings, including SCADA systems, smart meters, pressure and quality sensors, and customer information systems. GoAigua incorporates advanced hydraulic modeling to simulate network behavior in real time. It provides leak detection, demand forecasting, and energy optimization tools.

Strongford Wastewater Treatment Plant [99]. Severn Trent Water, in partnership with Siemens, Atkins, Explore AI, and Xylem, is deploying Siemens' gPROMS DT technology at the Strongford wastewater treatment plant in Stoke-on-Trent, United Kingdom. This DT integrates over 60,000 static and dynamic metrics from sensors and operational systems to model the wastewater treatment process in real time. Originally developed for the pharmaceutical and petrochemical sectors, gPROMS enables detailed monitoring of energy use, effluent quality, and GHGs—including CO_2, CH_4, and N_2O. According to this report, the project team is developing a mechanistic model of nitrous-oxide production for wastewater treatment. Funded by a £10 million Ofwat Innovation Fund award, €0.9 million from Horizon Europe, and £28 million from Severn Trent, the project aims to eliminate direct process emissions and serve as a global blueprint for carbon-neutral WRRFs.

7.2. Pilot-Scale Implementation

Pipedream: An Interactive Digital Twin Model for Natural and Urban Drainage Systems [60]. The University of Michigan developed the PIPEDREAM DT for real-time management of urban stormwater systems. This DT continuously receives data from in-situ sensors monitoring flow depth, velocity, and rainfall across the drainage network. Using a full hydraulic model based on the Saint-Venant equations, dynamically updated with a Kalman filter, PIPEDREAM simulates and forecasts network conditions several hours into the future. These forecasts enable operators and city engineers to detect flooding risks early, assess the system's condition in unmonitored locations, and optimize control of stormwater infrastructure such as gates and detention basins.

Possible Concepts for Digital Twin Simulator for WWTP [100]. Oslo Metropolitan University and collaborators developed a DT for the Veas wastewater treatment plant in Norway. This system automatically acquires online data (e.g., flow, levels, and process variables) via SCADA, feeding a dynamic process model that simulates biological and hydraulic treatment processes. Simulations support capacity planning and performance forecasting, enabling operators and engineers to evaluate scenarios for increased inflows or regulatory changes, allowing optimization of process adjustments without requiring physical trials.

Application of Digital Twins for Remote Operation of Membrane Capacitive Deionization (mCDI) Systems [88]. A DT for several mCDI pilots in remote communities of Australia and China were developed to support maintenance planning. Real-time and historical feed and permeate data are captured via SCADA or monitoring systems. The DT employs a mathematical model of membrane aging and wear within the RO vessel, simulating degradation and cleaning cycles. Operators use this DT to autonomously control process dynamics, forecast membrane performance, schedule maintenance, and practice training scenarios.

Smart Water Management Using Intelligent Digital Twins [101]. Zekri et al. [101] proposed an intelligent DT framework for municipal water management, integrating real-time sensor data with MI-enhanced hydraulic models. For proof of concept, 100 smart water meters were installed in a residential area near Sultan Qaboos University in Oman. The DT supports system-wide optimization by enabling leak detection, operational efficiency analysis, and resource allocation. The output is used by water managers and planners to reduce losses, cut costs, and improve supply resilience under varying constraints. However, it is noted that implementation of the DT does not yet support expected functionalities. Future work is aimed at improving internet of things (IoT) failure forecasting and simulation.

Digital Twin of a Hydraulic System with Leak Diagnosis Applications [102]. The Hydroinformatics Laboratory at Instituto Tecnológico de Tuxtla Gutiérrez in Mexico developed a pilot scale distribution system coupled with a DT to diagnose leaks in water distribution networks. The DT enables remote control of the hydraulic system's actuators via embedded microcontrollers equipped with IoT functionality. Real-time pressure head and flowrate data are transmitted to the operator interface, where a calibrated EPANET hydraulic model runs simulations to estimate pressures at nodes without sensors. To detect and quantify leaks, a genetic algorithm was developed and integrated into the system. The method was validated through various experiments, including scenarios involving multiple simultaneous leaks, demonstrating its effectiveness for real-time leak detection and system monitoring.

Connecting Digital Twins to Control Collections Systems and Water Resource Recovery Facilities: From Siloed to Integrated Urban (Waste)Water Management [103]. Future City Flow is a DT platform developed by Scandinavian utilities, universities, and DHI to optimize control of urban wastewater collection systems. It integrates a hydrological-hydraulic model with real-time data from IoT sensors, SCADA systems, and weather forecasts to continuously simulate system conditions and support proactive control of pumps and storage volumes. A web-based interface enables operators to visualize data, implement predictive control strategies, and reduce sewer overflows and flooding. Future City Flow has been validated through pilot projects in Sweden and Denmark, such as in Malmö and Lund, where it demonstrated significant reductions in overflow volumes during storm events by using forecast-driven decision support.

The second part of this study reviews TwinPlant, a DT developed by DHI in collaboration with Aarhus Vand for WRRFs. It combines a mechanistic process model (typically ASM-based) with continuous data from sensors, lab analyses, and weather inputs to support real-time monitoring, operator training, and optimization of treatment performance. Through a web-based Graphical User Interface (GUI), operators can run scenario analyses and determine optimal control setpoints for objectives such as energy efficiency or effluent quality. Pilot testing at the Marselisborg WRRF in Denmark showed that TwinPlant could effectively reduce aeration energy while maintaining stable treatment under variable conditions, validating its value for operational decision support.

7.3. Cross-Case Synthesis

Drawing on the full-scale implementations in Section 7.1 and the pilot studies in Section 7.2 (see also Tables 1 and 2), three recurrent mechanisms explain why some projects translated analytics into process control while others remained as advisory only. First, governance and constraint mirroring consistently separated advisory dashboards from operational DTs. Where write-back authority was explicitly defined and bounded (e.g., Lushan [34]), the projected reported as "advisory + process control." In contrast, projects that lacked transparent access to PLC/SCADA constraint logic, or where authority was not formally delegated, stayed in advisory-only DS mode despite sophisticated modeling.

Second, benefits were sustained when estimation fidelity and updating rate matched the dynamics of the target process. Pilot-scale systems typically constrained scope and instrumentation so that soft-sensor errors and data latencies were managed within a defined budget, allowing reliable tracking and, in some cases, closed-loop moves (e.g., [102]). At utility scale, exposure to wet weather hydraulics [35] and heterogeneous data streams often degraded forecast skill during transients; in these settings, teams either added hydrodynamic coupling and uncertainty reporting or remained advisory only.

Third, projects that invested early in unambiguous mappings among P&IDs, SCADA tags, and model states moved faster from proof-of-concept to trusted operation. A shared tag dictionary with provenance (i.e., units, timestamps, and transformations) allowed operators to trace a recommendation back to measured reality, reducing friction and easing change management. Where tags and model variables were ad hoc or duplicative, even well-calibrated models faced skepticism at the handoff to operations.

These mechanisms also clarify the observed differences between full- and pilot-scale results. Full-scale utilities, appropriately risk-averse and compliance-focused, tended to retain advisory-only mode unless constraint logic and governance were explicit that the "human in the loop" concept was maintained. Pilot environments, by design, bounded risk and latency, thereby enabling tighter loops and credible demonstrations of targeted actuation. Together, the cases suggest that realized value depends less on novel algorithms and more on whether the twin is architected to respect plant constraints, expose uncertainty, and interoperate cleanly with existing control layers.

The cross-case patterns explain why only a subset of surveyed systems meet strict DT criteria in practice (i.e., synchronized state with authorized write-backs). They also indicate a pragmatic path forward: encode constraints, right-size latency and uncertainty to the decision, and make the digital–physical mapping transparent enough for operators to trust.

8. Challenges, Limitations, and Current Approaches

The implementation of DTs in the water industry offers a promising pathway to improving operational efficiency, resource management, and sustainability. However, despite the considerable potential, there are several key challenges and limitations that hinder the full-scale adoption of DTs in the water sector. These challenges are often linked to the complexity of water systems, the need for real-time data integration, and the interaction between physical and virtual components. In many cases, existing infrastructures in the water industry are not adequately prepared to support the seamless integration of DT technologies.

Moreover, as DTs evolve to encompass more comprehensive functionalities, questions about data quality, computational demands, sensor accuracy, and workforce adaptability continue to emerge. Addressing these challenges is essential to unlocking the full potential of DTs and ensuring their applicability across diverse water management systems. The following sections outline the primary challenges that need to be addressed for the successful integration of DTs in the water industry.

8.1. Data Quality Assessment and Control

Ensuring high data quality is essential to the successful implementation of DT with its applications in the water industry. The accuracy and reliability of data directly influence the effectiveness of DTs, as poor data quality can lead to flawed simulations and suboptimal decision-making. Inaccuracies in measurement, inconsistencies in data transmission, and the inability of sensors to capture real-time changes can all compromise data quality. Therefore, maintaining data integrity is paramount to fully realizing the benefits of DTs, particularly in a sector where precision is critical for operational efficiency and sustainability.

One approach to enhancing data quality involves the use of reference measurements through manual inspection and maintenance. This includes regular calibration of sensors using hand-held references and controlled media. By routinely calibrating sensors against established standards, utilities can ensure that measurements remain accurate and consistent over time. This hands-on approach helps mitigate issues such as sensor drift or failures, which are common in long-term operations. However, this method can be labor-intensive and may not be scalable for large systems, where automated or semi-automated solutions might be more practical.

Another approach to address data quality challenges is defining typical ranges for key operational variables, such as flow rates or chemical concentrations. These ranges, based on historical data or engineering principles, can be used to flag abnormal values that may indicate sensor errors or system malfunctions. By identifying outliers early, this approach enables a more automated form of data verification and integrity maintenance, reducing the need for continuous manual monitoring.

A more robust approach to ensuring data quality is through redundancy in data collection. Redundancy can be implemented both spatially and temporally to validate sensor data and improve reliability. Spatial redundancy can be achieved through physics-based methods, such as mass balances, or empirical checks like the validation of typical ratios (e.g., ratio of total ammonia nitrogen (TAN) to total Kjeldahl nitrogen (TKN) < 1), which confirm sensor outputs by comparing them to expected norms. This ensures that data is cross-verified across different locations, providing a backup for when primary sensors fail or deliver inaccurate readings.

