Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 75-85, 2, 2025

Araştırma Makalesi

https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 75-85, 2, 2025

Research Article

Integration of Digital Twin Technology for Water Resource Management of Smart Cities and Communities: A Narrative Review

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(Received: 31 January 2025, Accepted: 03 February 2025)

(2nd International Conference on Pioneer and Innovative Studies ICPIS 2025, January 30-31, 2025)

ATIF/REFERENCE: Sardar, M. A., Amir, E., Rehman, M. A., Malik, K. F. & Khalid, M. A. (2025). Integration of Digital Twin Technology for Water Resource Management of Smart Cities and Communities: A Narrative Review. *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(2), 75-85.

Abstract **–** Digital Twin (DT) technology has acquired a great amount of significance in the areas of development engineering. It is increasingly being applied to water resource management, particularly for the development and maintenance of smart cities and communities. A Digital Twin creates a real-time digital model of an existing system, contributing to the monitoring and control of a physical system and aiding in predictive maintenance by carrying out calculated decisions based on analysis. When water management is concerned, DTs offer visualization of infrastructure along with forecasting demand, monitoring water quality, and assessing flood risks that can largely contribute to improving operational efficiency, sustainability, and resilience. These systems combine real-time data and provide connectivity to the Internet of Things with advanced modelling to optimize resource use and environmental management. Certain challenges Despite the advantages given, implementing Digital Twin Technology in water systems faces several challenges. The complex integration issues of diverse systems need to be addressed in order to harness the potential of Digital Twins completely. Growing concerns about data interoperability, data privacy, and ownership arise as time passes by. They need to be resolved in order to transform water management. This review examines the applications, benefits, and challenges of Digital Twin technology in managing water resources. Simultaneously, it highlights the emerging trends as well as the future innovations that could drive future developments. It concludes by discussing the transformative role of Digital Twins in supporting the creation of smarter, more sustainable water systems and communities.

Keywords – Digital Twins; Water Resource Management; Predictive Maintenance; Smart Cities; Flood Risk Assessment.

I. INTRODUCTION

Digital Twins (DTs) create a connection between physical assets and the virtual environment. It enhances water management systems and devises creative strategies to improve distribution networks. Thanks to the network of IoT sensors. The integration of these models enables real-time monitoring, as well as leak detection and quality control [1]-[2]. The deployment of DTs, along with optimization methods and ML techniques, can allow utilities to save water, increase system performance, and enhance overall water service management and decision-making [1]-[3]. The function of DTs also includes determining the hydrophobic attribute of water in mass simulations for processes like leak localization and disinfection injection [4]. For example, the combination of graph convolution networks with spatial attention improves both leak detection and operational efficiency in a large water distribution network [4]. Its use results in about 28% water savings and rapid leak detection, resulting in optimal pressure [1]. For cities, DTs help with the detection of floods and the management of water by coupling geospatial information with real-time sensor data. The existing technologies also enable fast flood predictions and mitigation models suitable to enhance the climate resilience of the city [5]-[6]. They eliminate the need for computational expensive processes of coupling hydrologic and hydraulic models with the help of embedded intelligence and learning processes [6]. DTs also analyze water consumption patterns, optimize operation, and comply with standards and regulations. Advanced IoT architectures monitor water quality metrics in time to provide alerts for the authorities and citizens in improving public water supply services. The stochastic simulation of water demand combines hydraulic models and DTs that allow utilities to detect emerging contaminants and improve system sustainability [7].

Digital twins (DTs) are increasingly becoming the transformative tools for sustainable urban development and smart city initiatives. They are virtual replicas of physical urban systems that allow for real-time connectivity, optimization of city infrastructures, and improved decision-making processes [8]. UDTs improve city management and planning toward environmental sustainability, integrating technologies such as IoT, machine learning, and advanced geospatial analytics to enhance resilience and resource efficiency [9]. The integration of DTs into urban systems has shown huge benefits, including a decrease in water demand, an increase in renewable energy use, and a reduction in CO_2 emissions, which support Sustainable Development Goals [10]. They aid in disaster management by providing flood predictions, synchronization analyses, and identification of vulnerable areas with deep learning and GIS techniques [6]. Additionally, DTs help policymakers simulate scenarios that support the development of effective action plans for urban resilience [11]. Despite everything, the implementation of DTs comes with several technical challenges, including data privacy, interoperability, and the complexity of integrating disparate systems. Poor compatibility between semantic standards hinders the effective use of DTs [12]. Non-technical obstacles include governance, data quality, organizational resistance, and the lack of skilled human resources that limit adoption [9]. Interoperability remains a crucial issue; it is very complicated because of the fragmented technologies, making data sharing difficult. It is recommended that the researchers standardize DT frameworks to align them with economic, environmental, and social sustainability goals in urban Planning [13]-[14]. Furthermore, the cost and technical complexity of DTs might hinder their adoption in smaller or developing cities and require innovative business models and interdisciplinary collaboration [15]. As DT technology advances, its applications are no longer limited to physical replication but now encompass integrated data ecosystems and service relationships. This evolution brings into focus the need to address current challenges to fully unlock the potential of DTs in urban environments to make cities smarter, more sustainable, and better prepared for the future [16].

