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Digital Twins for Wastewater Treatment: A Technical Review

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ABSTRACT

The digital twins concept enhances modeling and simulation through the integration of real-time data and feedback. This review elucidates the foundational elements of digital twins, covering their concept, entities, domains, and key technologies. More specifically, we investigate the transformative potential of digital twins for the wastewater treatment engineering sector. Our discussion highlights the application of digital twins to wastewater treatment plants (WWTPs) and sewage networks, hardware (i.e., facilities and pipes, sensors for water quality and activated sludge, hydrodynamics, and power consumption), and software (i.e., knowledge-based and data-driven models, mechanistic models, hybrid twins, control methods, and the Internet of Things). Furthermore, two cases are provided, followed by an assessment of current challenges in and perspectives on the application of digital twins in WWTPs. This review serves as an essential primer for wastewater engineers navigating the digital paradigm shift.

1. Introduction

As an essential resource common to all cities, water and its management are closely related to the quality of life in urban environments. Water management significantly impacts other urban services and their management, making it an essential part of the United Nations' description of smart cities: "inclusive, safe, resilient, and sustainable cities." As part of smart city initiatives, smart water management brings multiple benefits to cities facing risks such as water shortages, water quality deterioration, and security challenges, which are aggravated by aging infrastructure, lack of investment, growing urbanization, and climate change. Therefore, accelerating the water industry's digitalization is imperative, with the adoption of digital twins [1] being a key element. The focus of this paper is on wastewater treatment engineering, which is an essential element of the urban water cycle [2].

Currently, the Fourth Industrial Revolution (Industry 4.0) is in the process of integrating digital technologies and industrial processes to bring about innovative solutions in manufacturing [3], enhancing its dependence on real-time feedback. As part of this revolution, the application of digital twins has been extended from the manufacturing sector to a variety of fields such as medical interventions and virus response [4], biomanufacturing [5], earth system simulation and environmental monitoring [6], climate change mitigation and transportation (specifically smart electric vehicles) [7], food processing and manufacturing [8], energy production (particularly in enhancing methane production through anaerobic co-digestion) [9], and urban planning and development [10]. Along with the application of modeling, simulations, and digital threads, digital twins will accelerate progress in the planning, design, and management of wastewater treatment engineering [11].

As the connection between digital twins and smart water management becomes increasingly evident, there is a growing imperative for wastewater treatment plants (WWTPs) to adapt and optimize their wastewater treatment strategies accordingly [12,13]. This review synthesizes research and applications of digital twins across various facets of WWTPs and sewage networks, aiming to offer insights and guidance for enhancing operational

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efficiency and advancing sustainable wastewater treatment engineering. Section 2 presents a definition of digital twins in the context of wastewater treatment engineering. Section 3 showcases several advances in integrating and implementing digital twins in WWTPs and sewage networks, highlighting the potential of digital twins to significantly enhance these facilities by utilizing the former's core technologies. Section 4 describes two cases that exemplify the capacity of digital twins to elevate operational efficiency and decision-making. Finally, Section 5 summarizes the present challenges, future prospects, and conclusions from this study.

2. Digital twins

2.1. Concept

In the early stages of a budding technology or concept, the clear definition of relevant terms is pivotal. While the digital twins concept bears some resemblance to modeling, simulation, cyber–physical systems, and the Internet of Things (IoT), it has unique characteristics and applications [14], which play a crucial role in the intelligent oversight of WWTPs—a topic that will be delved into in Sections 2.3 and 3.

Originally developed by Grieves in 2005 [1], the digital twins concept was initially devised for industrial and space technologies. Various adaptations have led to a spectrum of definitions catering to different professional needs [5]. Table 1 [11,15–23] presents these definitions chronologically, offering a lens into the diverse interpretations borne from different sectors' requirements.

Today, the concept of digital twins is a dynamic, all-encompassing model, integrating elements such as personnel, products, assets, and processes. This concept fits seamlessly into the wastewater treatment landscape, where the aim is to enhance the development and management of WWTPs. Although the water sector lacks a precedent for a specific digital twins definition, developing a clear definition is crucial to facilitating the extension of digital twins into this arena. Accordingly, we propose the following description within the context of wastewater treatment engineering:

Definition: Using digital models of wastewater treatment structures, digital twins analyze real-time data to predict and adjust their conditions. As they evolve, digital twins enhance environmental decision-making, effectively streamlining control, data use, and integration between the wastewater industry and socioenvironmental interactions.

2.2. Entity

Digital twins serve as a digital counterpart for various entities, including manufacturing assets and production networks. The systems and processes involved in the digital twins paradigm are detailed in Fig. 1.

In this context, a *system* is a network of interrelated entities fostering enhanced decision-making throughout different life cycles, integrating a digital model with an actual entity through well-structured subsystems such as control and security mechanisms [24]. This integration has two main categories: physical entities and abstract entities.

A *physical entity* is present in the real world and stems from human-made elements such as vehicles and products. As each digital twin advances, it encompasses broader scopes such as supply chains, farms, and agriculture [25–28]. These entities are further subdivided into artifact, natural, and social entities, each with its own distinctive roles and origins. An *artifact entity* is a traditional human-made physical entity resulting from the transformation of a *natural entity* for a particular purpose. A *social entity* refers to social groups.

In contrast, an *abstract entity* is formed by isolating universal characteristics from specific entities, serving functions such as scheduling and health monitoring. These entities, which include conceptual models and theories, have the ability to interact and collaborate harmoniously [29].

An integral component of the digital twins concept is *process*, which refers to a chain of interlinked activities or continuous phenomena undertaking a series of changes to achieve desired outcomes [17,28]. These encompass diverse simulations and analyses and fall under categories such as physical processes and virtual processes, each facilitating a transition between the real and virtual realms. These transitions involve meticulous connections comprising different stages to simulate and realize physical and virtual attributes [28].

2.3. Domain

The digital twins framework encompasses several domains: namely, the user domain (UD), the digital twin domain (DTD), the sensing and controlling domain (SCD), and the physical domain (PD). The cross-domain functionalities and their relationships are illustrated in Fig. 2.

In the UD, elements such as human interaction, interface design, application software, and co-intelligent digital twins work in harmony, facilitating the optimal utilization of digital twins [11]. The DTD is responsible for representing the characteristics of physical entities through three vital functions: modeling management, simulation services [30], and twin co-intelligence [31]. These functionalities enable detailed visualization, dynamic simulation, and safe resource accessibility, aiding in data flow and transfer with assured security. The SCD plays a critical role in establishing real-time communication between the DTD and the PD [32]. There are two primary components: the sensing domain and the controlling domain. The sensing domain helps gather vital data from physical objects, whereas the controlling domain effectively implements strategies devised in the DTD. The industrial IoT is leveraged to perceive and convey physical world data. The PD is the realm of tangible components—that is, people, equipment, and processes, where the actual subjects of the digital twin models exist [33]. Cross-domain functionalities ensure a seamless and secure exchange of information across all these domains, promoting the integrated functioning of the system.

2.4. Key technologies

Leveraging the surge in data across diverse fields, digital twins create virtual replicas of physical entities and use cutting-edge tools such as artificial intelligence (AI) and virtual reality (VR) to digitally control and optimize these entities. The architecture of digital twins hinges on model-based system engineering (MBSE), which encompasses modeling, simulation, and digital threads as its core technologies, supported by the IoT as the foundational technology. Cloud computing, machine learning (ML), big data, and the blockchain constitute the ancillary technologies enhancing the capabilities of digital twins. Fig. 3 describes the interrelationships between these technologies.

