Digital Transformation of Resilient and Sustainable Smart Water Distribution Systems*

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Abstract. The increasing challenges of water scarcity and climate change need innovative digital solutions to enhance resilience, sustainability, and operational awareness of Water Distribution Systems (WDSs). This chapter presents an innovative perspective on the digital transformation of Smart Water Networks, integrating large-scale monitoring, Low-Power Wide-Area Network communications, physical modeling, and artificial intelligence. By connecting the physical infrastructure through an Internet of Things (IoT) network it is possible to achieve several data-driven ecosystem improvement and analytics. Within this framework, Digital Twin approaches are discussed as a mean to combine real-time measurements, hydraulic simulation, and machine learning for continuous monitoring and active system analysis. Graph-based representations and learning techniques are further examined as effective tools for modeling network structure and dynamics under sparse sensing conditions. The chapter also reviews data-driven methods for demand analysis, forecasting, and network monitoring, and illustrates their integration into operator-oriented platform.

1 Introduction

Water Distribution Systems (WDSs) are critical infrastructures in modern societies, responsible for delivering potable water at adequate levels of quantity, quality, and pressure. Meeting these requirements has become increasingly challenging as demographic growth, climate variability, and the progressive aging of infrastructures reshape the operational conditions of water utilities [1],[2]. This situation limits the traditional management operations, which are largely based on sparse instrumentation, sparse data availability, and reactive maintenance strategies.

In recent years, the notion of resilience in WDSs has evolved beyond robustness against isolated failures. It now encompasses the ability to continuously

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adapt to changing operating conditions, anticipate critical events, and recover efficiently from disruptions [3]. Achieving such capabilities requires a transformation of how water system are observed, modeled, and managed. In this sense, digital transformation is not only a technological upgrade, but a structural shift in the way information flows across the system and supports intelligent operations.

The digital transformation of WDSs is driven by the deployment of distributed sensing, including smart meters and pressure and flow sensors, which provide detailed visibility into network dynamics. However, the scale and topology of WDSs constrain communication, energy consumption, and maintenance, making Low Power Wide Area Networks (LPWAN) essential for large-scale monitoring. In this context, LoRaWAN has emerged as a key technology due to its scalability and suitability for heterogeneous environments [4]. This integration is embodied in the Digital Twin paradigm [5], where a dynamic digital representation continuously receives real-time data and supports the evaluation of operational scenarios, enabling a shift from passive monitoring to active analysis [6]. By coupling real-time observations with predictive and simulation capabilities, the Digital Twin provides a structured basis for informed operational decision-making, particularly under noisy and dynamic conditions.

Graph-based representations further enhance WDS modeling by explicitly capturing relational dependencies between components, enabling network-wide analysis under sparse sensing conditions. Advances in graph signal processing and graph neural networks support tasks such as state estimation, anomaly detection, and network inference [7],[8],[9].

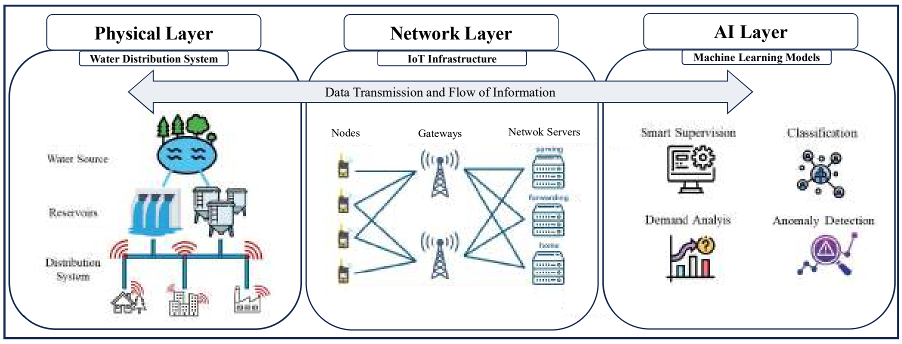

Fig. 1: Conceptual layered architecture of a smart water system, illustrating the interaction between the physical WDS, the IoT communication infrastructure, and the AI layer responsible for data-driven supervision and analysis.

The key aspects of our framework are presented in Fig. 1. This chapter provides a coherent view of the digital transformation of resilient and sustainable smart water systems by connecting enabling technologies with concrete modeling and management tools. We first recall the essential principles governing WDSs, then examine how large-scale data collection infrastructures support continuous monitoring. We subsequently discuss Digital Twin architectures that combine real-time data, hydraulic simulation, and machine learning, and introduce graph-based representations as a framework for network analysis. Finally, we illustrate how these components can be integrated into holistic platforms designed to support water operators in daily decision-making processes.