II. LITERATURE REVIEW

The trend of rapid urbanization coupled with changes in climate has impacted the supply of freshwater globally, which calls for radical approaches towards the management of water resources in smart cities. In recent years, the water industry has been making progress in digital transformation. Many experts who create models for water treatment plants are now moving from traditional models to using digital twin technology [17]. Digital twin technology refers to the interconnected mesh of the physical object created with its real-time data, models, and analytics to define simulation and optimize performance [18]. This technology is increasingly being adopted to improve water use efficiency, implement effective bottom-up approaches to water quality, and enhance resource planning. Consequently, cities' economies can benefit significantly from digital twins. Water management analysis depends on disciplinary developments and interdisciplinary interactions [19]. The application of digital twin technology in water resources management integrates various technologies to provide a virtual depiction of the water resources system [20]. Real-time data is collected through sensors in pipelines, treatment plants, and meteorological stations, as well as historical records, to gain a comprehensive understanding of the system [21]. Digital twins have fully transformed water treatment plant modelling from traditional process models to digital representations [17]. Computer-based models simulate various aspects of water infrastructure, including pipelines, reservoirs, and treatment plants [22]. These models are designed to reproduce water's flow, pressure, and quality under different conditions. Classifiers have the capability to analyze real-time and historical data to predict certain occurrences [18]. This predictive information is beneficial in the planning of water distribution, treatment, and conservation.

The data is worked upon and presented alongside the analysis that accompanies it on the integrated dashboards and visual tools. These are important for regional planners in formulating better strategies for water resources [1]. Multi-agent systems cultivate more intelligent and automated water management. The use of digital twins isolates problems such as leaks and monitors, the water flow and the pressure throughout the network [22]. Real-time analytics assist in dealing with physical damage to the assets and reducing water damage [21]. Leakage management ensures there is a fair distribution of water in the urban centres. Instruments meant for real-time monitoring can evaluate the water quality changes during the processes of PH, turbidity, and the level of chlorine and inject this information into the digital twin systems. Predictive analysis tools provide the opportunity to assess the situations and avoid contamination risks [21]. Digital twins also play a role in educating society about water resource demands and quality requirements, promoting water-saving and pollution-prevention activities [1]. Accuracy, reliability, and compatibility of data are critical for digital twin systems, which require significant computing resources to process real-time data. These systems must protect important data and adhere to standards to ensure uniformity in system interactions. The process of decision-making is further enhanced using Artificial intelligence, machine learning, and data analysis. A combination of physical and software entities facilitates interconnected simulations. Though high-level problems are solved with human assistance, ethical concerns such as data privacy and algorithmic fairness must be addressed to ensure equitable outcomes for society [23].

III. COMPONENTS AND FEATURES OF DIGITAL TWIN SYSTEMS IN WATER MANAGEMENT

In digital twin technology in water management systems, several critical components integrate to create an accurate representation of physical water systems. Some of the main components are data acquisition, modelling, predictive analytics, and real-time monitoring [24]. The classification of digital twins is either "living" or "prototyping." Living twins couple real-time observations from dynamic physical systems with simulation models, whereas prototyping twins represent system scenarios without direct real-time observation coupling [25]. Multi-agent systems integrated with Markov Decision Processes can improve the level of intelligence and autonomy of the water management solution, hence allowing data analytics for consumption evaluation and simulation of asset operation [26].

A. Data Acquisition and Integration

Digital twin systems rely on continuous and precise data acquisition from a network of sources, including sensors, IoT devices, and geospatial technologies. These digital twins are placed in the physical water systems, which may include pipes, treatment plants, and reservoirs, to capture real-time data for critical factors like flow, pressure, temperature, water quality, and consumption trends. Once captured, the data feeds into the digital twin model so that it is always reflective of the current state of the physical infrastructure. For the accurate simulation of water distribution systems, the integration of varied data types is fundamental. This data includes sensor readings, such as flow meters and water quality sensors, and therefore contributes to the dynamic and all-encompassing nature of the digital twin with other external inputs like weather forecasts, population growth projections, and land use patterns. Adding the geospatial data of the model using geographic information systems (GIS) enhances its capacity to address the representation of water distribution and management in a spatially organized relationship among various components of the infrastructure.

B. Modeling and Simulation

Modelling of water systems is essential after acquiring and integrating the data and is emerging into a transformative method through digital twins. These models include advanced tools and techniques to manage and plan, as well as optimize water distribution networks in an efficient manner. Digital twins integrate computer-aided design (CAD) models, hydraulic modelling, and artificial intelligence (AI) for the formation of Digital Water Services (DWSs). DWSs facilitate WDN management, Planning, and design [27]. By applying real-time data inputs, digital twins model scenarios like the COVID-19 situation on water quality, pressure, and energy consumption [28]. In these models, Graph Convolutional Neural Networks (GCNNs) may be applied to state estimation, for example, by computing pump speeds from pressure and flow measurements [29]. Digital twins enable remote monitoring and control of WDN components with real-time data, IoT capabilities, and hydraulic simulations [10]-[26]. These systems provide insights into water flow dynamics, pressure fluctuations, and leakage patterns, which allow for better optimization of operations [10].

Digital twins rely on computational mechanics and finite element analysis (FEA) to make detailed predictions about the performance of a system and its weaknesses, hence cost savings and operational efficiency [30]. Advanced techniques, such as RB-FEA, enable much faster analyses without sacrificing precision and are therefore suitable for the modelling of large assets [31]. These models combine machine learning, parameter identification, and inverse analysis to provide reliable simulations and support predictive maintenance throughout the system's lifecycle [32]. Techniques such as adjoint-based procedures improve modelling accuracy by identifying material properties and detecting structural vulnerabilities [33].