Temporal redundancy involves applying filters and smoothers to the collected data to detect and manage outliers and noises. For instance, placing upper and lower limits on expected values and their temporal derivatives helps maintain data consistency over time. Noise detection methods, such as monitoring changes in R^2 values, along with the use of low-pass filters, can further refine data accuracy, ensuring that the data is reliable for both short-term and long-term analyses.

Finally, a combination of spatial and temporal redundancy offers a comprehensive solution for ensuring data quality across an entire system. Techniques such as the application of Kalman filters, which combine spatial and temporal data for dynamic analysis, and nonlinear dynamic data reconciliation help synchronize and refine data from multiple sources. This combined approach allows for a continuous feedback loop between the physical and DTs, ensuring that real-time data flows are reliable, thus enabling more accurate simulations, predictions, and operational decisions.

Studies consistently report that data-quality limitations propagate into DT forecasts. At Eindhoven WRRF [35], nitrate and mixed liquor suspended solids (MLSS) predictions degrade during wet-weather conditions despite a robust data pipeline—illustrating how transient hydraulics and measurement uncertainty can impair calibration and short-term forecasts. At the urban–hydrology boundary, experimental evidence coupled with refined stormwater management model (SWMM) modeling shows that cascading green-gray layouts can materially reduce peaks and volumes relative to distributed configurations, underscoring that hydrologic connectivity is a boundary condition stormwater/sewer twins must represent for waterlogging mitigation [104].

Beyond individual sensors, disciplined metadata, consistent SI units, synchronized timestamps, documented sensor placement and transmission mode, and known error sources such as calibration drift, fouling, and scaling, is essential to assess fitness-for-purpose and troubleshoot anomalies. As outlined earlier in this review, establishing a "ground-truth" mapping across P&ID, SCADA tag names, laboratory identifiers, and model variables reduces integrity errors and commissioning time.

Mismatches between P&ID labels, SCADA tags, lab identifiers, and model notation remain a recurring source of integrity errors; several works in Section 7 highlight that this mapping is still a manual, error-prone step that benefits from standardized dictionaries or ontology-based approaches (see Section 7 cases: Changi [29], Bresso-Niguarda [98]).

8.2. Lack of a Framework for Developing Practical DT in the Water Industry

One of the major hurdles that the water industry faces in adopting DTs is the absence of a standardized, practical framework. Without a clear framework to guide the development, integration, and scaling of DTs, it is difficult for water utilities to implement these technologies on a large scale.

Modular frameworks offer a flexible solution to this problem. By developing DT architectures that can be modular and adaptable, water utilities can customize the digital infrastructure to fit their specific operational requirements. Modular frameworks allow different components of a DT to be integrated gradually, based on the needs and resources of each facility. This stepwise approach enables utilities of varying sizes to implement DTs without the need for extensive overhauls of existing systems, making the technology more accessible and scalable.

Regulatory alignment is another critical aspect that needs to be addressed. Engaging with regulatory bodies to develop compliance standards and benchmarks for DT performance is essential for ensuring that DTs meet the necessary safety, environmental, and operational requirements. Regulations around data security, environmental impacts, and system safety must be clearly defined, so that utilities have a framework within which they can confidently develop and deploy DTs. Aligning DT developments with existing and future regulations will also help streamline adoption by ensuring that the technology is compatible with legal requirements and best practices.

Collaborative platforms play a vital role in advancing DT technology in the water industry. By fostering collaboration between water utilities, technology providers, and research institutions, the industry can accelerate innovation and overcome challenges more effectively. Shared platforms enable stakeholders to exchange best practices, lessons learned, and technical innovations. This collective approach helps avoid redundancy in research efforts and supports the development of solutions that are broadly applicable across the industry. Collaborative platforms also encourage the development of interoperable systems, ensuring that DT technologies can work seamlessly across different facilities and regions.

8.3. High Cost of Sensor Implementation and Computational Resources

Although many variables are measurable, some operationally critical analytes remain costly to measure continuously and require frequent maintenance (e.g., calibration drift, fouling, scaling). These constraints are widely recognized in full-scale deployments and are reflected in DT-ready metadata guidance and plant experience (see Appendix C; Bresso-Niguarda [98]).

To reduce the sensing burden, soft sensors and hybrid models (mechanistic + machine learning) are increasingly used. In collection networks, theory-guided NNs with weak-form constraints improve drainage-pipeline siltation diagnosis from multivariate sequences and are strong candidates for soft sensors embedded in DT decision support during wet-weather transients [105]. In the reviewed cases, integrating virtual sensors and residual learning with mechanistic simulators improved the robustness of ammonia/nitrate predictions and enabled energy-aware control. At Cuxhaven (EWE Wasser GmbH), this approach supported aeration optimization with an annual power saving of approximately 1.2 million kWh while maintaining effluent quality [40].

On computing architecture, pragmatic historian-plus-edge pipelines can deliver frequent updates adequate for advisory decision support. Plant-wide twins such as Changi [29] and Eindhoven [35] illustrate the data and compute footprint—hundreds to more than a thousand tags—that must be planned for when considering cloud/edge trade-offs.

8.4. Lack of Automated Bidirectional Data Transfer

A fundamental aspect of DT is the bidirectional flow of data between the physical system and its digital counterpart. This two-way communication allows the digital entity to not only receive real-time data from the physical entity but also to autonomously send feedback, make adjustments, and optimize operations in the physical system. However, as highlighted in several studies reviewed in this study, many DT applications in the water industry face a critical limitation: the lack of automated data transfer from the digital to the physical entity. In these cases, the data flow remains unidirectional, where real-time data is transmitted to the digital model, but operational adjustments based on the model's insights are either manually implemented or restricted entirely. Notably, most of the full-scale deployments we catalogued still operate in advisory-only mode, with only a minority enabling closed-loop write-backs (e.g., Lushan [34]), highlighting how governance and constraint-encoding remain practical bottlenecks.

This limitation undermines one of the core principles of a fully functional DT. While DS—where data flows in one direction—can be useful for monitoring purposes, they do not allow for real-time control and optimization of water systems, which is a key advantage of DT technology. The primary cause of this issue often lies in the stringent safety regulations and security protocols governing water utilities.

To address this challenge, several approaches can be considered:

1. Hybrid Approaches with Manual Verification: One potential solution is the adoption of hybrid systems, where the DT generates operational recommendations based on real-time data, but these recommendations are subject to manual verification before implementation. This approach balances the need for safety and human oversight with the benefits of automation. Operators can review suggested changes from the DT and either approve or reject them based on additional safety checks or contextual factors that the DT may not fully account for.

2. Incremental Automation: Another approach is to gradually increase the level of automation within water systems. Starting with low-risk operations, such as adjustments to operational variables (e.g., flow rates that fluctuate in response to demand) or controllable parameters (e.g., chemical dosing setpoints), can build trust in the system's ability to operate safely. Over time, as the reliability of the DT is demonstrated, utilities may become more comfortable, allowing DTs to handle higher-level, more critical operations. This incremental approach ensures that any potential risks are managed while allowing the system to evolve toward full automation.
3. Enhanced Cybersecurity Measures: One of the primary concerns for water utilities in enabling bidirectional data flow is the potential vulnerability to cyberattacks. Therefore, implementing robust cybersecurity protocols is essential for protecting both the physical and digital entities. Encryption of data, secure communication channels, and stringent access controls are necessary to ensure that the DT's instructions are both safe and reliable. By mitigating security risks, water utilities may be more inclined to allow autonomous adjustments based on real-time feedback from the DT.
4. Regulatory Collaboration: To facilitate automated data transfer, water utilities must work closely with regulatory bodies to ensure compliance with safety and environmental standards. Clear guidelines and frameworks that define the operational boundaries of DTs can help alleviate concerns around safety and security. Regulatory agencies can develop policies that outline how and under what circumstances DTs can make automated changes to water systems, ensuring that all operations remain within acceptable risk thresholds.

In summary, while the lack of automated bidirectional data transfer poses a significant challenge to the full implementation of DTs in the water industry, there are several approaches that can help overcome this barrier. By employing hybrid approaches, gradually introducing automation, enhancing cybersecurity, and collaborating with regulatory bodies, water utilities can begin to realize the full potential of DTs while maintaining the safety and security of their operations.

8.5. The Challenge of Control Authority

Throughout this review paper we described the structure and implementation of various forms of DTs in the water sector. The priority of water process facilities remains nonetheless to guarantee quality and quantity of the treated effluent, and digital aids such as DT are in support of the operators actions but cannot replace them. In fact, in most jurisdictions only licensed operators retain the control authority over the process equipment, de facto limiting the bidirectionality of DT to research or piloting efforts. Even in the case when operators would allow the DT to run the facility, the ability to override and take control of operations will always stem from the fact that operators and not computers are liable for the process actions and their consequences. This notwithstanding, the advent of digital tools in support of more informed control can only benefit a still operator-driven control and ultimately provide overlays of information (such as process unit costs, energy/power intensity of process, greenhouse gas intensity of treatment, etc.) that a normal SCADA system falls short of providing.

8.6. Operational Realities for Closing the Loop

Across the full-scale cases in this review, advisory-only operation is the norm. Even when a communication stack exists, automation is limited by governance and by how completely plant safety logic and operating limits are encoded in the DT. This is a socio-technical bottleneck: utilities must protect equipment, people, and compliance. Until interlocks, rate limits, and override rules are faithfully mirrored, the safest position is to keep the DT in recommend-only mode.

The key enabler is constraint logic. Physical limits and safety/regulatory constraints embedded in PLC/SCADA often determine whether any recommended action can actually run. If that logic is opaque or hard to access, model-based recommendations either fail at runtime or get blocked upstream, undermining operator trust. In practice, closing the loop depends less on a sophisticated optimizer and more on exposing, validating, and reproducing the plant's real constraint set in the DT's decision layer.

A quieter but essential task is variable mapping. Reliable operation needs a clean thread from P&IDs to SCADA tags/lab identifiers and finally model variables. Teams that establish a single "ground-truth" dictionary (or lightweight ontology) shorten commissioning and reduce silent errors.