2 Background of the WDS

We now briefly outline the fundamental operating principles of WDSs [10, 11], whose main components, illustrated in Fig. 2, include:

1. *junctions*, which represent connection points between network elements and locations where water is supplied to or withdrawn from the system to serve end users under specified quantity, quality, and pressure requirements;
2. *reservoirs*, acting as external water sources for the network, such as natural or artificial basins;
3. *storage tanks*, used to accommodate demand variability, provide reserve capacity during emergency conditions, and support energy-efficient operation through flow balancing;
4. *pumps*, which supply energy to the flow in order to counteract elevation differences and friction-related losses;
5. *pipes*, forming the physical links that transport water between the various components of the network;
6. *valves*, serving as flow-regulation elements, including control and pressure-reduction devices, used to manage hydraulic conditions at specific network locations.

The fundamental objective in the WDS design is to ensure water service while maintaining adequate pressure across a range of operating conditions, usually determined by spatially distributed demand patterns. The flow rate, defined as the volume of water conveyed per unit time, is a key variable characterizing the hydraulic state of the system. As water moves through pipes, it undergoes a continuous redistribution of mechanical energy, associated with variations in elevation and velocity. Part of this energy is dissipated through frictional effects, typically resulting in negligible thermal changes. In hydraulic analysis, these energy components are conventionally expressed in terms of equivalent heads, represented as vertical distances and summarized in Table 1.

2.1 System state and governing laws of pipe flow

The hydraulic state of a WDS can be classified as *steady* or *unsteady* depending on whether loading conditions are constant or time-varying. Under steady operation, flows and nodal pressure heads remain time-invariant, while unsteady conditions involve temporal variations of these quantities. Hydraulic heads are

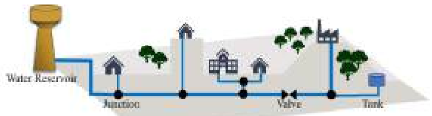

Fig. 2: Schematic illustration of the principal elements of a WDS [7].

Table 1: Hydraulic head components in fluid mechanics, with p indicating pressure, γ the specific weight, Z the reference elevation, v the velocity, and g gravity acceleration [7].

Head	**Definition**	**Description**
Pressure head	$\frac{p}{\gamma}$	Flow work
Elevation head	Z	Gravitational potential energy
Velocity head	$\frac{v^2}{2g}$	Kinetic energy
Piezometric head	$\frac{p}{\gamma} + Z$	Pressure + elevation head

typically evaluated at junctions where water is withdrawn from the network. Nodes with fixed total energy, such as reservoirs or tanks, are referred to as fixed-grade nodes. The governing principles of steady-state pipe flow in WDSs are as follows:

- *Mass balance*: at each junction, the net accumulation of water is equal to the difference between the total inflow and outflow. This condition can be written as
$$\sum Q_{in} - \sum Q_{out} = Q_{ext} \tag{1}$$
where Q_{in} and Q_{out} denote the flow rates entering and leaving the node through the connected pipes, and Q_{ext} represents the external demand.
- *Energy balance*: along any hydraulic path, the change in total energy is determined by the energy supplied by pumping devices and the energy dissipated through friction and local losses. Using the head-based formulation, this relationship is expressed as
$$\sum H_{\text{loss},i} + \sum H_{\text{pump},j} = \Delta\epsilon \tag{2}$$
where $H_{\text{loss},i}$ accounts for the head losses associated with network component i, and $H_{\text{pump},j}$ denotes the head increase provided by pump j.

The hydraulic state of a WDS is obtained by applying the governing equations to all pipes and nodes, resulting in a coupled system of nonlinear equations. Under assumptions such as known boundary conditions and nodal demands, this system can be solved using iterative numerical methods, typically implemented in hydraulic simulators such as EPANET [12].

For unsteady operation under the rigid pipe assumption, flow dynamics follow the conservation of momentum, whereby the net force acting on a fluid element equals the time derivative of its momentum:

$$\sum F = F_1 - F_2 - F_f = \frac{d(mv)}{dt}, \tag{3}$$

where F_1 and F_2 denoting forces on the pipe ends, F_f the frictional force, and mv the momentum.