Modeling, which is foundational to digital twins, simplifies the understanding of the physical world and its problems by portraying the causality or interrelations within a system through a model [34–37]. This critical process involves creating detailed digital representations of physical entities, encompassing their three-dimensional (3D) geometric structure and shape, operational mechanisms, interfaces, and the software and control algorithms they incorporate [38]. These digital twin models can vary

Table 1
Concept of digital twins in different periods.

Time	Proposer	Concept	Ref.
2016	Air Force Research Laboratory, USA	An airframe digital twin is an integrated system of data, models, and analysis tools that represents an airframe over its entire life cycle to provide actionable information for making decisions now (diagnosis) and for the future (prognosis) on a fleet-wide and individual-tail-number basis, considering all sources of uncertainty	[15]
2012	National Aeronautics and Space Administration, USA	A digital twin is an integrated multi-physics, multiscale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin	[16]
2011	Michael Grieves	A virtual product is a use-specific informational or bit-based representation and its associated rule-based environment of a physical or atom-based product and its natural behavior. Virtualization: creating an informational or bit-based representation of a physical or atom-based product. The IMM is a framework for conceptualizing PLM and exploring the implications of the duality of physical and virtual products. The ability to use virtual products in place of their physical counterparts drives the value of the IMM	[17]
2013	Air Force, USA	A digital twin is a virtual representation of a system as an integrated system of data, models, and analysis tools applied over the entire life cycle on a tail-number unique and operator-by-name basis	[18]
2015	General Electric Aviation, USA	Digital twins are software representations of assets and processes used to understand, predict, and optimize performance to achieve improved business outcomes. Digital twins consist of three components: a data model, a set of analytics or algorithms, and knowledge	[19]
2015	Parametric Technology Corporation, USA	A digital twin is a function of things (the devices and products generating data), connectivity (working to bring networks together), data management (cloud computing, storage, and analytics), and applications. As such, they likely will figure heavily into the construction and logic of IoT platforms	[20]
2017	Michael Grieves and John Vickers	The digital twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physically manufactured product can be obtained from its digital twin. Digital twins are of three types: digital twin prototype, digital twin instance, and digital twin aggregate. Digital twins are operated in a digital-twin environment	[21]
2019	CIRP Encyclopedia of Production Engineering, France	A digital twin is a digital representation of a unique active product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors employing models, information, and data within a single or even across multiple life-cycle phases	[22]
2021	ISO CD 23247, International Organization for Standardization	Digital twin: fit-for-purpose digital representation of some realized thing or process with a means to enable convergence between the realized instance and digital instance at an appropriate synchronization rate	[23]
2020	Ansys, USA	Based on the digital model(s) of one or more viewpoint(s) of the existing or future physical entity, the measured data from the physical entity is analyzed and processed through one or more algorithm engine(s) to perceive, diagnose, or predict the state of the physical entity, and then to synchronize the states between the digital model(s) and the physical counterpart, eventually to generate controlling information that optimizes the behavior of the physical entity	[11]

IMM: information mirroring model; PLM: product life-cycle management.

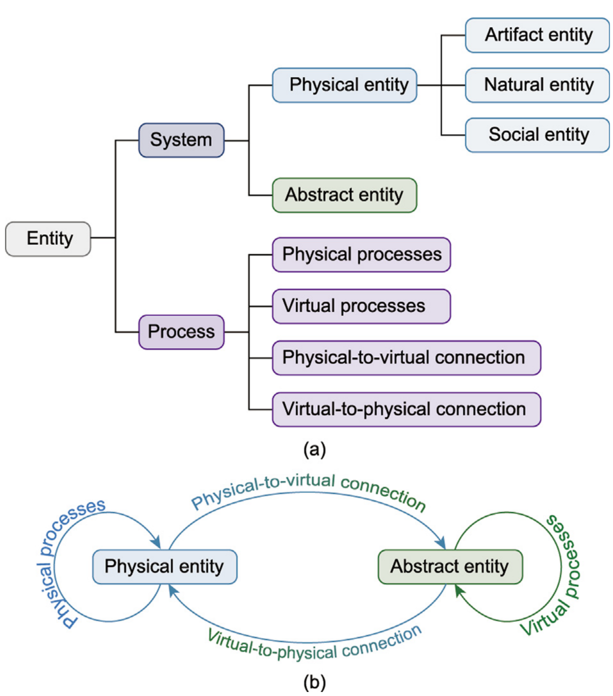

Fig. 1. General entity architecture of digital twins. (a) The entity is divided into two parts: system and process. The system is the twin of the physical and abstract entities, while the process is the twin of the steps. (b) The relationship between the system and the process.

significantly depending on the distinctive characteristics of different physical entities. Currently, tools such as computer-aided design (CAD) and MATLAB are used for foundational modeling, Revit is employed in building information modeling (BIM) [39], and CATIA is leveraged for advanced product life-cycle management (PLM) endeavors [40].

Virtual models are central to the digital twins concept, facilitating high-fidelity digital representations of physical entities across multiple dimensions and scales [33]. This core part of digital twins seeks to represent physical entities accurately and enhance their functionality through an immersive integration of the virtual and real. This necessitates visual and real-time depictions, supported by technologies such as VR [41], augmented reality (AR) [42,43], and mixed reality (MR) [44]. VR serves as a foundational technology, employing computer graphics and dynamic environment modeling to depict the various attributes, behaviors, and rules of physical entities as vividly and realistically as possible. Building upon VR, AR and MR introduce real-time data acquisition, scene capture, and real-time tracking to synchronize and fuse virtual models with physical entities, effectively enhancing the detection, verification, and guidance functionalities. Moreover, the metaverse concept represents an evolved and expansive virtual environment that integrates AR, VR, and MR technologies and content [45].

Technically, modeling and simulation are intertwined. Modeling articulates our comprehension of the physical world or specific challenges, while simulation validates the accuracy and relevance of this understanding [36,46,47]. In industry, simulation employs software to replicate the physical world based on models that integrate both deterministic rules and comprehensive mechanisms, as

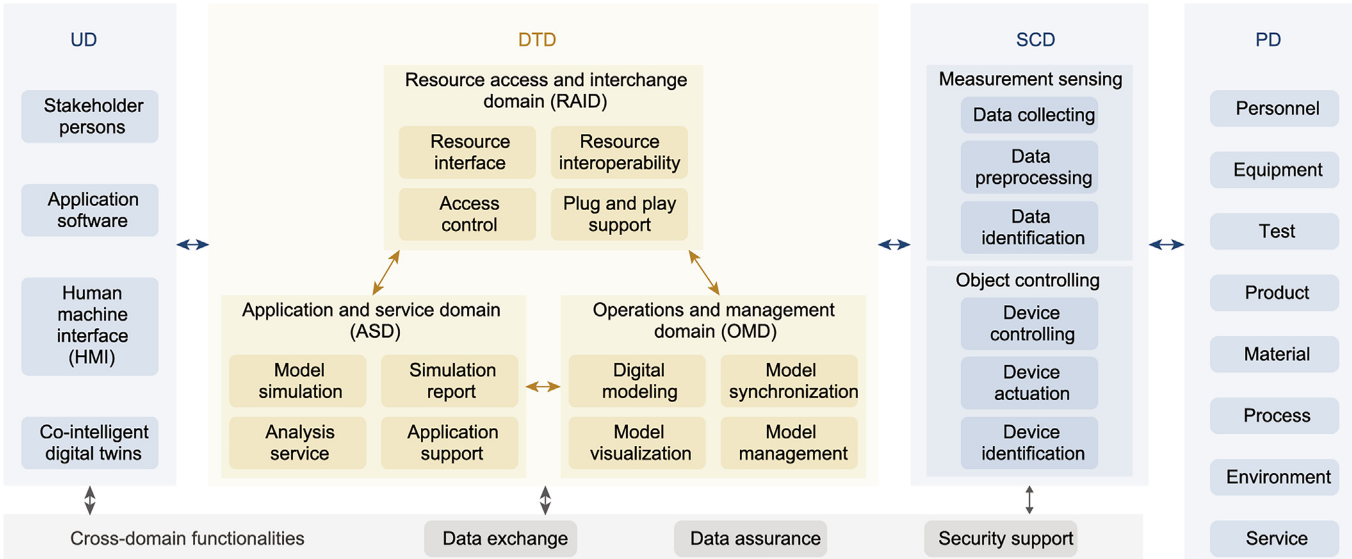

Fig. 2. General domain architecture of digital twins (the figure is adapted from Ref. [11]).