Simulation is critical in the analysis, understanding, and optimization of water distribution networks (WDNs). It provides an in-depth investigation of hydraulic behavior and system dynamics for different operating conditions. Hydrodynamic models have proven to be helpful in giving an idea of flow rates, pressures, and velocities in WDNs, using control mechanisms, such as valves and pumps, by advanced mathematical techniques to guarantee precision in the simulation [36]. These simulations may include complex hydraulic features, including flow regimes and direction reversals, by making use of the Poisson Rectangular Pulse to model water demand [35]. Hydraulic models such as those based on Epanet software support multi-period analysis to study the pressures and flows under varying conditions of operation. Such models may support alternative analyses, failure assessments, and optimum pipeline design for new installations [36]-[37]. Simulations address real-world challenges by incorporating evolving functionalities that reflect the complexities of modern WDN management. They also support predictive modelling, which enables water utilities to predict potential failures or inefficiencies in the system.

Digital twins enhance the simulation process significantly by including computational mechanics and finite element analysis FEA, which provides accurate predictions of system behavior for different conditions [30]. High-end simulation methods, such as reduced basis FEA, allow for condition-dependent modelling of large assets, providing results faster with good accuracy [31]. The precision of digital twin simulations is enhanced further by using adjoint-based techniques, especially in material properties assessment and the detection of structural vulnerabilities [33]. Simulations of water flow dynamics, pressure fluctuations, and leakage patterns enable utilities to optimize WDN operations, including leak detection and pressure management, thus leading to significant efficiency improvements. These simulations reduce water losses and improve sustainability through real-time decision-making and operational changes. By simulating scenarios that include environmental impacts and energy consumption, these tools help achieve sustainable development goals. They consider the social, economic, and environmental implications of water system operations [10].

C. Predictive Analytics and Decision-Making

Predictive analytics and decision-making are core components of digital twins (DTs) in water management, changing the way utilities anticipate and respond to challenges in water distribution networks (WDNs). DTs combine state-of-the-art machine learning strategies, such as artificial neural networks, random forests, and support vector regression, to predict water-main failures with excellent precision. Specific predictive models have achieved over 80% accuracy in predicting failures within a 90-day window, while other studies achieved an accuracy rate as high as 97.3% [38]-[39]. This allows utility managers to mitigate vulnerabilities before their issues materialize, minimizing service disruptions and improving resource allocations. Predictive analytics enables utilities to identify vulnerable pipe cohorts and predict network degradation, thereby guiding the optimization of inspection plans and replacement programs. By focusing resources on critical areas, utilities can improve service levels while minimizing costs [40]. DTs provide dynamic simulations of WDNs by incorporating IoT sensors and real-time data. This ability allows utilities to make informed, data-driven decisions regarding operational changes, such as pressure optimization and leak reduction [30]. The merging of real-time data with predictive analytics enables the shift from reactive to proactive decision-making. Predictive maintenance, based on DTs, decreases downtime by predicting potential equipment failures and allowing for proactive repairs. Moreover, DTs enable the regulation of optimal water quality and efficient resource distribution by analyzing both historical and real-time data, thus ensuring sustainable management practices [1].

D. *Real-Time Monitoring and Control*

Digital twin systems give real-time monitoring and control of water systems. This provides numerous benefits for utilities and urban water management. Critical analyses of complex pumping and distribution systems are conducted through virtual replicas called digital twins, which lead to cost savings, efficiency improvement, and rapid anomaly detection [30]. The integration of digital twin measurements also boosts sustainability by enhancing system awareness, allowing a more accurate assessment of its condition and performance. In the following example, water demand was reduced by 3.3 hm3, and renewable energy production improved by 1.2 GWh [10]. It further provides support for the real-time management of collection systems and water resource recovery facilities, reducing the impact of extreme weather events and enhancing process efficiency [41]. Digital twins in water distribution systems have become imperative in decision-making processes and were well deployed in Valencia, Spain, which experienced an excellent benefit in the day-to-day running of operations [2]. Advanced dashboards and visualization tools play a pivotal role in DT-enabled water management. These tools present key performance indicators and metrics through interactive interfaces, facilitating faster decision-making and proactive system management.

Digital twins are becoming critical for managing flood risks in cities. Real-time data, AI, and spatial networking are incorporated in DTs to form dynamic simulations of water movement resulting from rainfall events, thereby providing greater opportunities for disaster preparedness and mitigation. DTs analyze hydrological and meteorological parameters, allowing the authorities to devise more effective evacuation plans well before a flood [42]. Compared to traditional physics-based models, DTs facilitate quick evaluation of city resilience in terms of the projected flood scenarios. These models can mimic the progression of disasters by considering the characteristics of urban space [6]. Digital twins (DTs) increase decision-making processes by providing complexity in data for easier interpretation. When integrated with big data applications and remote sensing technologies, situational awareness is improved, and access to disaster zones is easy and rapid. As climatic changes intensify floods and make them more frequent and intense, DTs arm local administrations with critical tools to optimize flood prevention strategies, mitigate risks, and protect lives and property. Thus, DTs bolster the resilience of a city vis-a-vis extreme weather events through smart solutions like remote sensing and big data analytics.

IV. CHALLENGES IN DIGITAL TWIN IMPLEMENTATION

The challenges of digital twins (DTs) in implementation are found in the technical, organizational, and economic spheres. These challenges are complex and multi-faceted and, therefore, require broad strategies to solve them.

A. *Data Integration and Quality*

Data integration is one of the most critical challenges in DT implementation, especially in environments that are fragmented and diverse in nature. Data accuracy and reliability are critical in developing effective models for DT; however, the problems associated with data quality and harmonization have remained persistent in the way forward. Second, there are semantic standards that are not uniformly applicable or interoperable among the system components. It even complicates data integration further with the demand for real-time exchange [43]. Complexity grows stronger as the dynamic subsystems account for the model of social, biological, and ecological aspects within natural and environmental systems [44].