Energy dissipation in WDSs is primarily caused by friction along pipes and by changes in flow direction or velocity. Friction-related head losses depend on pipe characteristics and flow conditions and are commonly modeled using classical formulations such as the Darcy-Weisbach or Hazen-Williams relations [7]. Additional energy losses arise from fittings, valves, and geometric discontinuities and are typically represented through minor loss coefficients.

2.2 Hydraulic modeling of WDNs

A fundamental hydraulic characteristic of WDS is the dependence of nodal demand and pressure conditions. This behavior is commonly represented through Pressure-driven Analysis, which estimates the effective water demand at each node as a function of the local pressure, as follows:

$$D_i^* = \begin{cases} 0, & p_i < p_i^{min} \\ D_i \left(\frac{p_i - p_i^{min}}{p_i^{req} - p_i^{min}} \right)^{\delta}, & p_i^{min} < p_i < p_i^{req} \\ D_i, & p_i > p_i^{req} \end{cases} \tag{4}$$

where D_i^* is the actual demand, p_i is the pressure at node i, p_i^{min} is the minimum pressure for water delivery, and p_i^{req} is the required pressure for full delivery. The exponent δ is typically set to 0.5. This formula allows for modeling how nodal demand fluctuates with pressure, providing a basis for pressure-demand analysis. In Demand-Driven Analysis (DDA), the network provides the required demand at each node, regardless of the available pressure. The assumption is valid when the network is well-pressurized to meet all demands. However, this sometimes results in hydraulic solutions with negative pressures that are physically impossible.

Additionally, the leakage demand is expressed as:

$$D_{\text{leak}} = \mu A_{\text{leak}} p^{\alpha} \sqrt{\frac{2}{p}} \tag{5}$$

where μ is the flow coefficient, A_{leak} is the leakage area, p is the pressure, and α is used to represent leakage characteristics.

3 Enhanced data collection for WDS

The digital transformation of WDS infrastructures represents a crucial step toward more efficient, sustainable, and resilient water resource management [13, 3, 4]. By integrating large-scale IoT technologies such as smart sensors, LPWAN networks, and edge computing solutions, WDSs can benefit from enhanced data collection capabilities, enabling continuous, high-resolution monitoring and real-time control. This, in turn, supports operational optimization and the rapid detection of leaks and anomalies [4].

IoT technologies, especially those equipped with LPWAN, have become a consolidated way to deploy applications to monitor and control smart systems

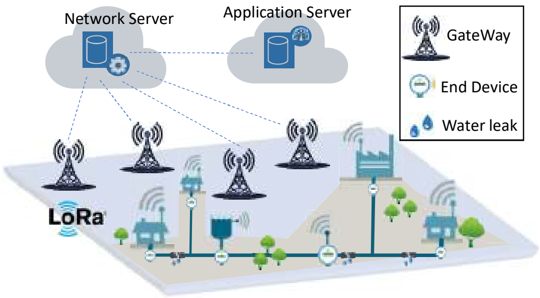

Fig. 3: LoRaWAN network architecture [15].

at a large scale [14]. LoRaWAN emerges as an ideal solution for WDS infrastructures due to its suitability for large-scale deployments, particularly in massive network scenarios [4]. Its extended coverage capability, which can reach several kilometers, enables the connection of a large number of sensors and devices across wide geographical areas without the need for complex or costly network infrastructures.

As shown in Fig. 3, LoRaWAN is based on a cell-free architecture in which IoT devices are connected to multiple GWs, depending on the GW coverage area. All GWs receive and forward appropriately demodulated packets to a central Network Server (NS).

Moreover, the low power consumption of LoRaWAN devices allows sensors and monitoring nodes to operate for many years on a single battery, significantly reducing maintenance and operational costs. The scalability of LoRaWAN, combined with its resilience and capacity to support thousands of devices in distributed environments, makes it particularly suitable for large WDS networks, where uniform coverage, reliability, and continuous operability are essential. Within this context of massive networks, LoRaWAN stands out as a technology capable of effectively addressing challenges related to distribution, security, and the optimization of water resources.

The following two subsections present studies and methodologies aimed at improving the efficiency of data acquisition in WDSs and analyzing how different LPWAN technologies can coexist within the same communication infrastructure.