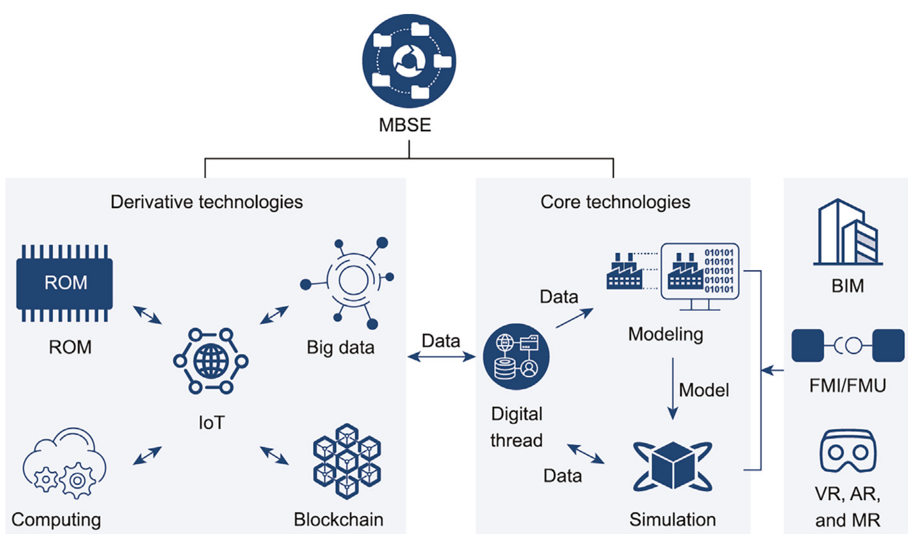

Fig. 3. General key technology architecture of digital twins. BIM: building information modeling; FMI: functional mock-up interface; FMU: functional mock-up unit; AR: augmented reality; MR: mixed reality; ROM: read-only memory.

well as stochastic, knowledge-based models in some cases. If the model is accurate and the input data are complete, the simulation effectively mirrors the attributes of the physical world.

Traditional WWTPs were not conceptualized with digital twins in mind. To modernize these plants for enhanced wastewater treatment efficiency, it is crucial to incorporate both two-dimensional (2D) and 3D model information into one digital model. However, many of these plants currently operate with 2D designs rather than the more advanced BIM model, making graph matching and model reuse challenging.

The functional mock-up interface (FMI) was introduced to address issues such as fragmented simulation tools, limited model reusability, and intellectual property protection [48]. The FMI offers a universal interface standard for model reuse, focusing on both model exchange and the co-simulation of functions and performance. The adoption of FMI makes model integration straightforward. Files exported using the FMI standard are labeled with a ".fmu" extension (functional mock-up units).

Digital threads act as connective bridges between entities, serving as an adaptable enterprise-level communication framework [49]. This structure enables a comprehensive perspective, encompassing cross-level, cross-scale, and multi-view models that span the entire system life cycle and value chain. The primary function of digital threads is to guide system activities throughout their lifespan and aid decision-makers. Essentially, digital threads ensure timely and appropriate information delivery to the right stakeholders throughout the system's life cycle [50].

MBSE is a structured approach for developing digital twins [51–53]. As the cornerstone of digital threads, MBSE leverages IoT data to ensure that simulations can detect potential failures, thus facilitating continuous improvements in existing operating systems.

The IoT acts as the foundation for digital twins [54], gathering information from the Internet, traditional telecommunications, and various tools such as sensors, radio frequency identification (RFID) [55], Global Positioning Systems (GPSs) [56], and laser scanners. This allows standalone objects to be transformed into a connected network, enabling seamless interactions between objects and people. The IoT allows for the intelligent recognition and management of items and processes, facilitating the timely, dependable, and efficient transmission of twin data.

Read-only memory stores fixed programs and data that can be read but not altered, working in a non-destructive readout mode. This system has a simple structure and offers stable data storage, ensuring that data remain unchanged even in the event of a power outage, making it both reliable and user-friendly.

The scalability of digital twins varies based on the demands. While unit-level digital twins might function on a local server, system-level and complex digital twins demand more computational and storage power. Cloud computing [57] caters to these needs by offering extensive resources and data centers, allowing digital twins to adapt to diverse computing, storage, and operational requirements. Fog computing [58] extends cloud computing by distributing resources across numerous decentralized nodes, thereby bringing data processing closer to the edge of the network. This approach enhances operational speed and efficiency by leveraging localized processing. Complementarily, edge computing directly processes data at or near its source, further optimizing real-time data analysis for improved perception, calculation, and control at edge nodes [59]. In tandem with cloud computing, edge computing forwards intricate twin data to the cloud for advanced processing. This cloud–edge collaboration addresses varied requirements, boosts data processing speeds, minimizes the cloud data burden, and curtails data transmission lags. In this way, the real-time functionality of digital twins is significantly enhanced. Notably, system-level digital twins are well aligned with fog computing, given their primary concentration within manufacturing enterprises and specific geographical locales.

Data are a dynamic and rapidly changing asset, requiring innovative processing techniques to enhance decision-making, insight, and optimization. Big data [60] leverages the voluminous data created by digital twins to elucidate and forecast real-world outcomes and processes, thereby extracting precious information. As a complement to this, ML [61] facilitates the automatic analysis of data to derive rules that can be used for predictions. Digital twins use ML to forecast future states and behaviors through data harvested from the PD through the IoT, offering valuable (albeit potentially imprecise) insights. Hence, big data and ML are invariably linked, working in tandem to provide a rich analytical foundation.

Digital twins represent digital assets and participate in digital transactions. Leveraging blockchain technology [62] has the potential to enhance the security of digital twins by preventing unauthorized alterations that could result in errors and deviations. This fosters a safer environment that promotes innovation. Furthermore, the decentralized trading mechanisms facilitated by the blockchain ensure secure, distributed, and real-time digital asset transactions, thus providing an optimal medium for digital twins' asset trading and fostering user trust in the services provided by digital twins.

In conclusion, the successful implementation and application of digital twins hinge on support from emerging technologies [63]. Through deep integration with these technologies, digital twins can achieve an authentic and comprehensive perception of physical entities. This involves the precise creation of multidimensional, multiscale models, extensive data fusion, customizable service usage, and full-scale, dynamic, real-time interaction.