B. *Technical Complexities*

Technical challenges are the other major challenge in adopting digital twins. The main problem in this respect is interoperability among various platforms and technologies to achieve seamless integration. Even though standard frameworks and modelling protocols need to be developed, these initiatives are still at an early stage of development. Designing efficient data structures and predictive modelling frameworks for water management remains particularly challenging, as these processes must handle large and assorted datasets while maintaining precision [45]. Moreover, the application of Geographic Information Science tools, such as Geo-simulation and Geo-AI, can enhance modelling accuracy and improve the integration of data based on location [5].

C. *Organizational and Human Resource Challenges*

Beyond technical hurdles, non-technical challenges also significantly impact DT implementation. Industry practitioners often cite a lack of expertise and skilled personnel as a major obstacle. Organizational resistance to change, unclear governance structures, and inadequate compliance measures further hinder progress. Effective DT implementation requires strong collaboration across departments and stakeholders, often necessitating cultural shifts within organizations [44].

D. *Cybersecurity Risks*

The reliance of DTs on large volumes of sensitive data expands the attack surface for cyber threats. Since DT systems simulate physical infrastructure, vulnerabilities in virtual models translate directly to risks for actual systems. Although off-premises approaches, such as cloud-based DTs, can reduce expenses and promote scalability, they raise additional security concerns. The use of distributed ledger technology can ensure secure data sharing, while machine learning algorithms can be employed to identify and combat threats effectively.

E. *Economic Barriers*

The high cost of developing and implementing DT infrastructure presents a significant barrier, particularly for smaller utilities and municipalities. The initial investment required for sensors, IoT devices, software, and staff training is prohibitively high. These upfront costs deter adoption, even though DT systems offer potential long-term savings, especially for resource-constrained organizations. However, technological advancements and decreasing costs for sensors and computing power are expected to mitigate these barriers over time.

F. *Application-Specific Challenges in Water Management*

The water sector encounters distinct challenges in the adoption of DTs. Questions regarding the predictive accuracy and appropriate selection of modelling frameworks are particularly relevant. Accurate, real-time location-based data is important, yet it remains a technical and logistical challenge for effective DT implementation in water distribution systems [5].

G. *Broader Systemic Challenges*

Several systemic challenges cut across different DT applications. In manufacturing, a Delphi study identified 18 challenges categorized into four groups, highlighting the broad spectrum of issues across industries [46]. Similarly, eight categories of challenges in urban contexts—ranging from infrastructure limitations to governance issues—must be addressed to enable effective DT adoption [14]. Unclear governance structures and a lack of standardization often hamper collaboration among stakeholders, underscoring the need for better communication and coordination mechanisms [44].

V. EMERGING TRENDS AND INNOVATIONS

Digital twins have started being increasingly regarded as transformational tools in smart city management and water resource systems. Innovations in this domain focus on making digital twins more adaptive, sustainable, and efficient for urban water infrastructure. Advanced GI Science techniques and spatially explicit data are being integrated into digital twins to enhance urban water infrastructure and flood management capabilities [5]. Emerging trends also focus on using digital twins for real-time control and decision support in water collection systems and resource recovery facilities, enabling proactive operations under extreme weather conditions [43]. Although water management remains the prime focus, digital twins are being expanded to optimize urban functions such as energy grids, transportation systems, and building management to create a holistic digital representation of cities [47]. The digital twin market is expected to grow rapidly, and it is projected to reach an estimated US $35.8 billion by 2025. This growth would be fueled by strategic investments being made by the IoT companies, increasing their respective market shares in the digital world [48]. Researchers are now developing holistic city digital twins that can not only assimilate the existing physical infrastructure but also integrate the socio-economic components into dynamic models of interaction between man and the environment [47].

A. *Integration with Artificial Intelligence (AI) and Machine Learning (ML)*

Artificial Intelligence (AI) and Machine Learning (ML) converge with digital twin (DT) technology to change water management systems for more efficient, adaptive, and sustainable efficiency. AI-driven DTs use real-time data coming from IoT sensors to predict future water demands, optimize resource allocation, and enhance decision-making processes [49]. Such capabilities can aid in conserving water while also solving climate variability and resource uncertainty challenges. These have been applied in the water treatment processes. Coagulation, flocculation, and membrane filtration performance are some of the aspects where digital twins enhanced with machine learning are seen to perform well. AI-based models can eliminate errors by up to 97% due to the real-time update in optimizing the usage of chemicals, thus saving operation costs [50]. In addition, AI-based DSSs also enable utilities to address issues of variability in water quality, financial constraints, and regulatory compliance [51]. Nevertheless, integrating AI with digital twins raises problems, such as data availability, high computational needs, and concerns about data safety and ownership.

B. *The Role of Big Data in Water Management*

That integrates big data, IoT and digital twins created a more proactive and efficient way to manage water. Of course, sensors supported by big data technologies provide utilities with vast datasets that allow real-time monitoring, leak detection, and immediate contamination alerts. With the potential integration of big data, IoT, and digital twins, water management is being redesigned in ways that not only make it effective but also sustainable and anticipatory in addressing challenges. Big Data technologies, aided by IoT sensors, help utilities collect and analyze massive amounts of data for real-time monitoring, leak detection, and contamination alerts. These systems predict demand, optimize water allocation, and improve overall decision-making [52]. D digital twins enhanced with Big Data analytics provide dynamic models of water distribution systems that utilities can rely on for operational optimization, master planning, and emergency mitigation [26]. Big Data and AI technologies offer actionable insights and simulate mitigation strategies on vulnerable areas with predictive flood modelling, early warning systems, and climate resilience [42]. Moreover, big data analytics improves water systems through smart metering, efficient scheduling, and loss reduction. However, challenges in data handling, storage, and analytics exist, which require utility companies to invest in workforce training and build architecture to address scalability and interoperability concerns [53].