3.1 Coexistence Analysis of LPWAN Devices in Smart WDS

A recent literature review revealed that LPWAN technologies are the most widely adopted in the WDS field [4], accounting for 55% of the analyzed studies (with LoRa at 37%, SigFox at 13%, and NB-IoT at 5%). This highlights the importance of solutions that ensure low energy consumption and long-range communication capabilities for IoT applications in water monitoring. Additionally, industry analyses indicate that NB-IoT, LoRaWAN, and Sigfox currently dominate the LPWAN landscape, comprising approximately 86% of the market, driven by widespread adoption among end users and robust support across the technological ecosystem. The study [16] challenges the coexistence of LPWAN technologies for large-scale urban IoT networks, with a focus on the most prominent ones in the ISM band, such as LoRaWAN and Sigfox. While NB-IoT uses licensed bands, both LoRaWAN and Sigfox operate in the sub-GHz ISM bands, potentially causing mutual interference, as illustrated in [16]. Interestingly, LoRaWAN and Sigfox use distinct modulation techniques: Sigfox uses a 100 Hz Ultra-NarrowBand (UNB) signal coupled with Binary Phase Shift Keying (BPSK) modulation, while LoRaWAN uses Chirp Spread Spectrum (CSS) modulation at 125–500 kHz [17].

Due to the different modulation techniques used by these technologies, it is crucial to evaluate their coexistence in realistic application contexts, such as smart cities and WDSs. To analyze the inter-technology coexistence in a mixed sensor scenario for WDS, where 50% of the sensors use LoRaWAN technology and the remaining 50% use Sigfox technology, the analytical interference model proposed in [16] was applied.

The model accounts for the number of simultaneously active nodes and models the number of active sensor nodes using a Poisson distribution, expressed as $\Pr[k] = e^{-A}A^k/k!$, where A is the offered traffic (i.e., the average number of active nodes in the considered area/time window), k is the integer number of active nodes, and e is the base of natural logarithms. The offered traffic is computed as $A = \delta\pi R_{\max}^2 \frac{DC_{eq}}{0.01\, n_{ch}}$, where δ is the node density, $R_{\max}$ is the maximum interference distance, DC_{eq} is the effective duty cycle, and n_{ch} is the number of available channels (8 for CSS and 3 for UNB). The model shows that as the density of sensor nodes increases, the average interfering node quickly approaches the GW, consequently the only relevant interferer is the closest node called the "main interferer" [16]. Therefore, assuming log-normal fading, if the number k of simultaneously active nodes is known, we can take as reference the distance between the closest interferer and the victim to calculate the probability of interference as follows:

$$\Pr[P_{Rx} > I_{th}|x] = \begin{cases} \frac{1}{2}\mathrm{erfc}\left(\frac{|P_{av}(x) - I_{th}|}{\sqrt{2}\sigma}\right), & P_{av}(x) < I_{th} \\ 1 - \frac{1}{2}\mathrm{erfc}\left(\frac{|P_{av}(x) - I_{th}|}{\sqrt{2}\sigma}\right), & P_{av}(x) > I_{th} \end{cases} \tag{6}$$

where P_{Rx} is the received power of the victim's signal, I_{th} is the interference power threshold referred to the closest interfering node, σ is the standard deviation of the log-normal fading, and $P_{\mathrm{av}}(x)$ is the average power received at distance x.

The analyzed scenario assumes a sensor node density of 1000 devices/km^2 distributed in a WDS, with a simulation radius of 1 km,which corresponds to about 3140 smart water meters in the considered area. In addiction, two different load conditions are considered:

- **Equal DC**: both LoRa and Sigfox are configured to transmit at the maximum duty cycle (1%). In this case, LoRa transmits a larger amount of data than Sigfox. Assuming a payload size of 12 bytes, 13,714 and 2,107 packets/day are sent using SF7 and SF10, respectively, compared to 144 packets/day for Sigfox.

- **Equal data rate**: both networks transmit 144 packets/day, which corresponds to duty cycles of 0.0105%, 0.068%, and 1% for CSS SF7, CSS SF10, and UNB, respectively.

Table 2: Interference probability for different RSS levels for the victim technologies UNB, SF7, and SF12 under Equal DC and Equal Data Rate scenarios.