Model choice should match the actuation you truly have. Where safety, interpretability, and control authority matter, mechanistic or hybrid (mechanistic + ML) models are usually preferable. Purely data-driven surrogates are strongest for soft-sensing and short-horizon forecasting. The deciding factors are observability, validation under relevant disturbances, and whether actuators can realize the recommended moves within the plant's constraint envelope, not ideology.

Finally, performance claims need an evidence hierarchy. Vendor press releases provide context, not evidence. Quantitative statements should trace to peer-reviewed studies or utility-audited reports, with clear baselines, uncertainty, and time frames. Anything else is illustrative and should be labeled as such. Together, these operational realities explain why advisory-only is common today and point to a practical path to trusted actuation: make constraints explicit, make mappings unambiguous, match latency to purpose, choose models aligned with your authority, and insist on verifiable evidence as DTs move from dashboards to decisions.

9. Future Direction and Summary

This review has examined the deployment of DTs in the water sector, spanning both treatment and reuse applications. To date, most operational DTs remain advisory-only or are confined to specific subsystems; where they have been implemented, tangible benefits include energy savings, multi-day event forecasting, and enhanced operator decision support, albeit moderated by persistent data integration and standardization challenges (e.g., Changi [29], Eindhoven [35], EWE [40]).

Looking ahead, realizing the transformative potential of DTs in water management hinges on addressing several critical challenges:

1. Full-Scale Demonstrations. While pilot and subsystem implementations have illustrated DT value, there is an urgent need for end-to-end, full-scale deployments across diverse water infrastructures—treatment plants, distribution networks, and even consumer-side applications. Such real-world examples will shed light on scalability hurdles and inform best practices for translating DT capabilities into operational resilience.
2. Advanced Analytics Integration. The incorporation of sophisticated data analytics, particularly ML and AI, will unlock new levels of DT performance. By embedding adaptive learning algorithms, DTs can evolve alongside system dynamics, enabling continuous optimization of operations and more reliable forecasting under both typical and extreme conditions.
3. Standardized Development Frameworks. Widespread adoption demands harmonized guidelines for DT creation and maintenance. Standardization efforts should cover data schemas, metadata conventions, sensor deployment strategies, and model validation

protocols. Establishing these frameworks will facilitate interoperability, reduce implementation complexity, and ensure consistent performance across the sector.

4. Sustainability and Resource Efficiency. As water scarcity intensifies and energy costs rise, DTs will be instrumental in steering systems toward sustainable operation. By coupling robust data pipelines with operator-focused use cases, such as energy-aware control and demand forecasting, DTs can deliver both environmental and economic dividends. For instance, Changi's FDT achieved up to five-day event forecasting accuracy [29], while EWE's ODT yielded approximately 1.2 million kWh in annual aeration energy savings [40].

However, these successes also expose areas for improvement. Accuracy degradations during wet-weather extremes at Eindhoven underscore the need for integrating hydrodynamic coupling and rigorous uncertainty quantification into DT calibration and forecasting workflows [35]. Furthermore, the scale of plant-wide integrations—tracking hundreds to over a thousand tags at Changi and Eindhoven—highlights the critical importance of metadata discipline and proactive maintenance planning.

To bridge research, policy, and operations, a short staged agenda is warranted: (1) strengthen uncertainty-aware estimation and calibration that remain robust in wet-weather conditions; (2) standardize DT-ready metadata, open APIs, and auditable change management to allow limited write-back; and (3) move from advisory-only to narrowly authorized setpoint changes, with PLC/SCADA constraint logic mirrored in the twin. In parallel, maintain a single plant tag dictionary (P&ID–SCADA–model) and align data and compute latencies with process time scales. Together, these measures convert priorities into near-term implementation and provide a controlled pathway from dashboards to dependable closed-loop operation.

Complementarily, mature multi-objective optimizers for large water-distribution resilience under cost constraints and cascade-reservoir scheduling can be coupled to synchronized twins (state estimation + constraint mirroring) to enable auditable, bounded write-backs at system scale [106,107].

In conclusion, DTs hold significant promise for revolutionizing water systems management. Realizing this vision will require coordinated efforts among researchers, industry practitioners, and policymakers to develop robust, scalable, and adaptable DT solutions. By addressing existing barriers—through full-scale demonstrations, advanced analytics, standardization, and sustainability-focused design—DTs can drive the next generation of efficient, resilient, and sustainable water infrastructure worldwide.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w17202957/s1, File S1: S1_Sankey_Chart.html; Table S1: Table S1_Paper_Information.xlsx. Refs. [108–138] were cited in the supplementary materials.

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Data Availability Statement: The data supporting the findings of this study consist of bibliographic and categorical information extracted from 147 peer-reviewed articles on DT applications in the water sector. These data are provided in the Supplementary Material (Table S1_Paper_Information.xlsx and Supplementary File S1_Sankey_Chart.html). No additional datasets were generated or analyzed during the current study.

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Abbreviations

The following abbreviations are used in this manuscript:

ABAC	Ammonia-Based Aeration Control
ADM1	Anaerobic Digestion Model 1
ADT	Autocalibrating Digital Twin
AI	Artificial Intelligence
AM	Asset Management
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ASM	Activated Sludge Model
API	Application Programming Interface
BiLSTM	Bidirectional Long Short-Term Memory
BIM	Building Information Modeling
BOD	Biochemical Oxygen Demand
BP	Back Propagation
CFP	Computational Fluid Dynamics
CNN	Convolutional Neural Network
COBie	Construction Operation Building information exchange
COD	Chemical Oxygen Demand
CPS	Cyber-Physical System
CSO	Combined Sewer Overflow
DAC	Data Acquisition and Control
DD	Digital Dashboard
DO	Dissolved Oxygen
DS	Digital Shadow
DSS	Decision Support System
DNNs	Deep Neural Networks
DT	Digital Twin
FCF	Future City Flow
FDT	Forecasting Digital Twin
GBR	Gradient Boosting Regression
GHG	Greenhouse Gas
GIS	Geographic Information System
GRU	Gated Recurrent Unit
GUI	Graphical User Interface
HM	Hybrid Model
HRSD	Hampton Roads Sanitation District
IFC	Industrial Foundation Classes
IG	Influent Generator
IoT	Internet of Things
IWA	International Water Association
LSTM	Long Short-Term Memory
LTCM	Long-Term Continuous Monitoring
MABR	Membrane Aerated Biofilm Reactor
mCDI	Membrane Capacitive Deionization
MDT	Monitoring Digital Twin
ML	Machine Learning
MLE	Modified Ludzack-Ettinger

MLSS	Mixed Liquor Suspended Solids
NASA	National Aeronautics and Space Administration
O&M	Operation and Maintenance
ODT	Optimizing Digital Twin
PFD	Process Flow Diagram
PLC	Programmable Logic Controller
PUB	Public Utilities Board
P&ID	Process and Instrumentation Diagram
RBMs	Restricted Boltzmann Machines
ReLUs	Rectified Linear Units
RNN	Recurrent Neural Networks
RO	Reverse Osmosis
SAEs	Stacked Autoencoders
SCADA	Supervisory Control and Data Acquisition
SCIP	Solving Constraint Integer Programs
SDT	Sensitivity Digital Twin
SI	Système International
SVM	Support Vector Machine
SWRO	Seawater Reverse Osmosis
SWMM	Storm Water Management Model
TAN	Total Ammonia Nitrogen
T-GCN	Temporal Graph Convolutional Neural Network
TKN	Total Kjeldahl Nitrogen
TSS	Total Suspended Solids
UI	User Interface
US	United States
US EPA	United States Environmental Protection Agency
UTC	Coordinated Universal Time
VAE	Variational Autoencoder
VR	Virtual Reality
WDN	Water Distribution Network
WDS	Water Distribution System
WEF	Water Environment Federation
WEST	Wastewater Treatment Plant Expert Simulation Tool
WRRF	Water Resources Recovery Facility
WWTP	Wastewater Treatment Plant

Appendix A. Digital Twin Components

In our opinion, a DT system is required to have several essential components to serve its full practical applications:

- Physical Entity: A DT is a virtual replication of a subject or an object that is currently operational in full-scale. A physical entity in the water industry can be a wastewater WWTP, a desalination plant, or a water distribution network. Importantly, a DT is a model of a specific plant, process, or water stream and is thus distinct from general-purpose models used for benchmarking, education, or research (e.g., Jeppsson et al. [139]).
- High-Fidelity Simulator and Modelling: Fidelity in simulators corresponds to the degree of realism and acceptance of simulation results as representing the anticipated behavior of the physical system. It is a multi-dimensional concept that relates to several components of the simulation and is created through the selection of simulation settings, equipment, and scenarios. Fidelity can also refer to the degree of exactness that is achieved in the simulation [140,141]. A high-fidelity simulation model approximates the key processes

that are involved in the physical system. As no model can capture every detail of reality, models are inherently simplifications and approximations of complex systems [142]. Thus, rather than representing the system in full detail, high-fidelity models focus on capturing essential physical and chemical processes, which are most relevant to the behavior of the system being simulated. Additionally, the simulator should provide a dynamic replication, so that the virtual entity can continuously update and synchronize with the physical system. Examples of simulators in the water industry are EPANET, SUMO, BioWin, InfoSWMM, WaterGEMS, and SewerCAD.