C. *Blockchain for Data Integrity and Security*

Blockchain technology looks promising for enhancing digital twins via improved data integrity and security. By empowering peer-to-peer data networks, blockchain ensures the authenticity of shared data using cryptography that enforces access control [54]. I am also exploring water management applications, with blockchain-based architectures addressing challenges related to data standardization, interoperability, and security within the Industrial Internet of Water Things (IIoWT) systems [55]. B blockchain ensures that water-related data is secure, tamper-proof, and traceable by providing a decentralized and transparent ledger for all data transactions. For example, Ethereum-based systems have proven effective in securing irrigation data in precision agriculture [56]. Studies have demonstrated that blockchains can improve data integrity, traceability, and security in water quality monitoring and management applications [57], offering significant advantages for securing data in IoT sensor networks.

D. *Cloud Computing and Edge Computing*

Cloud and edge computing technologies are increasingly being applied in water management systems to improve monitoring, control, and optimization. Cloud-based systems allow real-time monitoring and control over water supply networks. T ese provides certain alerts when parameters exceed base threshold levels [58]. Edge computing enhances these systems by reducing latency and enabling faster feedback loops. These technologies, when combined, offer water utilities enhanced scalability and flexibility, enabling efficient management and distribution of water resources. A hybrid edge-cloud approach has shown improved classification accuracy with low energy consumption [59]. Furthermore, edge computing leads to quicker decision-making for areas where real-time responses are required, such as flood control and water quality adjustments. These advancements are only making water management smarter and more efficient through the integration of IoT devices and cloud-based systems [60].

E. *Collaborative Platforms for Data Sharing and Decision Making*

In the near future, Digital Twin technology will assist with collaborative platforms for data sharing and decision-making. The aim will be to create sustainable water management that integrates data across multiple cities, regions, and even countries. Global water challenges like scarce water and pollution can be overcome by enabling cross-border collaboration to manage shared water resources.

Advanced digital twin systems, such as K-Twin SJ, integrate real-time data and utilize simulation models and AI to generate flood response strategies [61]. These data integration collaborative platforms are crucial for addressing fragmented water resources and global water management challenges.

F. *Autonomous Water Management Systems*

In the future, digital twin technology could promise to enable autonomous water management systems, allowing water resources to be monitored and managed with little to no need for human intervention. For example, a digital twin of an entire water network could detect leaks, reroute water flow upon blockage, eliminate scouring and damage to infrastructure, and even treat water based on real-time quality data. Such systems would significantly reduce operational costs, build resilience in water infrastructure, and improve water use efficiency, contributing to a more sustainable urban water future. It has already enhanced water management systems by optimizing operations and detecting problems in real time, paving the way for a more sustainable and efficient approach to water resource management [62].

VI. CONCLUSION

Digital twins have made the management of water systems much more manageable and easier by giving a real-time overview of operations, enabling predictive maintenance, and enhancing monitoring capabilities for water quality, flood risk assessment, and resource optimization. By combining advanced modelling, predictive analytics, and real-time data monitoring, operational efficiency, downtime, and proactive decision-making for utilities can be enhanced to a very large extent with the help of digital twins. These systems can optimize the allocation of resources, reduce waste, and ensure water availability in the face of increasing urbanization and climate challenges. The potential benefits of digital twins are unquestionable. While their creation poses a host of challenges, they do integrate complex data coming from many sources while concurrently mitigating cybersecurity risks. Digital twins can create dynamic, data-driven models of water infrastructure, enhancing our ability to respond more quickly and accurately to emerging issues, such as system failures or natural disasters. Besides this, they enhance sustainability and adaptation efforts to climate by optimizing the use of water resources, hence predicting and mitigating flood risks. Lastly, digital twins increase the resilience of water systems, especially in extreme weather conditions.

In the future, the advancement of digital twin technologies is expected to change water management practices that will be geared towards building smarter, more sustainable cities prepared for future challenges. Through constant innovation in technologies, the area that digital twins could cover extends further than what would be limited in traditional water management. Therefore, digital twins could enhance the better adaptation of transportation systems, urban infrastructures, and other utilities together with integrated water systems towards developing more effective, responsive, and resilient cities towards a more sustainable future. In conclusion, DTs illustrate a critical improvement in the management of our water systems. If we manage to harness the full potential of this technology, we can build sustainable and resilient water infrastructures that support long-term ecosystem health.

REFERENCES

[1] Ramos, H. M., Morani, M. C., Carravetta, A., Fecarrotta, O., Adeyeye, K., López-Jiménez, P. A., & Pérez-Sánchez, M. (2022). New Challenges towards Smart Systems' Efficiency by Digital Twin in Water Distribution Networks. Water, 14(8), 1304. https://doi.org/10.3390/w14081304

[2] Fuertes, P. C., Alzamora, F. M., Carot, M. H., & Campos, J. A. (2020). Building and exploiting a Digital Twin for the management of drinking water distribution networks. Urban Water Journal, 17(8), 704–713. https://doi.org/10.1080/1573062x.2020.1771382

[3] Chandaluri, R., & Nelakuditi, U. (2022). Monograph on Components, design, and Applications of Digital Twin. INTERNATIONAL JOURNAL OF

[4] Movva, S. S. (2024). Development of digital twins for urban water systems. Journal of Technology and Systems, 6(3), 19–33. https://doi.org/10.47941/jts.1833NEXT-GENERATION COMPUTING. https://doi.org/10.47164/ijngc.v13i3.768