	Interference probability (%)					
	Equal DC			**Equal data rate**		
RSS (dBm)	**UNB**	**SF7**	**SF12**	**UNB**	**SF7**	**SF12**
-130	29.496	–	31.03	12.25	–	14.4
-120	11.97	39.7	13.81	4.56	18.32	6.5
-110	4.01	19.86	5.05	1.327	9.36	2.36
-100	1.31	7.71	1.23	0.38	3.73	0.81
-90	0.38	2.73	0.57	0.094	1.2	0.23
-80	0.10	1.14	0.17	0.027	0.658	0.085

The table 2 shows the probability of interference (%) encountered by three LPWAN technologies (UNB, LoRa SF7 and LoRa SF12) when operating as victim technologies in a Smart WDS scenario characterized by a high density of IoT nodes. The probability of interference is assessed based on the received signal strength (RSS, from –130 dBm to –80 dBm), considering two different traffic configuration scenarios: Equal DC and Equal data rate. The results indicate that, in the Equal DC scenario, UNB exhibits an interference probability comparable to LoRa operating at SF12, while devices using SF7 appear to be more susceptible to interference. Under conditions of equal data transmission speed, all technologies show a reduction in the probability of interference, with UNB benefiting the most, mainly because LoRa uses a shorter ToA in this configuration. However, when evaluating performance in terms of average throughput, in the Equal DC scenario UNB manages to transmit only 101 packets per day, compared with 403 and 8270 packets per day achieved by LoRa at SF12 and SF7, respectively [16].

Finally, the results in this subsection indicate that UNB and CSS systems can coexist reliably when the RSS is sufficiently high (above -90 dBm). Under more challenging conditions (e.g., at the cell edge), UNB exhibits greater resilience to interference, while CSS typically achieves higher throughput.

3.2 Optimization Algorithms for Data Extraction in Massive WDS

In the massive WDS context, effectively supporting large sensor networks deployed over extensive areas requires increasing the number of strategically placed

GWs. Each GW can receive data only from a portion of the network, depending on its geographical coverage and the prevailing environmental conditions [18]. Optimal GW deployment improves network quality and efficiency by reducing data loss and ensuring more reliable communication, a key element for initiating the digital transformation of WDS infrastructures [18]. In fact, accurate and targeted GW placement not only improves network coverage and capacity, it also minimizes costs by optimizing resource utilization and accelerating the adoption of advanced technologies such as real-time monitoring, early leak detection, and intelligent water resource management. Thus, the deployment and effectiveness of the LoRaWAN network become fundamental tools in the digital transformation process, aimed at making water distribution networks more intelligent, resilient, and sustainable [8].

4 Digital Representation of WDS

A digital representation for a Water Distribution System (WDS) seeks to express the real-world system and its dynamics through a digital model structured in a way to facilitate analysis and monitoring. Such digital representation is the basis for the development of smart tools that offer a unified platform integrating multiple sources and simulation through a digital model. In the subsequent discussion, we start by examining the architecture for the digital twin for a WDS and proceed to explore the concept of a graph model as an alternative representation.

4.1 Digital Twin

The concept of DT has emerged as a promising paradigm to digitalize the WDS. However, many current DT implementations for WDS are limited to passive monitoring, acting primarily as advanced visualization dashboards that display real-time data alongside simulation outputs [19]. While valuable, this approach remains fundamentally reactive, placing the burden of interpreting data and formulating responses entirely on human operators.

To address these critical shortcomings, we introduce a proactive DT methodology that moves beyond traditional passive monitoring to enable intelligent operational control. We present SWIM (Smart Water Interaction & Monitoring), an innovative application that integrates the modern DT definition. Indeed, it will be deployed as a dynamic, high-fidelity virtual representation synchronized with its physical counterpart throughout its entire life cycle [20].

In the proposed approach, ML models establish a predictive baseline of normal system behavior, while real-time IoT data is used to detect deviations and automatically trigger "what-if" hydraulic simulations. The discussion further underscores that IoT-based WDS, especially those employing LPWAN and LoRaWAN, support efficient large-scale monitoring of flow, pressure, and water quality.

A modern DT is now understood as a dynamic, high-fidelity virtual representation that remains synchronized with its physical counterpart throughout its entire life cycle [20]. This synchronization relies on a continuous, two-way exchange of real-time data, supporting active monitoring as well as advanced simulations and predictive analytics.

Building on these principle, we propose SWIM as an innovative application that integrates DT, IoT devices interconnected via LoRaWAN, and ML techniques to enable smarter and more efficient management of Smart WDSs. SWIM enables real-time interaction with IoT systems deployed at each WDS node, facilitates efficient data processing, and ensures robust yet streamlined device management. Fig. 4 illustrates the SWIM technology stack: At the sensing level, IoT ED monitor key parameters such as pressure, flow rate, and water quality. These devices transmit data via LoRaWAN-enabled ED to a NS, which manages connectivity. The data is then processed within SWIM and synchronized with Ditto [22], which abstracts physical IoT devices into DT architecture, enables secure, bidirectional communication, allowing SWIM to retrieve and update digital twin states, ensuring seamless device integration and control.