3. Applications for WWTPs and sewage networks

3.1. Facilities

With advances in digital twins, accompanied by progress in modeling and simulation techniques, WWTPs have seen significant improvements in their facilities (Table 2 [64–70]). These developments have been observed in structures such as secondary settling tanks, biological aerated filters, and primary clarifiers, enhancing their treatment efficiency to a considerable extent. Advances have been driven by the use of ML to optimize the operation of essential equipment such as water pumps, air blowers, sludge pumps, and mixers in the trial stage, fostering their readiness for real-world applications.

In recent years, substantial advances have been made in various aspects of water treatment technology. For example, in terms of settling techniques, the amended Vesilind function for hindered settling has been developed and validated, leading to a new exponential function addressing the compression settling velocity [64]. This theme of refinement has continued with the verification and simulation of critical parameters (including the hydraulic loading rate, organic load rate, and surface area of packing materials) used in a packed-bed up-flow anaerobic sludge blanket followed by a biological aerated filter—a project undertaken by the Water Research Department at the National Research Center in Cairo, Egypt [65].

Progress has also been observed in pump technology. In 2016, Kim et al. [66] enhanced the hydrodynamic performance of single-channel pump impellers using a contemporary design approach. Building upon this, in 2020, the same team improved the hydraulic performance and prediction accuracy of two-vane pumps through the resolution of steady Reynolds-averaged Navier–Stokes equations [67]. In parallel, work spearheaded by Lozano Avilés et al. [68] capitalized on advanced flow modeling techniques to address deficiencies in fluid distribution and mixing, successfully reducing the necessary airflow to the reactor by over 3%.

Adding to the wave of innovations, advances facilitated by computational fluid dynamics (CFD) calculations in Ansys Fluent have

Table 2
Application of digital twins in WWTP facilities.

Facility	Specific facility	Year	Location	Application	Method	Ref.
Structure	Secondary settling tanks	2020	Europe	Lab	Settling column sensor, full-scale data, CFD	[64]
	Packed-bed up-flow anaerobic sludge blanket	2016	Egypt	Lab	Hydromantis GPS-X, modeling, simulation	[65]
Water pump	Single-channel pump	2016	Republic of Korea	Lab	CFD, Bezier curve	[66]
	Two-vane pump	2020	Republic of Korea	Lab	ML-based surrogate modeling	[67]
Air blower	Aeration installation	2020	Spain	Lab	Flow modeling, simulation, CFD	[68]
Sludge pump	Sludge pump	2012	Czech Republic	Lab	Ansys Fluent, CFD	[69]
Mixer	Submersible mixer	2011	China	Industry	Reverse engineering, three-coordinates measuring machine, 3D solid model	[70]

CFD: computational fluid dynamics.

underscored the improved applicability of vortex impellers in sludge pumps, marking a significant step in this domain [69]. These developments, which are characterized by enhanced mixing, propulsion, and abrasion resistance of the impellers, have been successfully implemented in Zhenjiang, China, demonstrating the real-world impact of this research [70].

3.2. Pipes

The evolution of water management has been deeply influenced by the integration of digital technologies, especially in the modeling and management of underground pipe networks. The advent of 2D and 3D pipe network models, developed with the help of CAD, Ansys computational fluid dynamics X (CFX), BIM, geographic information systems (GISs), and integrated catchment modeling (ICM) software, has paved the way for a unified standard in information digitization. This comprehensive approach not only enhances the monitoring and simulation of water flow and quality but also bolsters the prediction and verification of pollutants and streamlines the management of these intricate underground networks (Table 3 [3,71–79]).

In a notable application, China successfully launched a digital management platform for urban sewage networks in Sanya, Hainan Province. This innovative system integrates a sewage information control center with digital management, dynamic simulation, and emergency grid management. The system's prowess lies in its ability to perform dynamic simulations of drainage networks, employ GIS spatial management and analysis, and conduct meticulous sewage network grid management [71].

Further advances include the creation of an urban rainstorm model in Guangzhou's Donghaochong Basin. This model analyzes the interception efficacy in regard to combined sewer overflow pollution and assesses flood mitigation levels [72]. Using hydraulic and hydrological datasets generated by the US Environmental Protection Agency's Storm Water Management Model (EPA-SWMM), Sun et al. [73] explored how the flow rate, rain intensity, and pipe length influence the outputs from total suspended solids models in the Bordeaux region of France. On a more technical note, Fedorov et al. [74] investigated the two-phase flow dynamics of wastewater streams and a mixture of air and hydrogen sulfide, pinpointing areas of intense emission. Moreover, the quality of data has been the focus of several studies. Nie's [75] work emphasizes the validation and refinement of semantic and topological data, ensuring minimized data loss and fostering collaboration among various underground construction stakeholders. In summary, the digital transformation—manifested in the form of unified information systems [76] and web platforms [3]—underscores a pivotal shift toward standardized digitization in underground water management.

3.3. Sensors for water quality

To adapt to increasingly strict environmental regulations, future WWTPs will require intelligent control mechanisms empowered by AI. A core part of this progression is the development of data collection and processing [80], which are facilitated through the extensive deployment of water quality sensors. This makes the establishment of centralized and standardized databases imperative. These databases will not only store information for ongoing water quality monitoring but also integrate seamlessly with IoT software to foster online management systems, consequently reducing the costs associated with personnel training and other related expenses [81].

The supervisory control and data acquisition (SCADA) system is central to this transformation, assimilating data from various sensors to enable the autonomous optimization of process parameters and overseeing the functioning of aeration systems in WWTPs (Table 4 [81–89]). Leveraging SCADA will streamline water quality monitoring, allowing for real-time parameter measurement without the need for sampling or extensive user training, thereby supporting informed decision-making in wastewater treatment [82–84].

Another pivotal component in this landscape is metadata, which is primarily used for data collection and storage. Platforms such as Bluemix facilitate the acquisition and integration of both historical and real-time water data, spanning quantitative and qualitative metrics over extensive stream distances and thereby enhancing real-time water quality monitoring [85]. This inclusive database structure, underscored by a focus on metadata, ensures easy access to standardized, centralized data, thoroughly documenting all pertinent information associated with measurements [81].

Recent initiatives highlight the fruitful application of these technologies. In Xiamen, China, an online water quality management system has successfully stabilized urban scenic river water quality, leveraging data analytics to regulate the freshwater supply from Xinglin Bay [86]. AquaSat also promises to be a rich resource for future *in situ* water quality assessments [87].

The efficacy of SCADA has been demonstrated globally, including in Romania, where it governs WWTP operations autonomously while maintaining optimal technological parameters and recording vital operating data [84]. Similarly, in the Republic of Korea and China, SCADA has played a critical role in monitoring aeration systems and enhancing water quality, illustrating its crucial role in the modernization of WWTPs [88,89].

3.4. Sensors for activated sludge

In WWTPs, sensors play an integral role in identifying and detecting the diverse states and properties of activated sludge,

Table 3
Application of digital twins in WWTP pipes and sewage networks.