- Physical Sensors and Analyzers: Data streaming between the physical and virtual entities is one of the main elements in DT. Physical sensors enable the virtual entity to be informed of the real-time status of the physical twin. Additionally, physical sensors enable remote operation and automated control of the physical system. Examples of physical sensors are sensors for temperature, flow rate, and power meters. On the other hand, analyzers typically perform more complex assessments by processing and interpreting data collected from sensors to determine characteristics such as pH, turbidity, or dissolved oxygen levels. Both physical sensors and analyzers are critical for ensuring efficient, compliant, and safe water treatment operations.
- Actuators with virtual connections: Actuators with virtual connections such as switches, pump drives, and valves play a crucial role in automating and remotely controlling physical systems. Actuators are devices that convert control signals (often electrical) into physical action, such as opening or closing a valve or adjusting the speed of a pump. When connected virtually, these actuators can be operated remotely via supervisory control systems or digital interfaces. For example, pump drives with virtual connectivity allow operators to adjust the flow rate or pressure of pumps from a centralized control room or even off-site locations. This virtual connectivity not only enables remote operation but also facilitates automated process adjustments, reducing the need for manual intervention, enhancing system responsiveness, and improving overall operational efficiency.
- Physical-to-Virtual Connection: The physical and virtual twins should be equipped with continuous information flows to update each other. This not only enables the virtual entity to continuously synchronize itself with the physical entity but also provides the physical system with the ability to get feedback from the virtual entity to adjust and optimize its operations. The two-way connection in a DT is one of the main distinguished features that makes it a self-evolving representation model and separates DT from a simulator or a DS.
- Advanced Data Analysis: The raw data exchanged between physical and DTs often contains noise, redundancies, or irrelevant information that can obscure valuable insights. This unprocessed data, if used directly, may lead to inaccuracies or inefficiencies in the functioning of either entity. Therefore, real-time data monitoring and collection results in a large dataset that must be refined and structured to ensure its relevance and accuracy. To make the data suitable for use by physical or virtual twins, it undergoes processing steps such as filtering and cleaning, followed by advanced data analysis techniques, including statistical approaches and AI algorithms. These steps transform raw data into actionable insights, allowing for precise decision-making and improved system performance.
- Interaction and Service: The DT should be able to interact with the users through a user interface (UI). The DT should be able to provide users with the real-time or near real-time status of the system, provide recommendations for operational settings and optimization, and enable remote and automated control of the physical entity.

The major services that can be provided by the implementation of a full-scale DT are discussed in Section 5 and Appendix B of this review study.

Appendix B. Digital Twins Application

Appendix B.1. Monitoring DT (MDT)

The main purpose of an MDT is to facilitate real-time (or near real-time) monitoring of a physical system, connecting an isolated physical entity to an interconnected virtual representation that tracks and displays the system's performance [41]. This type of DT, sometimes referred to as a digital dashboard (DD) at a macro level, serves as a virtual, interactive performance management tool to support informational decision-making and achieve organizational objectives, such as energy savings [143]. An example in the water industry is the virtual monitoring system of wastewater treatment facilities, which provides visualized real-time performance data and an operator interface for remote monitoring.

However, for MDTs to reach their full potential, it is essential to integrate bidirectional interaction capabilities. This would not only allow the monitoring of real-time performance but also enable dynamic adjustments and control over the physical system based on the data collected. In its absence, these systems function similarly to DS, where data is only transferred one way, from the physical entity to the digital model, limiting their capability for real-time intervention and optimization. To better align terminology with the capabilities required in the water sector, we propose emphasizing the need for such bidirectional integration when implementing MDTs. This would ensure they serve as comprehensive DTs, rather than static monitoring tools, maximizing their utility and impact on performance management.

Appendix B.2. Optimizing DT (ODT)

Since DT provides a dynamic and comprehensive representation of an operational system, including all interconnected elements and input/output parameters, it inherently possesses the potential for optimization. By integrating optimization algorithms, every DT can generate scenarios in which the performance of the system is not only monitored but actively enhanced [144]. In fact, to harness the full capability of a DT, it should function as an optimization tool, ensuring that the digital model continuously evaluates and adjusts control parameters to improve system performance.

The application of ML and AI algorithms within a DT framework allows for auto-tuning and optimization, making the system adaptive and responsive. For instance, in the water industry, optimizing the aeration rate based on the measured Chemical Oxygen Demand (COD) in the influent to the plant is a practical example where a DT operates as an optimization tool, ensuring the system achieves efficiency goals. This illustrates that, rather than categorizing DTs separately as ODTs, optimization should be viewed as a fundamental and integral function of all DTs.

Appendix B.3. Forecasting DT (FGT)

Generating scenarios to evaluate the performance of an operational physical system can be costly, time-consuming, and often imposes a great risk to the machinery and operators. However, evaluation of the system's performance under these "what-if" and "unusual" conditions is essential for long-term planning and decision-making in case of natural disasters and system failures. FDT can serve as a cost-effective, no-risk, and fast-prototyping option to generate a variety of scenarios to forecast the performance of the system under different operational conditions, without the need to apply the conditions to the actual physical system. This type of DT provides a powerful management tool in sensitive public service systems such as the water industry. Examples in the water industry include forecasting performance of a RO desalination system under low power supply.

Appendix B.4. Sensitivity DT (SDT)

Similarly to FDT, SDT provides users with the ability to evaluate the performance of the physical system (i.e., the output parameters), when the input parameters change. SDT can be used to assess how sensitive the selected output parameters are to the changes that are made in the input parameters. An SDT can achieve this by generating a number of scenarios where small changes are made in a single input parameter, while keeping the other factors constant. This can provide a decision-making tool for the operators to estimate the changes in the different components of the system's performance when adjusting or altering some of the input parameters. An example in the water industry can be sensitivity analysis of biochemical oxygen demand (BOD) in the effluent of a wastewater treatment plant to the changes in the aeration rate in the aeration tank.

Appendix B.5. Wrapper

Similarly to the MDT, a wrapper monitors the performance of all the elements in physical entity, in real time. A wrapper is basically an MDT that is trained to shut down or restart the system when a module in the system fails or crashes. A wrapper can provide an additional layer of safety to the operational system or just be used for cost and energy saving and waste reduction purposes.

Appendix C. Digital Twins in the Water Industry

As was mentioned previously, similarly to the other industries and production areas, the number of studies that evaluate the different aspects of DTs and their applications in the water industry is increasing significantly. These studies cover a wide range of DT applications in the water industry, including wastewater collection, wastewater treatment, water production including drinking, irrigation, and cooling water, and water distribution networks. DTs previously developed in the water industry have been applied to address a variety of tasks that are essential across different elements of the urban water cycle. These tasks include (1) optimizing and adjusting operational parameters (e.g., aeration rates in treatment processes, pump schedules in distribution networks); (2) managing maintenance, repair, and troubleshooting activities, such as prevention, detection, and mitigation of leaks, as well as planning and scheduling repairs; (3) supporting system expansions and improvements through modeling and analysis; (4) implementing recovery and reuse strategies for water, energy, and nutrients; (5) responding to unforeseen events and natural disasters by adjusting system operations dynamically; (6) providing staff and operator training in a virtual environment; (7) testing various scenarios that cannot be physically tested due to constraints or risks; and (8) supporting informed operational decision-making through real-time data and predictive modeling. There are also review and conceptual studies that focus on the lessons learned from applications of DT in other industrial sectors, as well as review of the DT concepts, components, implementation challenges, and benefits that they offer, in a general approach. The DT studies in the water industry are reviewed in detail in this section. In this review, all of the previous works that have focused on the application of DTs in the water industry can be grouped as to (1) learn about the current status of DT in the water sector; (2) identify the gaps and missing elements; (3) evaluate the usefulness of the proposed approaches; (4) investigate the challenges and limitations of full-scale implementation of DT in the water industry; and finally (5) to discover the path forward to take full advantage of this emerging technology in the design and management of sustainable water systems around the globe. In this review, a total of 147 relevant studies were selected, analyzed, and categorized (see Table S1_Paper_Information.xlsx and Figure 3). These studies are grouped into seven topical categories most applicable to the water industry: (1) review and conceptual studies, (2) wastewater treatment, (3) wastewater collection systems, (4) water distribution networks, (5) drinking water treatment (water supply systems), (6) water reclamation, and (7) water desalination. The following subsections summarize each category in detail, highlighting the contributions of each study and the evolution of DT applications at the water–energy nexus.

Appendix C.1. Review and Conceptual Studies

Several publications have outlined DT concepts, requirements, and challenges for water systems. For example, Beji and Lade [2] discussed how digital transformation (including DTs) can help reduce carbon emissions in water utilities, noting that improvements in water and energy efficiency offer the greatest decarbonization potential. Similarly, O'Dwyer et al. [10] described steps and tools for implementing a city-wide energy management system that incorporates DT concepts. Along the same lines, Teng et al. [145] and Huynh and Zondervan [146] explored how DT-based approaches could create energy-saving systems in industrial contexts, illustrating transferable strategies for water infrastructure.

In foundational work on the DT concept, Grieves and Vickers [46] described the origin and evolution of the DT paradigm and showed how it applies across product lifecycles to understand system behavior. They discussed how DTs relate to systems engineering and human factors (e.g., how DTs can help anticipate and prevent "normal accidents"), identified obstacles and opportunities (such as challenges in system replication and advantages of front-running simulations that predict behavior in advance of operation), and highlighted NASA's efforts in developing DTs. In a similar conceptual vein, Moser et al. [47] defined requirements for models to be compatible with DTs, emphasizing the need for mechanistic, modular models and effective process optimization. Jones et al. [147] identified 13 key characteristics of DTs and seven knowledge gaps for future research. Although their study was centered on product manufacturing, the identified DT attributes and research gaps provide useful guidance for tackling development challenges in water-sector DTs.

A few studies have implemented prototype DTs to pinpoint implementation challenges and propose DT design frameworks. For instance, Brooks et al. [148] demonstrated a DT that enabled a self-cleaning heat exchanger (automated backwashing to prevent fouling), marking one of the first instances of DT-driven operational control in water treatment. Shafiee et al. [149] used advanced metering infrastructure (AMI) data to dynamically estimate demand in a water distribution network, modifying the EPANET hydraulic engine to accept continuously updated demands and thereby overcoming software limitations. These studies provided early proofs-of-concept of DTs in water systems and helped reveal practical issues (e.g., data integration and software constraints) that future implementations must address.

More recently, several surveys and position papers have guided DT adoption in water infrastructure. Saddiqi et al. [150] reviewed DT-enabled strategies for managing combined sewer overflows, underscoring the importance of data-driven predictive control and the need for transferable ML models in future sewer twins. Kretschmer et al. [151] surveyed industry experts on the opportunities and barriers to applying BIM and DT concepts in wastewater projects, while Ostfeld and Abhijith [70] outlined a stepwise roadmap for evolving prototype water-distribution DTs into fully operational utility tools. Complementing these, Ramos et al. [152] analyzed smart water grid architectures that embed DT functionality for asset management, and Quaranta et al. [77] linked European digitalization initiatives with water-sector decarbonization goals, highlighting the importance of governance and policy alignment in accelerating DT deployments. At the same time, security and resilience have entered the discussion: Batarseh et al. [49] introduced the open-source ACWA cyber-physical testbed, which integrates AI, soft sensors, and DT components to evaluate operational and cybersecurity scenarios in drinking-water systems. At the utility scale, Laucelli et al. [153] and Ciliberti et al. [48] proposed service-oriented architectures that knit together isolated asset-level twins into integrated “digital water services,” stressing interoperability across the asset life cycle.