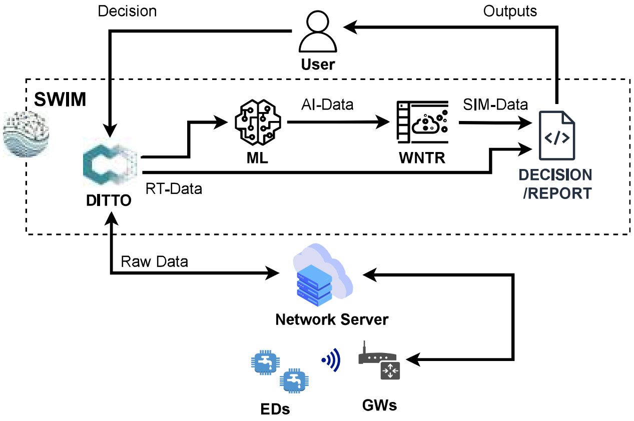

Fig. 4: SWIM technology stack [21].

The importance and the novelty of SWIM architecture is the interaction between its ML models and the WNTR hydraulic simulator [23]. To effectively bridge the gap between idealized synthetic data and noisy real-world measurements, which is an important challenge, SWIM employs a robust mitigation strategy by integrating a proactive feedback loop. Firstly, The ML models analyze real-time data to detect anomalies or predict future states. Secondly, Instead of direct reaction, SWIM exploit context-information as triggers for the WNTR-simulator. It runs "what-if" scenarios to evaluate potential responses (e.g. isolating a pipe or adjusting pump pressures) and quantifies their impact on the entire system's behavior. Thirdly, the system analyze simulation results to to obtain a data-driven basis for informed decision-making. SWIM is able to recommend the optimal intervention to the user or even automate control actions. This proactive, simulation-backed approach moves beyond simple monitoring, enabling intelligent operational control and risk mitigation. WNTR extends EPANET's capabilities, incorporating Pressure-Driven Analysis (PDA) to simulate demand variations based on available pressure and a pressure-dependent leak model that realistically represents water losses.

At the user level, SWIM provides an interactive interface for real-time monitoring and control. To demonstrate SWIM's predictive capabilities, we generate synthetic datasets from hydraulic simulations on benchmark WDS and train custom NN models on them. The results highlight the effectiveness of our models. A proactive and optimized management proposed by SWIM, is directly aligned with the core principles of Industry 5.0 [24]. Novel automated solutions improve sustainability and minimize water loss and optimize energy consumption in pumping operations in green IoT envision [25].

SWIM is a DT-based platform designed for real-time monitoring, analysis, and interaction with a digital replica of a WDS. It leverages an IoT sensor network utilizing LoRaWAN technology, where the authenticated devices at each node continuously stream hydraulic data to the platform. By integrating ML predictions with real-time sensor data and hydraulic simulations from tools such as WNTRand EPANET, SWIM enables users to analyze, compare, and validate system behavior through a unified, intuitive interface that requires minimal technical expertise. The integration of simulators such as WNTR is essential and widely reported in the literature in the water sector due to their high reliability, as they allow accurate simulation of real large-scale systems [26].

The platform is an integrated microservices application which includes interfaces to devices, a ML module, a WNTR module an intuitive web interface.

To improve IoT management, SWIM incorporates Eclipse Ditto [22], which abstracts physical IoT devices into DTs. This integration allows users to interact with and monitor these digital counterparts via a unified API, supporting both synchronous and asynchronous communication for real-time control and monitoring.

The main interface of SWIM presents a digital replica graph of the real WDS, allowing users to monitor and interact with the system dynamically. Users can interact with the graph by clicking on individual nodes, resizing the layout, and adjusting the visualization. A sidebar provides real-time updates and displays both current and historical data.

Each node in the graph is categorized as a Junction, Reservoir, or Tank, following the EPANET/WNTR classification system. By clicking on a node, users can access a detailed popup menu that displays static information such as Node ID, coordinates, and type, alongside hydraulic data from three sources:

- **RT:** Real-time data gathered from IoT devices registered to the node, exchanged via Eclipse Ditto.