Project	Year	Location	Application	Method	Ref.
Network	2014	China	Industry	GIS, IoT, wireless sensor networks, RFID	[71]
	2016	China	Industry	SWMM	[72]
	2020	Spain	Lab	SWMM	[73]
	2019	Russia	Lab	Ansys CFX	[74]
	2019	Netherlands	Lab	BIM, GIS, CityEngine	[75]
	2019	China	Lab	SuperMap.Net, OpenSceneGraph Binary, levels of detail	[76]
	2020	Europe	Lab	Directed graph from PI&D in Proteus DEXPI format, 3D CAD models in PCF format	[3]
Flow	2014	China	Industry	Steady flow, kinematic wave, dynamic wave	[71]
	2018	Poland	Lab	Quantum GIS, SWMM	[77]
	2020	Malaysia	Lab	SuperMap, GIS, Infoworks ICM software	[78]
Water quality	2016	India	Industry	IoT, Wi-Fi, cloud storage	[79]

SWMM: storm water management model; PI&D: piping and instrumentation diagram; DEXPI: data exchange in the process industry; PCF: piping component file; Wi-Fi: wireless fidelity.

and their application is set to expand in the future. Technologies such as soft sensors, liquid chromatography–tandem mass spectrometry (LC–MS/MS), low-field ^{1}H nuclear magnetic resonance, and independent component analysis facilitate a range of assessments, enabling the identification of sludge bulking [90], the detection of quorum sensing signal substances from both water and solid sludge phases [91], and the measurement of water content and moisture distribution within the sludge [92]. Moreover, these tools determine the quantities of different water types in wastewater sludge by assessing the relevant parameters [93]. Research related to these advances has been extensively undertaken in Poland, China, and Finland (Table 5 [90–93]).

3.5. Hydrodynamics

The design of a WWTP is predominantly influenced by the target pollution removal rate, with the efficiency largely depending on the hydrodynamics of the bioreactors incorporated in the WWTPs. The development of CFD, the compartment model, and the tanks-in-series (TIS) model has enabled the modeling and prediction of these hydrodynamic characteristics, which are crucial in predicting the relevant parameter values and aiding in the removal and degradation of pollutants (Table 6 [94–103]).

The use of CFD has facilitated the prediction and determination of a range of parameters. For example, Matko et al. [94] leveraged CFD to enhance the design of oxidation ditches and aerators by forecasting the gas–liquid flow pattern and dissolved oxygen distribution. Similarly, CFD was applied by Elhalwagy et al. [95] to identify the relationship between suspended solids (SS) and the efficiency of a new disinfectant in a municipal contact tank. Other research groups have used CFD to optimize conditions for pollutant degradation in different reactor setups [96–99].

Complementing this, the compartment model and TIS model have further refined the prediction accuracy. Hormann and Fischer [100] improved the forecasts of radioiodine movement in public sewer systems, while Ng [101] focused on predicting the transport of urban radiocesium during wet weather events. Moreover, studies have examined the qualitatively the reactor's mixing regime [102] and quantified accurate values of mobile volume and immobile volume [103].

3.6. Power consumption

The design of WWTPs necessitates careful consideration of power consumption—a demand propelled by global population growth, industrial advancements, lifestyle alterations, and climate change. The surge in energy requirements poses a substantial

Table 4
Application of digital twins in sensors for WWTP water quality.

Project	Year	Location	Application	Method	Ref.
Metadata	2013	China	Industry	Online water quality monitoring, digital data transmission, and data processing	[86]
	2016	India	Industry	Hanna Instruments 9829, IoT, Wi-Fi	[85]
	2019	—	Lab	Big data, Structured Query Language	[81]
	2019	USA	Lab	Overlapping of *in situ* water quality monitoring, Landsat imaging schedules, Python	[87]
SCADA	2013	China	Industry	Online water quality monitoring, digital data transmission, and data processing	[86]
	2016	India	Industry	Real-time sensors, Bluemix, heatmap	[85]
	2017	India	Lab	Multi-parametric sensors, smartphone, Bluetooth, ad hoc network	[82]
	2020	Spain	Industry	IoT, wireless sensor networks, ion chromatography detection, nitrate and nitrite analyzers	[83]
	2020	China	Industry	Current sensors, water quality sensors, Hydromantis GPS-X 7.0	[88]
	2021	Romania	Industry	Sensors and actuators, PLCs, HMI, virtual private networks	[84]
	2022	Republic of Korea	Lab	Sewage wastewater monitoring system, IoT	[89]

PLCs: programable logical controllers; HMI: human machine interface.

Table 5
Application of digital twins in sensors for activated sludge of WWTPs.

Year	Location	Application	Method	Measurement	Ref.
2020	Poland	Lab	Soft sensor, classification model	Temperature in the activated sludge chambers, quantity and quality of wastewater	[90]
2018	China	Lab	LC–MS/MS	Type and concentration of acyl homoserine lactones	[91]
2016	China	Lab	Low-field ^{1}H nuclear magnetic resonance	Directly measure	[92]
2016	Finland	Lab	Independent component analysis	Water content, nuclear magnetic resonance relaxation data	[93]

Table 6
Application of digital twins in WWTP hydrodynamics.

Project	Year	Location	Application	Method	Measurement	Ref.
CFD	2018	UK	Lab	An Euler–Lagrange CFD model	Velocity, shear rate, apparent viscosity flow patterns, and the concentration of a non-diffusive scalar tracer	[98]
	2021	UK	Lab	CFD	Gas–liquid flow, oxygen mass transfer, dissolved oxygen	[94]
	2020	India	Lab	Ansys Fluent software, Gambit software	Inlet concentration of 4-CP, flow rate, bed height, and porosity	[96]
	2021	Indonesia	Lab	Minitab 17, Ansys Fluent 18.1	Water velocity, pipe diameter	[97]
	2021	—	Lab	Exposure inactivation rate expression	SS, *Escherichia coli*, peracetic acid	[95]
	2021	India	Lab	Standard k–ε turbulence model	Plane of inlets	[99]
Compartment model	2018	Germany	Lab	A compartment model of radioisotope ^{131}I reaction flow	Inflow and outflow radioisotope ^{131}I	[100]
	2019	Japan	Industry	SWMM, STELLA software	Surface fixation, wash-off coefficients	[101]
TIS	2005	Spain	Lab	TIS	LiCl	[102]
	2013	France	Lab	Stirred TIS	TOC, NaCl, DO, pH	[103]

4-CP: 4-chlorophenol; TOC: total organic carbon.

challenge for WWTPs, especially in the context of the push for carbon neutrality and the imposition of energy limitations. Leveraging data-driven soft-sensor methodologies, which incorporate traditional time series and deep learning, enables the formulation of power consumption predictive models for WWTPs, facilitating the reduction of energy use during the initial stages of water treatment (Table 7 [88,99,104–111]).

Sean et al. [88] used current and water quality data to forecast optimal airflow rates and energy expenditure, offering a valuable reference for the initial phase of plant operation, while Saini et al. [99] explored the energy dynamics of pumped recirculation in an existing anaerobic digester, focusing on the inlet planes. Moreover, Harrou et al. [104] and Cheng et al. [105] have attempted to predict the short-term energy needs of WWTPs using flow rates, temperature data, and biochemical oxygen demand, fostering data-driven management of these plants. In addition, De Canete et al. [106] applied ML to determine variables affecting influent quality, such as chemical oxygen demand (COD), total nitrogen (TN), and total suspended solids (TSS), thus optimizing energy consumption and minimizing violations in biological wastewater treatment facilities. WEST, a Belgian simulation platform initially created for wastewater treatment, is a versatile environment for dynamic network modeling and long-term simulation development [107]. Cechinel et al. [108] considered the prediction of effluent quality, while Muoio et al. [109] identified the optimum solid retention time of a large industrial WWTP in an attempt to minimize the operating costs. Kovács et al. [110] modeled biofilm reactors that contributed to a base module in SUMO. Kirchem et al. [111] proposed a flexible demand scheme for the power sources of WWTPs.