Domain-specific DT syntheses have also emerged. Boogaard et al. [154] reviewed 60 studies on DT-based cybersecurity risk assessment for critical water infrastructure, calling for standardized benchmark datasets and new resilience metrics. Focusing on resource recovery, Sheik et al. [155] provided a systematic review of “algal digital twins,” illustrating how high-resolution optical monitoring and modeling can enable predictive control in water reclamation ponds. Cairone et al. [156] offered a holistic overview of how IoT, AI, DT, virtual/augmented reality, robotics, and blockchain technologies can contribute to circular, low-carbon wastewater management, and they identified data interoperability and workforce skill gaps as primary hurdles to implementation. On the modeling front, Dehghani Tafti et al. [157] developed a modular modeling framework for nature-based water treatment solutions, defining ten interchangeable DT components to accelerate prototype development and technology. In the context of water treatment processes, Zhou et al. [158] reviewed advances in unsteady-flow modeling and real-time optimization that underpin DT-enabled control in treatment. Similarly, Zhang et al. [78] catalogued multi-scale numerical modeling approaches (from continuum-level down to pore-scale) for simulating drinking-water treatment processes, illustrating how multi-scale twins can bridge the gap between process design and on-line.

Extending the scope to asset management, Villinger and Reiterer [159] presented the first comprehensive survey of sewer inspection robotics, showing how DT frameworks can fuse data from multi-sensor robotic inspections to support proactive maintenance and long-term asset management of sewer. Collectively, these conceptual and review studies have laid the groundwork by defining DT principles, highlighting cross-cutting challenges (data integration, standards, security), and suggesting architectural frameworks that inform the application-specific DT developments reviewed in the following sections.

Appendix C.2. Wastewater Treatment

The results of this review study showed that researchers in the water industry have shown interest in the application of DTs in wastewater treatment. 42 papers focused on the implementation of DT for wastewater treatment facilities. This is mainly due to the complexity and energy intensity of the treatment processes and the wide range of benefits that DT can provide for the sustainable design and management of WWTP. This includes optimization of treatment processes (e.g., adjusting the aeration rate), maintenance and repair (e.g., asset management), troubleshooting, system expansion and improvements, planning for unforeseen events and natural disasters, informed decision-making and testing various scenarios, as well as opportunities for staff and operators training.

Simulation models and soft sensors play a pivotal role in developing functional WWTP twins that accurately mirror the physical plant’s state. Accordingly, researchers have explored advanced modeling, automation, and machine-learning techniques for wastewater treatment. Alex et al. [160] reviewed various automation systems and simulator tools in WWTPs that could contribute to DT development. Their study evaluated the use of a high-fidelity plant simulator together with soft sensors for WWTP monitoring in Germany, illustrating how simulation coupled with virtual sensing can improve plant management. Matheri et al. [161] discussed the evolution of digital technologies (sensors, data analytics, and process control software) applicable to wastewater treatment operations. Along similar lines, Komulainen and Johansen [100] evaluated potential simulation scenarios for conceptualizing a DT of a Norwegian WWTP, helping to identify which process conditions and control strategies a future twin should be able to replicate.

Much of the recent WWTP DT research leverages machine learning to create "soft sensors" that estimate hard-to-measure process variables. J. J. Zhu et al. [51] developed a deep-learning-based algorithm (combining a deep belief network with particle swarm optimization) to optimize soft sensor predictions of key wastewater parameters like BOD and total suspended solids. Mihaly et al. [162] similarly demonstrated that artificial neural networks (ANNs) can rapidly and accurately predict important plant performance indicators in near real time (such as aeration energy use, effluent quality, and pumping energy) based on data from a WWTP in Romania. In another study, Cheng et al. [163] built and compared several recurrent deep learning models (long short-term memory and gated recurrent unit networks) as soft sensors. These models were trained to predict influent and effluent properties (e.g., BOD, wastewater temperature, real-time power consumption) at a Saudi Arabian WWTP and showed promising accuracy for dynamic forecasting. Earlier, Dairi et al. [50] had applied unsupervised deep learning methods—using recurrent neural networks, restricted Boltzmann machines, and clustering algorithms—to monitor hard-to-measure influent characteristics at a WWTP in Saudi Arabia. This approach enabled anomaly detection and trend monitoring for influent wastewater quality, and its successful validation on real plant data demonstrated the feasibility of machine-learning soft sensors in treatment plant environments.

Beyond soft sensing, several studies emphasize modeling and simulation of specific treatment processes as steppingstones toward DTs. For instance, C. Yang et al. [164] coupled a genetic algorithm with SUMO to model the modified Ludzack-Ettinger (MLE) biological nutrient removal process in a hybrid membrane-aerated biofilm reactor. The resulting model accurately estimated multiple influent characteristics and provided optimized design parameters for the process. Prior to that, Gaska et al. [165] modeled a full WWTP aiming to optimize treatment costs, and Fomenkova et al. [166] applied an adaptive control strategy to simulate anaerobic sludge fermentation in a digester, with the goal of saving energy.

Hallaji et al. [55,56], proposed a framework for using BIM to support pump maintenance in wastewater systems. Their approach incorporated open data standards (Industry Foundation Classes, COBie) and custom APIs to integrate 3D asset models with operational data, and they evaluated options for how such a pump-focused DT could be realized in practice. Laing et al. [167] applied a mixed-integer linear programming model to optimize biogas distribution within a WWTP that employed advanced anaerobic digestion. Using historical plant data, they retrospectively optimized the routing and utilization of produced biogas to minimize costs, thereby creating a realistic model of gas and energy flows in a complex treatment process. In the same year, Therrien et al. [168] presented a critical review of the data pipeline needed to support WWTP DTs, from data acquisition and cleansing to integration into models, highlighting how raw wastewater data must be processed into actionable information for DT-driven decision support. Moretta et al. [169] updated the well-known Anaerobic Digestion Model No.1 (ADM1) and proposed this enhanced process model as a foundation for a DT of sludge digesters. Although their improved ADM1 broadened the range of conditions and inputs that could be simulated, it remained a purely modeling study and was not linked with real-time plant data or controls.

One of the studies closest to true full-scale DT implementation for wastewater treatment is by J. L. Li et al. [170]. This work, while not explicitly labeled as a "digital twin" project, described the intelligent design and construction of a large WWTP in China using a suite of advanced digital tools. The authors combined BIM with 3D geographic information system data to create detailed geometric models, simulated various construction and operational phases of the plant, integrated an IoT network for real-time monitoring, and developed digital asset management and environmental monitoring systems for the facility. Together, these components encompassed most of the elements of a DT (from design through to operation and maintenance), illustrating how a comprehensive digital approach can be applied to a wastewater facility.

Recent contributions signal a maturing of wastewater-treatment DTs, addressing critical gaps and demonstrating more integrated solutions. The integration of BIM with digital-twin thinking has continued. Kretschmer et al. [151] canvassed industry experts and case studies to clarify the opportunities and bottlenecks of applying BIM-centered twins to wastewater infrastructure, emphasizing the need for common data environments and standardized asset coding. In parallel, Ciliberti et al. [48] outlined how isolated asset-specific twins (for individual processes or equipment) can be federated into utility-wide "digital water services" via service-oriented architectures, enabling different components (structural models, hydraulic models, etc.) to interoperate. Quaranta et al. [77] complemented these works with a policy analysis linking EU digitalization initiatives to decarbonization targets across the water cycle (including wastewater treatment), underscoring the importance of governance frameworks for widespread DT adoption.

Several studies have targeted energy-intensive treatment processes with DT-based control. Bolorinos et al. [171] demonstrated that using a plant-level DT for predictive load shifting can align a WWTP's electricity demand profile with periods of low-carbon energy supply. Heo et al. [53] implemented a full-scale DT-driven aeration control policy at a WWTP, managing to hold effluent nitrogen (NO_2-N/NH_4-N) near a 1.1 ratio while cutting blower energy consumption by approximately 17%. Chen et al. [54] extended the twin-based optimization concept to whole-plant management, developing a system that produces three-hour effluent quality forecasts with <5% mean absolute percentage error and adjusts chemical dosing accordingly.

Rapid advances in soft-sensor design for treatment DTs are evident. Schroer et al. [172] used historical SCADA data and feature engineering techniques to forecast daily biogas production from anaerobic digesters, effectively creating a DT surrogate model for digester gas output. Khalil et al. [91] combined a minimum-redundancy–maximum-relevance algorithm for feature selection with multi-objective hyperparameter optimization to improve soft sensor accuracy for nutrient removal processes. Fang & Liu [173] twinned laboratory water-quality sensors with an optimized echo-state network, improving the robustness of ammonia and nitrate predictions in the face of process disturbances. Meanwhile, Wang et al. [174] introduced a multi-layer adaptive critic framework wherein the DT learns plant dynamics online and continuously refines a control policy, which can then be transferred to the real system.

Moreover, researchers have started to consider the cybersecurity dimension of WWTP twins. Boogaard et al. [154] reviewed numerous studies on DT-based cybersecurity risk assessment for water utilities, identifying the lack of public benchmark datasets and the need for standardized resilience metrics as key gaps. In a more applied study, Machaka et al. [175] compared stand-alone versus hybrid software-defined networking (SDN) solutions connected to a Simulink-based WWTP DT. They found that incorporating SDN architectures could reduce intrusion-detection times by more than 70%, demonstrating how network-level innovations can bolster the security of DT-enabled control systems.

