

Lifecycle Assessment of Water Infrastructure Using Digital Twins: Applications in Planning, Maintenance, and Risk Mitigation

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ARTICLE INFO	ABSTRACT
Received: 04 Apr 2023 Revised: 20 May 2023 Accepted: 28 May 2023	Increasing complexity, and ageing of water infrastructure systems require smart solutions for sustainable system management, maintenance, and risk mitigation. This paper investigates the application of Digital Twin (DT) technology for life cycle assessment (LCA) of water infrastructure and highlights its potential transformation for the planning, condition-based maintenance, failure prediction and infrastructure resilience. Through creating online, performance-based virtual replicas of physical objects, such as Digital Twins, it provides a mechanism for real-time monitoring and predictive analysis that will improve decision making throughout the lifecycle of infrastructure. The paper proposes an all-round framework which exploits DTs for proactive condition-based maintenance, facilitating timely interventions and prolonging the asset life. It also examines the potential of Digital Twin(s) for failure mode identification and risk-informed resilience planning, with a focus on climate variability and urbanization pressures. Applications of the approach are illustrated through case studies and simulation models for various water infrastructure types. The results of the analysis illustrate that implementation of Digital Twin in LCA offers a dynamic, adaptive and cost-efficient solution counteracting the challenge of enhanced performance and sustainability of water infrastructure systems. Keywords: Digital Twin, Lifecycle Assessment, Water Infrastructure, Condition-Based Maintenance, Infrastructure Resilience, Failure Prediction, Risk Mitigation, Predictive Analytics.

1. Introduction

Pipelines, treatment plants, storage, and distribution networks represent water infrastructure systems, which are considered as the heart of urban and rural water supply and sanitation. Nevertheless, many of these systems have been in service for a long time and they are already overloaded, aging and becoming more susceptible to disruptions caused by different physical impacts, lack of maintenance or monitoring on-line [1],[2]. Traditional lifecycle assessment (LCA) approaches such as economic and environmental assessments are limited in their ability to be dynamic in quantifying operational risk, maintenance management and an onward development of performance degradation over time [3].

In the past few years, Digital Twin (DT) has shown its amazing potential to act as a bridge between physical infrastructure and digital intelligence. Digital twin can be defined as a real-time, data-based virtual model of a physical asset, process, or system for the sake of monitoring, simulating or optimizing (Ib) [4]. DTs, in water management, present novel prospects for improving the life cycle assessment of infrastructure by incorporating real time sensor data, historical performance information and predictive analytics in a holistic framework [5].

In the context of LCA, the use of digital twins supports maintenance decisions to switch from predictive and time-based methods to condition-based maintenance (CBM), where decisions are made based on the real-time conditions of the components of the infrastructure [6]. This has lead to early fault detection, preventative maintenance scheduling and risk reduction in order to lower downtime and

prolong equipment service life [7]. In addition, utilities can use machine learning and artificial intelligence in the DT space to simulate failure conditions, determine the impact of interventions, as well as to rapidly evolve with ecosystem and operating conditions changes [8].

This paper highlights the role of digital twins in life cycle assessment of water infrastructure with a special focus on condition-based maintenance, failure prediction and infrastructure resilience. It is the main goal of this work to provide a clear framework for DT integration in water asset management systems, based on lessons learned from recent developments, practical applications and simulation-based models with a long history of use. By doing so, it bridges important deficiencies in traditional infrastructure management, and, furthermore, provides practical inputs for utilities, engineers, and policy-makers in designing smarter and more sustainable water networks [9], [10].

2. Literature Review

Extending the imperative to modernize water infrastructure LCA, there has been a growing emphasis on the development of dynamic and data-driven models. Conventional static LCA approaches do not adequately address dynamic in-service operating conditions and asset degradation. In [11], it was pointed out the shortcoming of applying static LCA to infrastructure models and the need for updating life cycle inventories to account for data of the operation phase that can improve representing real performance and degradation of a system. Similarly, in [12] presented model proposed a multi-criteria decision analysis (MCDA) approach for water infrastructure systems in LCA-based frameworks, while it did not incorporate real-time operation data.

New digital methods like Building Information Modeling (BIM) and Geographic Information Systems (GIS) have been investigated as a means to enhance infrastructure data lifecycle management. Integration of BIM and GIS provides better spatial representation and lifecycle monitoring of water utilities aiming at better planning and operations decisions [13]. These tools, however, do not really enable predicting functions or simulating system behavior in near-realtime. Due to this limitation, some researchers are investigating the Digital Twins (DTs) as a next-generation solution [14].