3.7. Knowledge-based and data-driven models

Since their introduction, data-driven models have served three main purposes in WWTPs: fault detection, variable prediction, and advanced control. Deeper insights into activated sludge models (ASMs) and advanced control are presented in Sections 3.8 and 3.10, respectively [112]. Section 3.7 will focus on knowledge-based and data-driven models (Table 8 [113–123]). This approach uses methods such as control charts, principal component analysis, partial least-squares (PLS), and neural networks for fault detection while employing tools such as transfer function models, multiple regression, and neural networks for variable prediction.

The domain of fault detection, which is crucial for the smooth operation of WWTPs, leverages various methodologies. Control charts enabled Santos et al. [113] to monitor membrane permeability and dictate necessary interventions, and allowed Trubetskaya et al. [114] to identify specification limits using industrial data. Similarly, principal component analysis has aided in pinpointing suitable sub-period division strategies for paper mill sequencing batch reactor (SBR) processes and performing statistical analysis of WWTP quality parameters [115,116]. Using PLS, Liu et al. [117] detected sensor faults within processes with nonlinear and dynamic features and improved the prediction performance and stability of effluent quality indexes [118]. Moreover, neural networks have facilitated a nuanced understanding of the intricate relationship between raw influent and treated effluent water quality data in Iraq [119].

Concerning variable prediction, a range of studies have attempted to forecast elements such as sedimentation reservoir outflow turbidity, removal efficiency of different wastewater

Table 7
Application of digital twins in WWTP power consumption.

Year	Location	Application	Method	Refs.
2020	China	Industry	SCADA, Hydromantis GPS-X 7.0	[88]
2020	Saudi Arabia	Industry	Deep learning, soft sensors, traditional time series	[104,105]
2021	Spain	Lab	Machine learning-based control strategy, neural networks, soft sensors, MATLAB, Hydromantis GPS-X 6.0	[106]
2021	India	Lab	CFD, standard k–ε turbulence model	[99]
2002	—	Lab	WEST	[107]
2019	Italy	Industry	WEST, ASM1Temp	[109]
2024	Brazil	Industry	WEST, LSTM	[108]
2013	France	Lab	SUMO	[110]
2020	Ireland	Lab	Demand response, SUMO	[111]

The ASM1Temp model is an extension of Activated Sludge Model No. 1, which considers carbon removal, nitrification, and denitrification with temperature correction.
LSTM: long short-term memory.

Table 8
Application of knowledge-based and data-driven models in WWTPs.

Objective	Method	Year	Location	Application	Measurement	Purpose	Refs.
Fault detection	Control charts	2021	Brazil	Lab	MLVSS, sludge filterability, pH, COD, temperature	Detect membrane permeability reductions	[113]
		2021	Ireland	Lab	Concentration of ammonia, TN, SS, COD	Determine the limits	[114]
	Principal component analysis	2021	China	Lab	Blower current, level of SBR reactor, DO	Investigate division strategies	[115]
		2021	Iraq	Industry	BOD_5, COD, TSS, TP, TN	Analyze quality parameters	[116]
	PLS	2021	China	Lab	Flow rate, TSS, BOD, COD, TN, TP	Detect sensor faults	[117,118]
	Neural networks	2021	Iraq	Lab	COD, BOD, TSS	Capture relationships	[119]
Variable prediction	Transfer function models	2015	Republic of Korea	Lab	Inflow and outflow water quality, treatment flow rate	Predict turbidity	[120]
	Multiple regression	2020	India	Lab	pH, TSS, BOD_5, COD, oil and grease, NH_3-N, phosphates	Analyze BOD removal efficiency	[121]
		2021	Japan	Lab	Nitrogen, pH, concentration of organic matter	Predict the D-N_2O concentration produced	[123]
	Neural networks	2021	Iran	Industry	Kerman's sewage data	Predict the wastewater discharge	[122]

MLVSS: mixed liquor volatile suspended solids; SBR: sequencing batch reactor; DO: dissolved oxygen; TP: total phosphorus; BOD_5: five-day biochemical oxygen demand; BOD: biochemical oxygen demand; D-N_2O: dissolved nitrous oxide.

treatment technologies, and daily urban wastewater discharge, thereby contributing to more efficient management of WWTPs [120–122]. Moreover, detailed evaluations have been conducted to explore periodic fluctuations in water quality parameters over extended periods [123].

3.8. Mechanistic models

In the field of wastewater treatment, technological improvements have fostered the evolution of mechanistic models, notably ASMs [124,125], anaerobic digestion models (ADMs) [126,127], and soft-sensor mechanisms [128,129]. These models are used to simulate specific treatment processes, facilitating the prediction of target outputs and aiding in the assessment of the entire operation, as outlined in Table 9 [90,104–106,125,127,128,130–148].

ASMs and ADMs have been instrumental in the optimization and estimation of numerous variables. Employing these models has allowed researchers to enhance the operational conditions of coking WWTPs, thus reducing costs [130], as well as to gauge the removal efficacy pertaining to antibiotics [131], explore the implications of sludge vertical stratification on the spatial and temporal distributions of ASM components [132], and predict biogas production in various phases within anaerobic reactors [133].

Soft sensors occupy a substantial segment of the mechanistic model domain, with applications across a wide spectrum in WWTPs. They aid in the forecasting of intricate variables, such as the nitrate concentration in denitrifying post-filtration units [134] and the emulation of weather predictions for controlling WWTPs [135]. Various studies have leveraged soft-sensor mechanisms to devise real-time control strategies for diverse parameters, including the sludge lysate return ratio under fluctuating influent low C/N ratios [136], total Kjeldahl nitrogen (TKN) estimation in long-term complex wastewater treatment processes [137], and the enhancement of soft-sensing model efficiency and precision in predicting effluent quality [138]. In addition, soft sensors have facilitated the prediction of challenging-to-measure yet quality-relevant variables in WWTPs [139], the online monitoring of pivotal variables in wastewater procedures while capturing nonlinear and non-Gaussian data [140], and the extraction of dynamic characteristics for quality variable prediction [141].

3.9. Hybrid twins

Leveraging the digital twins concept, hybrid twins combine real data with digital replicas, creating a complementary and supplementary virtual model grounded in physical principles that encapsulate causality. Hybrid twin models refine their simulation outcomes based on actual test parameters, thereby reducing the testing costs and enhancing data precision. Within the context of WWTPs, hybrid twins play a pivotal role in mitigating ambiguities

Table 9
Application of mechanistic models in WWTPs.