[5] Sabri, S., Alexandridis, K., Koohikamali, M., Zhang, S., & Ozkaya, H. E. (2023). Designing a spatially-explicit urban digital twin framework for smart water infrastructure and flood management. *2023 IEEE 3rd International Conference on Digital Twins and Parallel Intelligence (DTPI)*, Orlando, FL, USA, 1–9. https://doi.org/10.1109/DTPI59677.2023.10365478

[6] Ghaith, M., Yosri, A., & El-Dakhakhni, W. (2022). Synchronization-Enhanced Deep Learning early flood risk predictions: the core of Data-Driven City Digital Twins for Climate Resilience planning. *Water*, *14*(22), 3619. https://doi.org/10.3390/w14223619

[7] Iancu, G., Ciolofan, S. N., & Drăgoicea, M. (2024). Real-time IoT architecture for water management in smart cities. *Deleted Journal*, *6*(4). https://doi.org/10.1007/s42452-024-05855-9

[8] Hämäläinen, M. (2020). Smart city development with digital twin technology. In *Bled eConference*. https://api.semanticscholar.org/CorpusID:226716335

[9] Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). A systemic review of urban digital twin challenges, and perspectives for sustainable smart cities. *Sustainable Cities and Society*. https://api.semanticscholar.org/CorpusID:261020154

[10] Ramos, H. M., Kuriqi, A., Coronado-Hernández, O. E., López-Jiménez, P. A., & Pérez-Sánchez, M. (2023). Are digital twins improving urban-water systems efficiency and sustainable development goals? *Urban Water Journal*, *21*(10), 1164–1175. https://doi.org/10.1080/1573062x.2023.2180396

[11] Astarita, V., Guido, G., Haghshenas, S. S., & Haghshenas, S. S. (2024). Risk reduction in transportation systems: The role of digital twins according to a Bibliometric-Based Literature review. *Sustainability*, *16*(8), 3212. https://doi.org/10.3390/su16083212

[12] Lei, B., Janssen, P., Stoter, J. E., & Biljecki, F. (2023). Challenges of urban digital twins: A systematic review and a Delphi expert survey. *Automation in Construction.* https://api.semanticscholar.org/CorpusID:255536144

[13] Quek, H. Y., Sielker, F., Kraft, M., Akroyd, J., Bhave, A., Von Richthofen, A., Herthogs, P., Yamu, C., Wan, L., Nochta, T., Burgess, G., Lim, M. Q., Mosbach, S., & Balijepalli, V. S. K. M. (2021). The conundrum in smart city governance: Interoperability and compatibility in an ever-growing digital ecosystem. In *Proceedings of the Conference on Smart City Ecosystems.* https://api.semanticscholar.org/CorpusID:250084932

[14] Ferré-Bigorra, J., Casals, M., & Gangolells, M. (2022). The adoption of urban digital twins. Cities, 131, 103905. https://doi.org/10.1016/j.cities.2022.103905

[15] Abayadeera, M. R., & Ganegoda, G. (2024). Digital twin technology: A comprehensive review. International Journal of Scientific Research and Engineering Trends, 10, 1485–1504. https://doi.org/10.61137/ijsret.vol.10.issue4.199

[16] Tyagi, A. K., & Richa. (2023). Digital twin technology: Opportunities and challenges for smart era's applications. In Proceedings of the 2023 Fifteenth International Conference on Contemporary Computing (IC3-2023) (pp. 328–336). Association for Computing Machinery. https://doi.org/10.1145/3607947.3608015

[17] Saba Daneshgar, Fabio Polesel, Borzooei, S., Sørensen, H. R., Peeters, R., Weijers, S., Ingmar Nopens, & Torfs, E. (2024). A full-scale operational digital twin for a water resource recovery facility—A case study of Eindhoven Water Resource Recovery Facility. Water Environment Research, 96(3). https://doi.org/10.1002/wer.11016

[18] Li, X., Luo, J., Li, Y., Wang, W., Hong, W., Liu, M., Li, X., & Lv, Z. (2022). Application of effective water-energy management based on digital twins technology in sustainable cities construction. Sustainable Cities and Society, 87, 104241. https://doi.org/10.1016/j.scs.2022.104241

[19] Dinar, A. (2024). Challenges to Water Resource Management: The Role of Economic and Modelling Approaches. Water, 16(4), 610–610. https://doi.org/10.3390/w16040610

[20] Mazzetto, S. (2024). A Review of Urban Digital Twins Integration, Challenges, and Future Directions in Smart City Development. Sustainability, 16(19), 8337–8337. https://doi.org/10.3390/su16198337

[21] Sharifi, A., Khavarian-Garmsir, A. R., Allam, Z., & Asadzadeh, A. (2023). Progress and prospects in planning: A bibliometric review of literature in Urban Studies and Regional and Urban Planning, 1956–2022. Progress in Planning, 100740. https://doi.org/10.1016/j.progress.2023.100740

[22] Schuh, G., Kelzenberg, C., Wiese, J., & Kessler, N. (2020). Creation of digital production twins for the optimization of value creation in single and small batch production. Procedia CIRP, 93, 222–227. https://doi.org/10.1016/j.procir.2020.04.125

[23] Pesantez, J. E., Alghamdi, F., Sabu, S., Mahinthakumar, G., & Berglund, E. Z. (2022). Using a digital twin to explore water infrastructure impacts during the COVID-19 pandemic. Sustainable Cities and Society, 77, 103520. https://doi.org/10.1016/j.scs.2021.103520