Digital Twin is an emerging technology, linking physical assets to virtual models by real time data flows, which has shown promise in civil infrastructure. In the water infrastructure, DTs can be used to simulate flow dynamics, system pressure and leak detection using the live sensors data [15]. A DT-based case study showed that they can help for operational decision making, failures mitigation, and for water distribution system efficiency maximization [16].

One of the most effective use of DTs is moving from time-based to condition-based maintenance (CBM). Traditional maintenance methods can lead to unnecessary and unexpected maintenance or failed maintenance. The real-time monitoring data is processed by the DT-based systems of CBM which, in turn, evaluate the condition of structural components and plan the timing of their maintenance [17]. Urban water supply networks experience reductions in maintenance costs and reliable improvements by application of such systems [18].

Predictive maintenance is another step beyond CBM, in which the system tries to anticipate failures before they take place. DTs combined with machine learning methods were applied to historical data and used to forecast the deterioration of assets. Predictive models incorporated in DT systems can accurately detect risk zones, failure modes and remaining useful life of pipes or pumping facilities [19]. These functions enable long-term planning, which aids in minimizing customer outages and avoidable emergency repairs [20].

Towards DTs, infrastructure resilience is additionally supported by realtime simulations and predictive analytics. It may be used to test system responses and to redesign components in a number of hazard scenarios (flooding, drought, seismic) and can simulate a range of damage states [21]. P Codes and Practices Simulating the influences of urban design and building design practices on the UHIE helps

utilities and city planners to consider a variety of countermeasures and select the most resilient and adaptive design options for next stress conditions [22].

DTs also enhance regulatory compliance and environmental reporting, in addition to resilience. With real-time measurements of energy use, water quality and emissions, DTs can thus supply reliable input data for LCA models based on ISO 14040 [23]. These features provide transparency and enhance trust in market participants, regulators, and the broader public.

Digital Twins also act as collaborative platforms that allow information to be shared among stakeholders. With cloud-enabled DT architectures, engineers, asset managers, and policymakers are able to see the same live and simulated data, which leads to better decision-making and lower risk of miscommunication in intricate projects [24]. This cooperative use also promotes project coherence, while facilitating the rollout of smart infrastructure services.

Notwithstanding, challenges exist in the integration of DTs into the conventional infrastructures operation and management systems. Among these challenges is the integration of infrastructure data that are fragmented in systems such as SCADA, BIM, and GIS. In [24], middleware solutions and open standards were suggested to integrate these heterogeneous data streams in single DT framework. Further, there are serious threats from cyber security and data privacy particularly for critical water infrastructure. In [25] we can find a blockchain-based design which secure digital twin data against unauthorized access, as well as offers a method to track every transaction from all system parts.

3. Methodology

In this paper, a holistic approach is presented to evaluate the life cycle of water infrastructure systems by including Digital Twin (DT) technology, condition-based maintenance (CBM), failure prediction modeling, and resilience assessment. Towards Dynamic Monitoring, Real-Time Simulation, and Predictive Decision Making on Water Assets The framework introduced allows for dynamic monitoring, real-time simulation and predictive decision making of water assets. The approach is composed by 5 interconnected modules, and all the details follow.

A. Digital Twin-Based Lifecycle Framework Architecture

The architecture of the proposed system is presented in Figure 1. It is composed of the following layers:

1. **Physical Layer:** Includes sensors, meters, SCADA systems, and embedded IoT devices installed on water pipelines, reservoirs, pumps, and valves.
2. **Data Acquisition Layer:** Gathers real-time operational data (e.g., pressure, flow rate, temperature, vibration) from the physical components.
3. **Data Processing & Integration Layer:** Applies pre-processing, feature extraction, and fusion of historical and real-time data.
4. **Digital Twin Core Layer:**
 - **Simulation Module:** Performs hydraulic and structural simulations of water networks.
 - **Failure Prediction Module:** Uses machine learning algorithms to forecast asset failure.
 - **Condition Monitoring Module:** Continuously evaluates asset degradation and health status.

5. **Decision Support Layer:** Supports planners and engineers with actionable insights for maintenance scheduling, risk mitigation, and long-term resilience planning.