Method	Year	Location	Application	Measurement	Purpose	Refs.
ASM	2007	Sweden	Lab	TSS, COD, TKN, BOD	Evaluate the control strategies at the level of the whole plant	[125]
	2016	China	Lab	COD, NH_3-N	Optimize operation, reduce operating costs	[130]
	2016	Denmark	Lab	Sulfamethoxazole, ciprofloxacin, tetracycline	Evaluate and measure the removal effect of three antibiotics	[131]
	2020	USA	Lab	A water–sludge multiphase CFD model of a full-scale oxidation ditch	Investigate the effect of sludge vertical stratification	[132]
	2012	Canada	Lab	CO_2, CH_4, and N_2O	Estimate greenhouse gas emissions from WWTPs	[142]
ADM	2006	Sweden	—	—	Describe the development of ADM1	[127]
	2018	Brazil	Lab	Gaseous concentrations of CH_4, N_2, H_2, and acetic acid	Estimate the production of biogas	[133]
	2013	France	Industry	COD, proteins, carbohydrates, lipids, individual VFAs concentrations, and inorganic carbon and nitrogen concentrations	Better represent the bioaccessibility of particulate organic matter	[143]
	2016	Sweden	Industry	CO_2, CH_4, and N_2O	Improve the evaluation of energy efficiency and include greenhouse gas emissions	[144]
Soft-sensor	2007	Denmark	—	—	A systematic approach for soft-sensor development	[128]
	2005	Chile	Lab	pH, O_2	Estimate ammonia degradation and nitrite accumulation	[145]
	2012	Finland	Lab	NO_3^--N, SS, DO, PO_4^--P, TP, TOC, effluent temperature	Estimate nitrate concentration	[134]
	2019	Spain	Lab plus	Inflow rate, COD, BOD, NH_3-N, and N-Kjeldahl	Predict the current weather conditions	[135]
	2020	Poland	Lab	Temperature in the activated sludge chambers, quantity and quality of wastewater	Identify activated sludge bulking	[90]
	2020	Saudi Arabia	Industry	Flow, temperature, chloride, BOD_5	Predict energy consumption	[104,105]
	2021	Spain	Lab	Influent variables	Optimize energy consumption	[106]
	2021	China	Lab	COD, NH_3-N, NO_3^--N, and sludge concentration	Establish a real-time control strategy	[136]
	2020	China	Lab	Oxygen, alkalinity, nitrogen, flow, temperature	Estimate the TKN	[137]
	2021	China	Lab	COD, BOD, DO, NO_3^--N, NH_3-N, SS, pH, water temperature	Model and predict effluent quality	[138]
	2020	China	Lab	SS, COD, NH_3-N, flow rate	Predict the quality-relevant variables	[139]
	2021	China	Lab	BOD, COD, and TSS	Online monitor key variables	[140]
	2021	China	Lab	DO, flow rate, instantaneous SWR, instantaneous PE	Extract dynamic characteristics and predict quality variables	[141]
Commercial modeling products	2020	India	Lab	Catechin, pentadecanoic acid, heptadecanoic acid, octadecene, catechol, reserpine	Determine biodegradability	[146]
	2022	Canada	Lab	Nitrogen removal efficiency, removal rate, and loading rate	Assess volumetric nitrogen conversion rates	[147]
	2017	Australia	Industry	Influent flow rate, total COD, TKN, TP, TSS, and NO_3^--N	Study the dynamic (time-dependent) behaviors	[148]

TKN: total Kjeldahl nitrogen; ADM1: anaerobic digestion model No. 1; VFAs: volatile fatty acids; SWR: sludge wastage rate; PE: pumping energy.

[149]. Furthermore, they assist in the comprehensive design of operation variable systems tailored for multi-objective control of the anaerobic ammonia oxidation process [150], as detailed in Table 10 [149–151].

3.10. Control methods

Control systems in WWTPs are differentiated into four main categories: linear control, linearizing control, nonlinear control, and AI-based control [135]. Each category encompasses a range of strategies, as detailed in Table 11 [152–165]. Linear control strategies are applied to individual parameters within WWTPs to enhance processes. For example, aeration costs have been reduced through the efficient control of dissolved oxygen (DO) in activated sludge process-based treatments [152–154], N_2O emissions have been mitigated during nitrification [155], and effluent quality has been bolstered while conserving energy through the minimization of effluent COD and organic nitrogen content [156].

Linearizing control serves to harmonize multiparty conditions in WWTPs, thus reducing large fluctuations in influent flow rates and concentrations, as well as uncertainties in measurement noise and kinetics. This control strategy improves the efficiency of WWTPs [157,158] and enhances the reliability of processes such as denitrification and dephosphorization in anaerobic–anoxic–oxic (A^2/O) reactors [159]. Linearizing control has also been applied to the optimization of aeration in water resource recovery facilities, in alignment with distinct management objectives [160].

Nonlinear control facilitates the prediction and handling of dynamic parameters. Specific applications include maneuvering the reverse osmosis process to remove dimethylphenol from wastewater [161], energy conservation without sacrificing aeration efficiency [162], and forecasting TN peaks well in advance to modulate airflow and maintain stringent effluent standards, while also saving energy [163].

AI-based control uses mapping models to further refine effluent quality and reduce the frequency of plant measurements [164]. This strategy can also pre-emptively calculate outlet results to facilitate forward planning [165].

In summary, these varied control strategies form a comprehensive toolkit, enhancing the efficiency, reliability, and predictive capabilities of WWTP operations. Overall, they are pivotal in fostering improvements in both energy conservation and treatment efficiency.

4. Case study

4.1. Boai County No. 2 WWTP

The Boai County No. 2 WWTP in Jiaozuo, China, stands as the world's inaugural digital twins WWTP operating on PLM technology [166]. Designed to serve 150 000 residents, it boasts a daily municipal wastewater treatment capacity of 60 000 t. The plant complies with China's stringent class-A pollutant discharge standards, as outlined in Discharge Standard of Pollutants for Municipal Wastewater Treatment Plant (GB 18918—2002), treating influent with specified concentrations of various substances, including COD (270 $mg\cdot L^{-1}$), five-day biochemical oxygen demand (BOD_5, 140 $mg\cdot L^{-1}$), SS (200 $mg\cdot L^{-1}$), NH_3-N (35 $mg\cdot L^{-1}$), total phosphorus (TP, 4 $mg\cdot L^{-1}$), and TN (50 $mg\cdot L^{-1}$), to produce effluent suitable for release into natural water bodies. This treatment employs an A^2/O process complemented by coagulation, sedimentation, and filtration procedures.

Upon establishing its foundational model, the WWTP brought together design, operational, maintenance, and real-time data to enhance three core functionalities:

(1) **Virtual inspection**: Leveraging the synergy between 3D models and real-time data, virtual inspections have been introduced to address the challenges of arduous control and debugging

Table 10
Application of hybrid twins in WWTPs.

Year	Location	Method	Purpose	Ref.
2021	China	ASM, convolutional neural network, LSTM neural networks with knowledge and data-driven characteristics	Reduce the influence of fuzziness	[149]
2020	Republic of Korea	Fuzzy-decision-making method, extended power-pinch analysis	Tackle the dynamic power loads of the WWTP	[151]
2018	China	PCA-LSSVM, NSGA-II, MCSSM, least-squares support vector machine	Design the operating variations for multi-objective control	[150]

PCA-LSSVM: least square support vector machine optimized with principal component analysis; NSGA-II: non-dominated sorting genetic algorithm-II; MCSSM: multi-objective control strategy mixed soft-sensing model.

Table 11
Application of control method in WWTPs.

Method	Controller	Year	Location	Application	Purpose	Refs.
Linear control	Proportional–integral–derivative	2018	China	Lab	Better control DO with adaptive adjustment	[154]
	Internal model control	2020	Spain	Industry	Control the DO and denoise the noise-corrupted measurements	[153]
	Pole placement control	2012	Romania	Lab	Control the DO	[152]
	Cascade control	2017	Spain	Lab	Avoid peaks in N_2O emissions	[155]
	Feed-forward control	2018	Romania	Lab	Reduce the effluent COD and organic nitrogen content	[156]
Linearizing control	Adaptive control	2019	Romania	Lab	Deal with harsh conditions that act upon the process	[157,158]
	Optimal control	2021	China	Lab	Improve the reliability of denitrification and dephosphorization	[159]
	Predictive control	2021	Denmark	Lab	Optimize wastewater aeration	[160]
Nonlinear control	Nonlinear geometric control	2018	—	Lab	Capture the dynamics of the reverse osmosis process	[161]
	Gain scheduling control	2021	Denmark	Lab	Save energy	[162]
	Nonlinear predictive control	2020	Italy	Industry	Predict the output TN peaks	[163]
	Multivariable nonlinear control	2019	Romania	Lab	Improve plant efficiency	[157,158]
AI-based control	Fuzzy control	2021	India	Lab	Improve effluent quality	[164]
	Hybrid neural network	2021	—	Lab	Calculate outlet results in advance	[165]

tasks, simplify personnel training, and facilitate multidimensional data analysis by portraying data information accurately and comprehensively in real time.