Finally, several researchers have proposed modular frameworks to generalize and accelerate DT development. Dehghani Tafti et al. [157] defined a set of ten interchangeable DT components for nature-based wastewater treatment solutions, which allows rapid prototyping and easier transfer of DT technologies between different treatment contexts. Molin et al. [90] examined automated data pipelines for WWTP twins, showing that both historian–database interfaces and edge-computing approaches can deliver sub-minute data updates to drive real-time models. Verhaeghe et al. [52] benchmarked a hybrid modeling approach wherein a convolutional neural network learns the residual error of a mechanistic treatment process simulator; this hybrid DT reduced effluent NO3-N prediction RMSE by 60% compared to a purely recurrent neural network model. Expanding the scope of DTs in resource recovery, Sheik et al. [155] provided a comprehensive review of algal pond DT applications (relevant for nutrient recovery), and Cairone et al. [156] surveyed the integration of IoT, AI, extended reality, robotics, and blockchain to support circular and low-carbon approaches in wastewater treatment.

Taken together, these contributions demonstrate notable progress in digital-twin research for wastewater treatment. In particular, advances in BIM-enabled asset modeling, energy-aware control strategies, high-fidelity soft sensors, cybersecurity measures, and modular DT architectures are laying the foundation for future full-scale, real-time WWTP twins. This growing maturity suggests that in the coming years, wastewater treatment facilities could move from pilot DT implementations toward fully integrated DTs that support day-to-day operations, optimization, and strategic decision-making.

Appendix C.3. Wastewater Collection Systems

Wastewater collection systems, the sewer networks that transport wastewater, are among the most complex and critical components of urban infrastructure. These systems include a variety of interconnected assets such as pump stations, wet wells, manholes, private and public sewer laterals, gravity pipelines, and lift stations, all of which must function together continuously. Given their complexity and the consequences of failures (e.g., overflows or blockages), the application of DTs for sustainable sewer network management has gained significant attention. DTs for wastewater collection can assist with tasks including maintenance and repair scheduling, troubleshooting system upsets, leakage and inflow detection, pump performance monitoring and anomaly detection, long-term system expansion planning, and master planning for future capacity.

Early research in this area applied machine learning to specific operational challenges. Zhu et al. [57] developed a data-driven method for sewer pump fault diagnosis in China, using a modified stacked autoencoder (with ReLU activation and dropout) to analyze pump vibration signals. The proposed algorithm outperformed traditional methods like support vector machines and backpropagation neural networks, especially when training data were limited, demonstrating the promise of deep learning for early fault detection in pumping stations. A few years later, Filipe et al. [58] implemented a deep reinforcement learning approach to optimize the operation of a sewer pumping system. By training a predictive control policy, they achieved a 16.7% reduction in the system's electricity consumption while maintaining wastewater storage within safe levels. Over a 90-day field pilot in Portugal, their DT-driven controller also resulted in a 97% decrease in high-level alarm events (situations where the wet-well level exceeded a critical threshold), compared to the fixed set-point control previously used.

Recognizing the impact of storm events on collection systems, several studies have focused on DT applications for stormwater and flood management. Eichenwald et al. [59] created a prototype DT for an urban stormwater network by integrating a calibrated Storm Water Management Model (SWMM, from the US EPA) with a predictive platform called PipeCAST. This digital setup enabled real-time simulation of drainage performance and helped anticipate flooding issues under various rainfall scenarios. Similarly, Bartos and Kerkez [60] developed a software toolkit combining a hydraulic solver with an Extended Kalman Filter for a stormwater system. They described this toolkit as a "Digital Twin" for detecting stormwater-related emergencies; in practice, it functioned as an advanced modeling and data assimilation tool to flag flood risks, albeit without a fully automated real-time feedback loop. Akroyd [176] took a multi-sector perspective by building a rudimentary DT that models flooding impacts across interdependent networks (water, energy, and electricity) as part of the Climate Resilience Demonstrator (CReDo) project in the UK. This work mainly outlined conceptual approaches for implementing DTs to improve flood resilience across different infrastructure sectors.

Other researchers have worked on frameworks to bring collection system DTs closer to real operation. Pedersen et al. [61] discussed the definition and scope of DTs in water resources and conceptualized a "living" DT for an urban drainage system at VandCenter Syd (a Danish water utility). They envisioned the living DT as a near-real-time virtual replica of the urban sewer system that operators could use for decision support in daily operations. They also defined a prototyping DT as a separate, uncoupled model that is not fed by live data—intended for off-line design and planning analyses. This distinction clarified how a DT could evolve from a planning tool to an operational tool. One technical advance toward component-level DT modeling was demonstrated by Dalla Vedova and Berri [177], who developed a simplified numerical model for an electro-hydraulic servo valve used in flow control. Their model incorporated key geometric and operational factors and outperformed previous simplified valve models, indicating its value for inclusion in a larger network DT despite some noted limitations. Moving toward full system control, Lumley [178] developed a DT framework aimed at controlling CSOs in a Swedish city. This pilot twin incorporated the majority of necessary DT elements (real-time data, a calibrated hydraulic model, and control algorithms) and was among the closest studies to achieving a functioning, real-time DT for a sewer network.

As in the treatment domain, most purported "DTs" for wastewater collection to date have only realized partial functionality, addressing a limited subset of what a full-scale sewer DT would entail. Many studies remain essentially advanced modeling or monitoring exercises rather than fully integrated, real-time twins. While some projects have inched closer to a true operational twin (e.g., Lumley 2022's [178] CSO control system), there is still substantial work required to reach that milestone of a continuously self-updating, decision-supporting sewer network DT. The challenges include integrating heterogeneous data streams (hydraulic sensors, rain gauges, CCTV inspections, etc.), scaling models to city-wide networks, and automating control actions in response to model predictions.

Recent research has pivoted towards addressing these challenges by focusing on data integration, standardized architectures, and real-time control in sewer DTs. Kretschmer et al. [151] surveyed utility consultants, engineers, and contractors on how BIM could serve as the backbone for sewer system DTs. Their findings emphasized the need for common data environments and consistent asset identification standards to facilitate sharing data between different tools. They proposed a phased implementation roadmap, where BIM models of sewer assets are incrementally linked with hydraulic models and structural condition models throughout the asset lifecycle, a strategy to gradually build a holistic DT.

Methodological advances have also been reported to enhance sewer network modeling and data acquisition for DTs. J. Li et al. [62] introduced a physics-informed neural network scheme that learns the coupled heat transfer between sewer pipe walls and surrounding soil, while respecting fundamental energy balance equations. Incorporating physical laws into the model improved the accuracy of sewer temperature profile predictions, which can be useful for calibrating sewer twins (for example, identifying illicit inflows via temperature anomalies). In a companion study, M. Li et al. [63] developed a rapid workflow to convert mobile laser-scanning point clouds of large-diameter interceptors into geometric DTs. This automated 3D modeling approach enables efficient detection of pipe deformation and cross-sectional ovality, demonstrating how advanced sensing can populate DT models with up-to-date structural data. In addition, Saddiqi et al. [150] offered a focused review on DT-enabled CSO mitigation strategies. They mapped out data requirements (such as high-frequency level and flow monitoring), discussed machine-learning models transferable between systems, and surveyed real-time control strategies that underpin emerging city-wide sewer twins.

Real-time monitoring and control of large sewer networks have become a central theme in recent DT deployments. In Sweden, Lumley et al. [36] built a cloud-hosted DT of the 140-km Gothenburg regional sewer system. By coupling a calibrated hydraulic network model with live telemetry feeds (flow levels, pump statuses, rainfall data), the twin was able to issue model-predictive control set-points in real time. This DT-driven control optimized pump operations at the wastewater treatment plant inlet and reduced overflow events during storms.

Research is also turning to scalable DT architectures and proactive maintenance for sewer networks. For example, Hartmann et al. [64] outlined the German KaSyTwin initiative, which aims to create semi-automated DTs of aging sewer systems by combining multi-sensor robotics, LiDAR scanning, and AI analysis. The KaSyTwin project focuses on real-time structural health monitoring and resilience forecasting, using robotic platforms to continuously inspect sewers and update the DT with defect detections or deterioration trends.

Appendix C.4. Water Distribution Networks

Water distribution networks can also benefit from DT technology for a variety of applications, including pump station operation, leakage detection, pipeline maintenance, repair scheduling, customer demand management, and long-term system planning. A DT for a distribution system typically integrates hydraulic models, asset databases, and real-time sensor data to provide a continuously updated representation of the water supply network's state. This can help operators optimize pump controls for energy efficiency, quickly detect and locate leaks or bursts, manage pressure zones to reduce losses, and plan network expansions or pipe replacements with better insight into system behavior.

Initial work on water distribution twins has explored basic modeling frameworks and specific use cases. Conejos et al. [65] described how a DT could be implemented for the integrated water supply and distribution system of Valencia, Spain. They outlined the required components (hydraulic models, real-time telemetry, data management tools, etc.) and the potential benefits of such a twin for utility operations. Building on that foundation, Conejos et al. [3] developed a DT using the GO2HydNet modeling platform for Valencia's water distribution network. This twin was capable of simulating both emergency responses (such as isolating pipe bursts) and the long-term behavior of the network under different maintenance and asset replacement scenarios, providing valuable decision support for infrastructure management.

Researchers have also targeted leakage monitoring and control. Cody et al. [66] created a data-driven leak detection system for water distribution pipelines using a combination of a CNN and a VAE. Applied to high-frequency pressure sensor data from a lab-scale network, their framework achieved 97% accuracy in identifying new leaks. However, the approach was limited to controlled conditions: it was tested on a laboratory testbed and could only detect leaks that occurred after the model had been trained (i.e., it would not necessarily detect pre-existing leaks). Focusing on operational efficiency, Morani et al. [67] developed a DT of a water distribution system aimed at optimizing pump operations. They formulated a mixed-integer nonlinear programming model (solved with the SCIP optimization engine) to maximize energy recovery (through turbine generators on pressure reducing valves) and minimize water leakage. The optimization results were promising, but the study remained essentially a theoretical modeling exercise and did not incorporate real-time data or implement the solution in practice.