[24] Walton, R. B., Ciarallo, F. W., & Champagne, L. E. (2024). A unified digital twin approach incorporating virtual, physical, and prescriptive analytical components to support adaptive real-time decision-making. *Computers & Industrial Engineering*, *193*, 110241. https://doi.org/10.1016/j.cie.2024.110241

[25] Pedersen, A. N., Borup, M., Brink-Kjær, A., Christiansen, L. E., & Mikkelsen, P. S. (2021). Living and Prototyping Digital Twins for Urban Water systems: Towards Multi-Purpose Value Creation using models and Sensors. *Water*, *13*(5), 592. https://doi.org/10.3390/w13050592Deuerlein, J., Cembrowicz, R. G., & Dempe, S. (n.d.). Hydraulic simulation of water supply networks under control. In Impacts of Global Climate Change (pp. 1–12). https://doi.org/10.1061/40792(173)24

[26] Movva, S. S. (2024). Development of digital twins for urban water systems. *Journal of Technology and Systems*, *6*(3), 19–33. https://doi.org/10.47941/jts.1833

[27] Ciliberti, F. G., Berardi, L., Laucelli, D. B., Ariza, A. D., Enriquez, L. V., & Giustolisi, O. (2023). From digital twin paradigm to digital water services. *Journal of Hydroinformatics*, *25*(6), 2444–2459. https://doi.org/10.2166/hydro.2023.237

[28] Pesantez, J. E., Alghamdi, F., Sabu, S., Mahinthakumar, G., & Berglund, E. Z. (2022). Using a digital twin to explore water infrastructure impacts during the COVID-19 pandemic. *Sustainable Cities and Society*, *77*, 103520. https://doi.org/10.1016/j.scs.2021.103520

[29] Bonilla, C. A., Zanfei, A., Brentan, B., Montalvo, I., & Izquierdo, J. (2022). A Digital Twin of a Water Distribution System by Using Graph Convolutional Networks for Pump Speed-Based State Estimation. *Water*, *14*(4), 514. https://doi.org/10.3390/w14040514

[30] Bernard, M. (2024). Using digital twins to improve pumping and distribution system operations. *American Water Works Association*, *116*(1), 6–15. https://doi.org/10.1002/awwa.2211

[31] Löhner, R., Airaudo, F. N., Antil, H., Wüchner, R., Meister, F., & Warnakulasuriya, S. (2023). High-fidelity digital twins: Detecting and localizing weaknesses in structures. arXiv. https://arxiv.org/abs/2311.10925

[32] Schuh, G., Kelzenberg, C., Wiese, J., & Kessler, N. (2020). Creation of digital production twins for the optimization of value creation in single and small batch production. Procedia CIRP, 93, 222–227. https://doi.org/10.1016/j.procir.2020.04.125

[33] Medeiros, V. d. S., dos Santos, M. D., & Brito, A. V. (2024). Case Study for Predicting Failures in Water Supply Networks Using Neural Networks. Water, 16(10), 1455. https://doi.org/10.3390/w16101455

[34] Deuerlein, J., Cembrowicz, R. G., & Dempe, S. (n.d.). Hydraulic simulation of water supply networks under control. In *Impacts of Global Climate Change* (pp. 1–12). https://doi.org/10.1061/40792(173)24

[35] Buchberger, S. G., Li, Z., & Tzatchkov, V. G. (2003). Hydraulic characterization of pipe networks subject to stochastic water demands. In *Proceedings of the Hydraulic Engineering Conference.* https://api.semanticscholar.org/CorpusID:110728914

[36] [31] Kepa, U., & Stanczyk-Mazanek, E. (2014). A hydraulic model is a useful tool in the operation of a water-pipe network. *Polish Journal of Environmental Studies, 23,* 995–1001.

[37] [32] Balut, A., & Urbaniak, A. (2011). Management of water pipeline networks supported by hydraulic models and information systems. In *Proceedings of the 2011 12th International Carpathian Control Conference (ICCC)* (pp. 16–21). https://doi.org/10.1109/CarpathianCC.2011.5945807

[38] Medeiros, V. d. S., dos Santos, M. D., & Brito, A. V. (2024). Case Study for Predicting Failures in Water Supply Networks Using Neural Networks. *Water*, *16*(10), 1455. https://doi.org/10.3390/w16101455

[39] Omar, A., Delnaz, A., & Nik-Bakht, M. (2023). Comparative analysis of machine learning techniques for predicting water main failures in the City of Kitchener. *Journal of Infrastructure Intelligence and Resilience*, *2*(3), 100044. https://doi.org/10.1016/j.iintel.2023.100044

[40] Saran, N., Rolland, B., Gill, N., & Motala, I. (2022). Using machine learning techniques to optimize infrastructure investment for the water distribution network. In *Pipelines 2022* (pp. 18–24). https://doi.org/10.1061/9780784484302.003

[41] Lumley, D. J., Polesel, F., Sørensen, H. R., & Gustafsson, L.-G. (2024). Connecting digital twins to control collection systems and water resource recovery facilities: From siloed to integrated urban (waste)water management. *Water Practice and Technology*, *19*(6), 2267–2278. https://doi.org/10.2166/wpt.2024.128

[42] Manocha, A., Sood, S. K., & Bhatia, M. (2023). Digital twin-assisted fuzzy logic-inspired intelligent approach for flood prediction. *IEEE Sensors Journal.* https://doi.org/10.1109/JSEN.2023.3322535

[43] Lei, B., Janssen, P., Stoter, J. E., & Biljecki, F. (2023). Challenges of urban digital twins: A systematic review and a Delphi expert survey. *Automation in Construction.* https://api.semanticscholar.org/CorpusID:255536144