(2) **Digital delivery**: Integrating 2D and 3D representations of real-time data, digital delivery overcomes the issues associated with paper delivery, such as complexity and reuse difficulty in operations and maintenance. This strategy minimizes the maintenance workload and enables automated control systems to operate with reduced or no human supervision.

(3) **Predictive analysis**: By engaging simulations across input/output, equipment, and process layers, the system can forecast the inlet flow rate, DO fluctuations, and effluent indices. This intelligent analysis uses stored data for self-diagnosis, pinpointing the causes of any issues and issuing early warnings to preempt them.

This comprehensive approach ensures that the plant operates effectively, maintaining a commitment to environmental standards while streamlining operations through technological innovation.

4.2. Nosedo WWTP

The Nosedo WWTP is the primary municipal wastewater treatment facility in Milan, Italy, and is also Europe's largest, with an impressive capacity that can serve 1 250 000 population equivalents [167]. The facility boasts a handling capacity of 432 000 tonnes per day and processing rates of 5 $m^3 \cdot s^{-1}$ in dry weather and 15 $m^3 \cdot s^{-1}$ under rainy conditions. A significant 60%–70% of the treated water is subsequently channeled to support agriculture. The WWTP's operational efficiency, which has resulted in yearly savings of approximately 630 000 EUR, spans three critical areas:

(1) **Integrated operation**: The WWTP has orchestrated the seamless integration of the sewer system and its treatment processes. This system empowers real-time decision-making, optimal control of biochemical processes, and a marked reduction in energy consumption, constituting 40% of the plant's total energy use. Aided by this system, the plant expertly manages variations in biological load, ensuring minimal manual adjustments and offering a more comprehensive process overview.

(2) **Operational savings**: A strategic focus on reducing energy use, chemical consumption, and sludge production has borne significant savings. Breakdowns show a 25% energy reduction in biological treatment, 9% in grit chamber aeration, and an impressive 80% in $FeCl_3$. The decrease in the usage of $FeCl_3$ is attributed to the enhancement of the phosphorus precipitation process. Furthermore, chemical sludge production has been reduced by 126 tonnes per year as a result of reduced precipitation.

(3) **Enhanced hydraulic capacity:** The Nosedo WWTP has optimized its biological processes to better manage wet weather scenarios. With the aid of stormwater-mode assessments using rain gauges and sewer measurements, the plant has boosted its hydraulic capacity by 20%–30% during inclement weather and rainstorms, ensuring greater resilience and efficiency.

By honing its strategies in these critical areas, the Nosedo WWTP has emerged as a beacon of efficiency and sustainability in wastewater treatment. Continual optimization of its processes has helped to safeguard the environment while maintaining economic viability.

5. Concluding remarks

Over the years, the digital twins concept has steadily cemented its role as a transformative force in various industries, including the critical sector of wastewater treatment. As we navigate the intricacies of its applications and developments thus far, it is pertinent to delineate existing challenges while casting a speculative eye on future prospects.

The synthesis of real-time data and established models poses a considerable technical challenge, mandating advanced control systems that are adept at handling multiple variables. These intricacies have the potential to produce a steep learning curve, complicating the task of training personnel to manage these complex systems proficiently. Furthermore, the sector is grappling with the optimization of energy and chemical consumption, where striking a balance between efficiency and efficacy is essential. As exhibited in practical applications, the precise prediction of dynamic parameters requires enhanced focus and development to secure reliable and safe effluent standards.

The future integration of digital twins in WWTPs marks a pivotal shift toward smarter urban water management. The pioneering cases of the Boai County No. 2 and Nosedo WWTPs exemplify the capacity of digital twins to elevate operational efficiency and decision-making. This innovation transcends traditional monitoring, embracing advanced predictive maintenance and resource optimization. Coupled with the IoT, the digital twins concept is set to redefine the standards of sewage treatment and environmental stewardship [89,168,169]. In the future, digital twins are expected to seamlessly blend into broader digital water infrastructures, heralding an era of enhanced, interconnected water services that prioritize efficiency, resilience, and sustainability.

In conclusion, we have summarized the concept, entity, domain, and key technologies of digital twins in the context of wastewater treatment engineering in this technical review. Digital tools have been developed to aid decision-making across various aspects of WWTPs and sewage networks. Furthermore, the two decision-support digital-tool cases given herein exemplify the potential for improving sewage treatment processes and environmental outcomes. It is anticipated that the integration of digital twins with emerging technologies, such as the IoT, will strengthen the monitoring, predictive maintenance, and adaptive strategies for resource optimization in WWTPs. Through the use of real-time analytics, decision-support digital tools are poised to significantly enhance the efficiency and decision-making capabilities of WWTPs. It is recommended that future efforts should expand digital integration, innovate data analysis techniques, and broaden the scope of environmental applications to further augment the potential of digital twins.

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Compliance with ethics guidelines

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Nomenclatures

ADMs	Anaerobic digestion models
ADM1	Anaerobic digestion model No. 1
AI	Artificial intelligence
AR	Augmented reality
ASMs	Activated sludge models
BOD	Biochemical oxygen demand
BOD_5	Five-day biochemical oxygen demand
BIM	Building information modeling
CAD	Computer-aided design
CFD	Computational fluid dynamics
CFX	Computational fluid dynamics X
D-N_2O	Dissolved nitrous oxide
DEXPI	Data exchange in the process industry
DO	Dissolved oxygen
DTD	Digital twin domain
EPA	Environmental Protection Agency
FMI	Functional mock-up interface
FMU	Functional mock-up unit
GIS	Geographic information system
GPS	Global Positioning System
HMI	Human machine interface
ICM	Integrated catchment modeling
IMM	Information Mirroring Model
IoT	Internet of Things
LC–MS/MS	Liquid chromatography–tandem mass spectrometry
MBSE	Model-based system engineering
MCSSM	Multi-objective control strategy mixed soft-sensing model
ML	Machine learning
MLVSS	Mixed liquor volatile suspended solids
MR	Mixed reality
MUCL	Mycothèque de l'université catholique de louvain
NSGA-II	Non-dominated sorting genetic algorithm-II
PCA-LSSVM	Least square support vector machine optimized with principal component analysis
PD	Physical domain
PE	Pumping energy
PCF	Piping component file
PI&D	Piping and instrumentation diagram
PLM	Product life-cycle management
PLS	Partial least-squares
RFID	Radio frequency identification
ROM	Read-only memory
SBR	Sequencing batch reactor
SCADA	Supervisory control and data acquisition
SCD	Sensing and controlling domain
SS	Suspended solids
SWR	Sludge wastage rate
SWMM	Storm water management model
TIS	Tank-in-series
TKN	Total Kjeldahl nitrogen
TOC	Total organic carbon
TP	Total phosphorus
UD	User domain
VFAs	Volatile fatty acids
VR	Virtual reality
Wi-Fi	Wireless fidelity
WWTPs	Wastewater treatment plants
4-CP	4-chlorophenol

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