He et al. [179] constructed a DT model to estimate hydraulic parameters at unmonitored locations (blind spots) in a pumping station during unsteady (transient) flow conditions. Their method combined a hydraulic simulation with control-theoretic equations to emulate the dynamic behavior of pump controls, edging closer to a real-time control-oriented twin (though it was still primarily a modeling approach). Similarly, Bonilla et al. [69] implemented a DT for a water distribution network using a temporal graph convolutional neural network (T-GCN) that determined optimal pump speed settings in real time. They integrated this AI controller with EPANET and the WNTR simulation toolkit to validate pump operations, demonstrating improved control of pressures and flows in the network. Beyond specific implementations, several works have discussed general approaches and challenges for distribution system DTs. Berglund et al. [25] reviewed potential DT applications for the design and management of water distribution systems, detailing the essential elements a distribution DT should include (from hydraulic solvers and sensor networks to data analytics and user interfaces). In a practical demonstration, Ramos et al. [180] built a DT for a district metering area in Lisbon, Portugal, and used it to develop leakage reduction strategies, comparing two different implementation approaches for DT integration into existing operations. Krejcik [181] also described how emerging digital technologies such as AI and DTs are aiding water utilities in tackling issues like leak reduction, asset maintenance, efficiency improvements, and water quality assurance. Despite these advances, achieving a fully functional DT for an entire water distribution network remains an open challenge. It likely requires coupling a calibrated hydraulic model of the entire system with rich infrastructure data (GIS maps, asset conditions) and real-time consumption patterns. Researchers have suggested that high-resolution hydraulic models (even computational fluid dynamics sub-models for critical areas), combined with network energy analysis, could identify operational adjustments for energy savings and loss reduction.

In recent years, attention has shifted to practical frameworks and advanced analytics to bridge the gap between prototype models and operational distribution twins. Ostfeld and Abhijith [70] laid out a staged migration path for utilities to evolve their static hydraulic models into self-updating, self-learning DTs. Their roadmap involves sequential steps: improving data acquisition (adding sensors and telemetry), performing hydraulic model calibration, enabling real-time model updates with incoming data, and finally tracking the value generated by the DT to justify its integration into routine operations. Building on this, Quaranta et al. [77] examined how European Union digitalization initiatives (e.g., funding programs and standards development) can accelerate these kinds of integrated deployments in support of water-sector decarbonization goals.

On the methodological front, several innovations have emerged to enhance distribution network monitoring and control. Brahmbhatt et al. [182] fused a hydraulic simulation model with live sensor streams in an Indian city's district metered area (a subdivided network zone) to create a DT that optimizes chlorine residuals and pump schedules in real time. They demonstrated improved maintenance of water quality and energy efficiency through this real-time model predictive control approach. Chew et al. [68] introduced an online calibration routine for distribution system models, which continuously adjusts diurnal demand patterns based on pressure sensor feedback. This helps the DT model stay accurate as consumption behavior changes, improving its usefulness for pressure management and leak detection. In the realm of leak localization, Gómez-Coronel et al. [102] coupled an Extended Kalman Filter with a grey-box hydraulic model to identify the likely locations of leaks. Mücke et al. [183] took a probabilistic approach, generating leak probability maps by combining a stochastic hydraulic surrogate model with a conditional random field that accounts for spatial correlations in leak occurrences. These methods significantly enhance a twin's ability to pinpoint leaks quickly and reliably.

Cybersecurity considerations for distribution DTs are also gaining prominence. Katulić et al. [184] proposed a lightweight cryptographic scheme tailored to DT-enabled control loops in water systems, aiming to secure communications (such as sensor readings and control signals) without overburdening limited-resource devices. Expanding the toolkit for researchers and practitioners, Batarseh et al. [49] released the open-source ACWA testbed, a combined hardware–software platform that emulates a water distribution system with cyber components, to facilitate testing of intrusion detection and response algorithms in a DT context.

Publications from 2024 and 2025 have started reporting on full-scale implementations and field trials of water distribution DTs, indicating a consolidation of earlier research into practice. Fu et al. [185] deployed an event-triggered control scheme within a pressure zone twin, which successfully reduced pipeline burst risk by dynamically adjusting pressure settings, all while maintaining service levels for customers. Menapace et al. [186] trained a graph neural network as a fast surrogate model for leak detection; integrated into a DT, it can localize a leak within seconds of a pressure anomaly being observed. In Denmark, Kallesøe et al. [187] demonstrated a cloud-hosted cyber-attack detection system linked directly to digital replicas of pump station PLCs (programmable logic controllers), enabling real-time identification of malicious interventions in pumping operations. Sinagra et al. [188] showed how data-driven hydraulic emulators (simplified, AI-driven models of network behavior) can be used to recover energy from excess pressure head in water networks, for instance by guiding the operation of in-line microturbines to generate electricity without compromising service pressure. Finally, Travaš et al. [189] reported a hardware-in-the-loop DT built around low-cost microcontrollers and edge computing devices for real-time leak detection in Croatian distribution zones. This twin processes pressure and flow data at the network edge and feeds results to a central dashboard, illustrating a practical, field-ready DT solution that leverages affordable technology. These latest examples show how the earlier theoretical frameworks, service architectures, and security measures are now being translated into day-to-day operational tools. In summary, the water distribution network domain is seeing its DTs move from concept to reality, with demonstrable benefits in leak management, energy optimization, and system security.

Appendix C.5. Drinking Water Treatment

This category covers unit processes that convert raw surface or ground water into potable water, including coagulation/flocculation, sedimentation, filtration, disinfection, and in-plant pumping. In recent years, the application of AI, machine learning, and "smart" design principles to water treatment has grown substantially. Within this context, DTs have the potential to greatly improve the sustainability and resilience of water treatment systems by providing capabilities for process optimization, distribution network management, predictive maintenance and repair, leakage detection and reduction, emergency response, and system expansion planning.

Early investigations relevant to drinking water DTs concentrated on anomaly detection and cyber-physical system (CPS) monitoring. Inoue et al. [71] applied two unsupervised machine learning models for anomaly detection in a water distribution CPS. They compared a DNN against a one-class support vector machine (SVM) and found that while DNN produced fewer false positives, the one-class SVM detected a broader range of anomalies. The following year, Chen et al. [72] developed a deep learning method to detect anomalies in drinking water quality time-series data. Their approach used a convolutional neural network to preprocess raw sensor inputs and a BiLSTM network (optimized with the Adam algorithm) to capture temporal patterns, successfully identifying deviations in water quality that could indicate incidents like contamination or sensor faults.

Subsequent research has extended DT concepts to equipment maintenance and operational optimization in water systems. Wang et al. [73] proposed a DT-based predictive maintenance model for hydraulic electromechanical devices common in water utilities and industrial water systems. By using transfer learning in conjunction with a DT, their model could more accurately predict the remaining useful life of pumps and valves, leading to improved maintenance decision-making compared to traditional prognostics. Wei et al. [74] introduced a coverage-based model updating framework aimed at improving the real-time predictive accuracy of models in a water treatment facility. They observed that excessively long training times can actually worsen prediction errors due to overfitting or concept drift; thus, they recommended limiting the size of training datasets to maintain an optimal balance between computational time and accuracy in online model updates. In a related effort, Huang et al. [75] explored the use of long-term continuous monitoring (LTCM) in water systems. By deploying a dense sensor network that operates with minimal maintenance over extended periods (collecting data at intervals of less than one hour), they demonstrated that high-temporal-resolution data streams can significantly enhance the detection of gradual changes and transient events throughout water treatment and distribution processes.

Researchers have also presented broader digital transformation frameworks for water utilities. For example, Carvalho [76] described a framework that combines BIM with asset management principles to address the challenges faced by Brazilian water and wastewater companies. This approach integrates detailed physical asset models with operational data and socio-environmental considerations, aiming to improve decision-making in a holistic, sustainability-aware manner. Several studies have surveyed emerging technologies and begun to outline pathways toward actual water supply DT implementations. Fu et al. [190] reviewed deep learning algorithms and their potential applications in the water sector, specifically noting how such algorithms could be used to develop smarter control systems and predictive models within water supply DTs. Savić [191] discussed recent technological developments influencing the water industry—including IoT, advanced sensors, and DTs—and used a forensic engineering lens to analyze major failures in other industries (e.g., dam collapses, chemical spills) to derive lessons that can inform the design of robust water infrastructure DTs. Zekri et al. [101] proposed a framework grounded in the DT paradigm combined with multi-agent systems for water demand management in Oman. In their framework, autonomous agents (software modules) within the DT perform data analytics on consumption patterns and then generate feedback to help select appropriate dynamic pricing strategies, illustrating an intelligent demand-side management application of DTs.

Building on this groundwork, recent contributions (2023–2025) have started linking individual digital solutions into more cohesive, large-scale DT architectures for water treatment and supply. Quaranta et al. [77] framed DT development within the context of the European Green Deal, showing how policy-driven incentives for decarbonization could accelerate the adoption of DT technologies in drinking water and wastewater utilities. They emphasized that aligning DT projects with broader environmental and digital transition policies can provide funding and momentum for implementation.

During 2024, focus in the literature shifted to demonstrating full-scale platforms, advanced control algorithms, and cyber-physical security measures for water treatment twins. Zhang et al. [78] conducted a comprehensive survey of modeling techniques from continuum-scale down to pore-scale for processes like reaction kinetics and membrane fouling in filtration systems. They described how multi-angle numerical twins, combining models at different scales, can bridge the gap between detailed process design and on-line optimization in treatment plants. Moving into active control, Wang et al. [79] embedded a deep deterministic policy gradient (DDPG) reinforcement learning agent within a treatment plant's DT to adjust chemical dose. The AI based process controller proposed in this paper is a new idea of deep reinforcement learning applied to chemical process control optimization. At the system integration level, Rodríguez-Alonso et al. [80] deployed a microservices-based, edge-computing DT platform at two full-scale drinking water treatment plants in Spain. Their platform aims to optimize the operation and maintenance processes of the plant's systems, by employing machine learning techniques, process modeling and simulation, as well as leveraging the information contained in BIM models to support decision-making. To enhance human readiness against cyber-physical threats, Sarshartehrani et al. [81] created a virtual reality training environment linked to a treatment plant DT, enabling operators to practice responding to simulated cyber-attacks or process upsets in a realistic but safe virtual plant. Complementarily, Moradi et al. [192] introduced the CRYSTAL framework, which couples formal verification methods (to check control logic) with coordinated detection and response strategies, in order to harden treatment plant control systems against cyber intrusions. At the unit process scale, improvements were also noted: Zhou et al. [82] implemented a DT-based dynamic scheduler for high-lift pump stations, achieving a 9.8% reduction in specific energy consumption by optimizing pump combinations and set-points in real time. Belay et al. [193] developed an unsupervised anomaly detection algorithm using low-rank and sparse matrix decomposition to detect multivariate sensor faults or anomalous events in treatment plant data within three sampling intervals, improving DT's ability to maintain data quality and early warning of issues.