[44] Dhakal, S. R., & Parry, H. (2023). Digital twins for natural landscape management: Opportunities and challenges. *MODSIM2023, 25th International Congress on Modelling and Simulation*. Retrieved from https://api.semanticscholar.org/CorpusID:260758228

[45] Torfs, E., Nicolaï, N., Daneshgar, S., Copp, J. B., Haimi, H., Ikumi, D., Johnson, B., Plosz, B. B., Snowling, S., Townley, L. R., Valverde-Pérez, B., Vanrolleghem, P. A., Vezzaro, L., & Nopens, I. (2022). The transition of WRRF models to digital twin applications. *Water Science and Technology*, *85*(10), 2840–2853. https://doi.org/10.2166/wst.2022.107

[46] Saporiti, N., Cannas, V. G., Pozzi, R., & Rossi, T. (2023). Challenges and countermeasures for digital twin implementation in manufacturing plants: A Delphi study. *International Journal of Production Economics*, *261*, 108888. https://doi.org/10.1016/j.ijpe.2023.108888

[47] Shahat, E., Hyun, C. T., & Yeom, C. (2021). City Digital Twin Potentials: A Review and Research Agenda. *Sustainability*, *13*(6), 3386. https://doi.org/10.3390/su13063386

[48] El Saddik, A., Laamarti, F., & Alja'Afreh, M. (2021). The potential of digital twins. *IEEE Instrumentation & Measurement Magazine*, *24*(3), 36–41. https://doi.org/10.1109/MIM.2021.9436090

[49] Ingle, N. V., Sable, S. D., Ghadge, D. P., & Mane, S. (2022). Artificial intelligence-based water management system. In *2022 5th International Conference on Advances in Science and Technology (ICAST)* (pp. 180–184). https://doi.org/10.1109/ICAST55766.2022.10039523

[50] Wei, Y., Law, A. W. -K., & Yang, C. (2022). Real-Time Data-Processing Framework with Model Updating for Digital Twins of Water Treatment Facilities. *Water*, *14*(22), 3591. https://doi.org/10.3390/w14223591

[51] Raseman, W. J., Kasprzyk, J. R., Rosario-Ortiz, F. L., Stewart, J. R., & Livneh, B. (2017). Emerging investigators series: A critical review of decision support systems for water treatment: Making the case for incorporating climate change and climate extremes. *Environmental Science: Water Research & Technology*, *3*(1), 18–36. https://doi.org/10.1039/C6EW00121A

[52] Nie, X., Fan, T., Wang, B., Li, Z., Shankar, A., & Manickam, A. (2020). Big data analytics and IoT in operation safety management in under water management. *Computer Communications*, *154*, 188–196. https://doi.org/10.1016/j.comcom.2020.02.052

[53] Walshire, L. A., Gonzalez, M. E., Lillycrop, J., Seamster, E., & Winters, K. E. (2023). Water resources infrastructure digital twins: Design, development, and future efforts. In *Geo-Congress 2023* (pp. 400–408). https://doi.org/10.1061/9780784484692.041

[54] Huang, S., Wang, G., Yan, Y., & Fang, X. (2020). Blockchain-based data management for digital twin of product. *Journal of Manufacturing Systems*, *54*, 361–371. https://doi.org/10.1016/j.jmsy.2020.01.009

[55] Mohammed, M. A., Lakhan, A., Abdulkareem, K. H., Abd Ghani, M. K., Marhoon, H. A., Kadry, S., Nedoma, J., Martinek, R., & Garcia Zapirain, B. (2024). Industrial Internet of Water Things architecture for data standardization based on blockchain and digital twin technology. *Journal of Advanced Research*, *66*, 1–14. https://doi.org/10.1016/j.jare.2023.10.005

[56] Sumarudin, A., Putra, W. P., Puspaningrum, A., Suheryadi, A., Anam, I. S., Yani, M., & Hanif, I. (2022). Implementation of IoT sensored data integrity for irrigation in precision agriculture using Blockchain Ethereum. *2021 4th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 29–33. https://doi.org/10.1109/isriti56927.2022.10052902

[57] Lin, Y. -P., Mukhtar, H., Huang, K. -T., Petway, J. R., Lin, C. -M., Chou, C. -F., & Liao, S. -W. (2020). Real-Time Identification of Irrigation Water Pollution Sources and Pathways with a Wireless Sensor Network and Blockchain Framework. *Sensors*, *20*(13), 3634. https://doi.org/10.3390/s20133634

[58] Muthukumar, V., Selvakumar, V., Nalini, M., & Chitradevi, B. (2023). Cloud-based smart water management system. In *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)* (pp. 1633–1638). https://doi.org/10.1109/ICSCSS57650.2023.10169753

[59] Shahra, E. Q., Wu, W., Basurra, S., & Aneiba, A. (2024). Intelligent Edge-Cloud framework for water quality monitoring in water distribution system. *Water*, *16*(2), 196.

[60] https://doi.org/10.3390/w16020196

[61] Hazrat, M. A., Hassan, N. M. S., Chowdhury, A. A., Rasul, M. G., & Taylor, B. A. (2023). Developing a Skilled Workforce for Future Industry Demand: The Potential of Digital Twin-Based Teaching and Learning Practices in Engineering Education. Sustainability, 15(23), 16433. https://doi.org/10.3390/su152316433

[62] Menapace, A., Zanfei, A., De Luca, A., Pauli, D. D., & Righetti, M. (2022). Towards a Digital Twin Model for the Management of the Laives Aqueduct. *Environmental Sciences Proceedings*, *21*(1), 70. https://doi.org/10.3390/environsciproc2022021070