By 2025, we see these various elements converging into more hybrid, self-adapting DTs for drinking water treatment. Zhang et al. [83] reported a coagulation process DT that automatically switches between a first-principles jar-test simulation and a lightweight LSTM surrogate model depending on raw water quality conditions. This adaptive twin-maintained prediction root-mean-square error below 0.2 NTU for effluent turbidity across a range of influent water conditions, illustrating how combining mechanistic and AI models can yield robust performance. Collectively, the advancements in the recent studies, including policy-aligned governance frameworks, service-oriented data architectures, advanced reinforcement learning policies, edge-to-cloud deployment platforms, and enhanced cyber-resilience techniques, represent critical building blocks in transforming water-treatment DTs from isolated algorithmic tools into integrated, plant-wide decision support systems. These building blocks are pushing the water treatment sector closer to realizing the full promise of DTs for safe, efficient, and sustainable water service delivery.

Appendix C.6. Water Reclamation

Water reclamation and reuse, treating wastewater to a level suitable for reuse in applications like irrigation, industrial processes, or even indirect potable use, has become one of the most sustainable strategies to address water scarcity. This is especially true in arid regions and places facing moderate to severe water shortages (e.g., parts of the Middle East, North Africa, and western United States). Numerous studies have highlighted the importance of advanced digital tools in designing and operating water reclamation facilities. Applications of smart automation, AI, and DT technology are increasingly being explored for such systems (which are also known as water resource recovery facilities, or WRRFs). Notably, a water reclamation system typically includes both a treatment component and a distribution component (to deliver reclaimed water to end uses), thus inheriting the complexities of both domains (treatment and distribution). This dual complexity further motivates the use of DTs to coordinate and optimize the entire reuse process.

Some early efforts have examined how DT concepts might apply to water reuse facilities. Curl et al. [84] discussed DTs as a next-generation tool to aid the operations of advanced water purification facilities. Their study anticipated that DTs could help operators manage the multi-barrier treatment processes often used in reuse (such as microfiltration, reverse osmosis, advanced oxidation, etc.), by providing real-time insights and predictive control. C. Yang et al. [85] designed a real-time adaptive dynamic model—essentially a type of soft sensor combined with an observer—for a WRRF, using the SUMO simulation platform. They employed an Extended Kalman Filter to transform a static grey-box process model (which merges empirical data and mechanistic knowledge) into an adaptive model that could adjust its parameters as conditions changed. This virtual plant was able to accurately estimate ammonia concentrations at various treatment stages in real time, thereby supporting advanced process control and operations for the facility.

Recognizing that hybrid modeling approaches can be very powerful for complex processes, Schneider et al. [20] and Torfs et al. [29] both examined the benefits of combining mechanistic and data-driven models in wastewater treatment and reclamation. They discussed how such hybrid models (and other simplified surrogate models) could be integrated into DT frameworks for WRRFs to capture the best of both worlds: the interpretability and reliability of first-principles models, and the adaptability and precision of machine-learning models. As part of improving data utilization in WRRFs, Therrien et al. [168] addressed how raw operational data can be converted into actionable insights. In their review, they specifically asked how the data pipeline in WRRFs (from sensor measurement to data cleaning, storage, and analysis) can be improved to support advanced tools like DTs. Their conclusions pointed to the need for better data organization, quality control, and analytical techniques to fully leverage the information available in modern WRRFs. Along similar lines, Quaghebeur et al. [194] compared different modeling strategies—purely mechanistic, purely data-driven, and hybrid—for simulating flow rates in a WRRF. They found that a hybrid model (combining elements of both approaches) provided the best accuracy in estimating key operational parameters, reinforcing the value of hybrid DT models for reclamation facilities.

In addition to process models, realistic input characterization is crucial for water reclamation DTs. F. Li and Vanrolleghem [86] developed an Influent Generator ANN to produce realistic, high-resolution influent wastewater time series for WRRFs. While this tool was not itself part of a DT, it can serve as a valuable module for testing and developing DTs by providing synthetic but realistic influent patterns (including variability and extreme events) on which to run simulations or control algorithms. Turning to implementation, only a small number of projects have ventured toward actual full-scale DT deployment in reuse systems. Patriarca et al. [87] created what they termed a semi-DT by linking a MATLAB/Simulink process model with an EPANET hydraulic model to simulate an entire water reuse system (a seawater reverse osmosis plant in Israel coupled with its product water distribution network). They used this setup to assess the system's cyber-resilience under various scenarios. However, because it lacked real-time data feeds and automated control, it was essentially a sophisticated modeling study rather than a live DT. Lian et al. [88] took a significant step closer to real implementation: they deployed three pilot-scale membrane capacitive deionization units (an emerging technology for desalination/reuse) in remote areas of China and Australia, each paired with a DT for monitoring and control. These DTs provided remote visibility into the units' performance in treating brackish water or secondary effluent and allowed the researchers to adjust settings and maintain optimal operation from afar. The Lian et al. study was one of the closest to a true design-and-implementation of a DT for water reuse, containing most of the needed elements for a functional system (real-time data, control algorithms, and remote decision support).

Recent literature shows a trend toward integrating these individual advances into broader frameworks and demonstrating them at larger scales. At the treatment-plant level, Schroer et al. [172] mined historical SCADA data from a U.S. wastewater co-digestion facility (which co-treats wastewater solids with organic wastes) and built a machine-learning surrogate model to serve as its DT. By careful feature engineering and training of a supervised learning model, they managed to forecast daily biogas production with 14.2% lower error than baseline regression models. This kind of predictive twin can help operators anticipate energy production and adjust feeding rates or process conditions accordingly.

Work published in 2024 translated much of this strategic groundwork into full-scale, real-time DT implementations for water reclamation. Serrao et al. [89] developed a hybrid DT for a very large WRRF by coupling a modified Activated Sludge Model (incorporating biofilm processes) with a feed-forward neural network. After training on 15-min interval data, their hybrid twin was able to reduce the error in nitrate concentration predictions from about 12% (with a purely mechanistic model) to 2% in training (and ~8% in a validation test). The model is structured to directly interface with a model predictive control system, for example to optimize carbon source dosing for nutrient removal in near-real-time. At the same time, Daneshgar et al. [35] reported a plant-wide operational twin at the full-scale Eindhoven WRRF in the Netherlands. Their twin continuously runs two-hour-ahead simulations of the entire plant (updated every hour), incorporating 48-h ahead influent flow and load forecasts. This allows operators to use the DT to stress-test "what-if" failure scenarios (like a blower failure or a process upset) in silico and adjust controls proactively, essentially providing a real-time decision support. In parallel, Khalil et al. [91,92] focused on the pressing issue of greenhouse gas (particularly nitrous oxide, N_2O) emissions from WRRFs. In one study, they used an mRMR (minimum redundancy maximum relevance) algorithm and an NSGA-II genetic algorithm to select a compact set of input features and then trained an AdaBoost ensemble model (R^2 = 0.94) for online prediction of N_2O emissions across three full-scale facilities. In another, they calibrated a detailed biofilm-and-floc process model as a twin to investigate trade-offs in N_2O production under different sidestream nitrogen removal strategies. Together, these works contribute to making DTs not only operationally useful but also environmentally aware. Additionally, Molin et al. [90] compared two architectures for DT data pipelines at WRRFs: one using a traditional historian database interface and another using edge computing devices for on-site data processing. Both approaches achieved sub-minute latency in updating the twin with new data and deploying soft sensor predictions, proving that real-time or near-real-time twins are feasible with current technology. On the industrial reuse side, Alferes et al. [93] deployed a sensor network-driven twin in an industrial cooling water reuse loop. Their twin integrated a salinity transport model with the cooling tower's control system and demonstrated reductions in freshwater intake and energy consumption by dynamically adjusting operations based on the twin's predictions (for instance, modulating blowdown rates to maintain water quality while saving water and energy).

In summary, recent studies are adding crucial pieces to the puzzle of practical water reclamation DTs. They bring together policy-aware governance frameworks, service-oriented data architectures for interoperability, hybrid modeling techniques that blend mechanistic understanding with AI flexibility, automated data pipelines for continuous model calibration, and performance metrics that include greenhouse gas emissions and sustainability indicators. These elements are collectively advancing water-reuse DTs from proof-of-concept pilots toward integrated, plant-wide decision support systems. As these building blocks mature, we can expect water reclamation facilities to increasingly adopt DTs that help optimize their operations for reliability, efficiency, and environmental performance.

Appendix C.7. Water Desalination

The energy-intensity and popularity of desalination technologies (e.g., RO) place them in the center of focus for further improvement to lower the overall costs, energy consumption, and environmental footprints, as well as increasing efficiency and recovery rates. In this regard, applications of smart design and informed decision-making are becoming increasingly more adopted to achieve sustainability goals in water desalination. In this context, Alsarayreh et al. [95] reviewed the simulation and optimization studies that have previously focused on improving the RO processes. The studies include approaches to (1) measure the influence of control parameters on the performance indexes; (2) adjust the key variables at optimized values; (3) find the optimum production values. Prior to that, Rivas-Perez et al. [94] developed a real-time expert model predictive controller for a pilot-scale brackish and seawater desalination plant. The pilot plant and the controller were designed to obtain the optimal operational parameters for a RO desalination plant in Peru by implementing different control strategies. A dynamic mathematical representation model of the plant was developed to estimate and predict the outcomes. Additionally, Gunter et al. [96] designed a DT to predict the specific energy consumption (kWh/acre-foot) and applied it to the Santa Barbara, CA desalination plant. Finally, van Rooij et al. [97] built a DT as a decision support system to optimize membrane cleaning and replacement process in an RO desalination plant that was experiencing biofouling due to seasonal algae blooms. The DT was implemented at the Carlsbad Desalination Plant in California. This study is one of the closest efforts to the design and implementation of a full-scale operational DT, including all the required elements for a functioning DT.

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