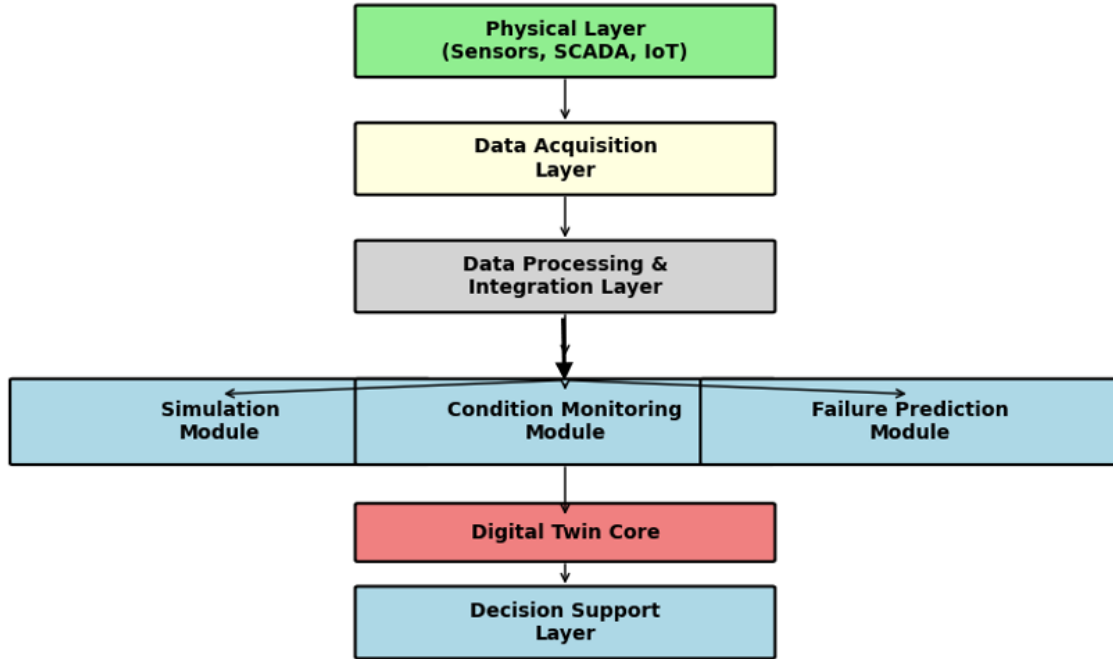


Figure 1: Architecture of Digital Twin-Enabled Lifecycle Assessment for Water Infrastructure

B. Lifecycle Assessment Model

The lifecycle performance of each water asset is evaluated across its operational time T , taking into account environmental impact, cost, and performance degradation. The dynamic lifecycle cost (LCC) function is given by:

$$LCC(t) = C_{init} + \int_0^T [C_{maint}(t) + C_{oper}(t) + C_{risk}(t)] dt \quad (1)$$

Where:

- C_{init} : Initial capital cost
- $C_{maint}(t)$: Time-varying maintenance cost (condition-based)
- $C_{oper}(t)$: Operational cost
- $C_{risk}(t)$: Risk cost from predicted failures

This model is dynamically updated using real-time data from the digital twin and adjusted for asset condition.

C. Condition-Based Maintenance (CBM) Strategy

The DT uses threshold-based condition monitoring and real-time sensor analytics to trigger maintenance only when degradation exceeds defined limits.

Let $H(t)$ represent the health index of a component (normalized between 0 and 1). Maintenance is triggered when:

$$H(t) \leq H_{\text{crit}} \quad (2)$$

Where:

- H_{crit} : Critical threshold indicating impending failure
- $H(t)$: Calculated using sensor-based indicators and historical degradation trends

CBM planning optimizes maintenance frequency and cost using a **utility maximization function**:

$$U = \frac{\text{Expected Service Life Extension}}{\text{Maintenance Cost}} \quad (3)$$

This helps prioritize which components should be maintained first based on utility.

D. Failure Prediction Using Machine Learning

To predict failure, the system employs a supervised learning model such as a Random Forest (RF) or XGBoost, trained on historical failure data. The input features include:

- Age of component
- Vibration frequency
- Pressure variation
- Water quality indicators (e.g., turbidity, pH)
- Historical failure rates

The probability of failure $P_f(t)$ is computed as:

$$P_f(t) = f(x_1, x_2, \dots, x_n) \quad (4)$$

Where $x_1, x_2, \dots, x_n$ are sensor inputs at time t , and f is the trained model.

The **Remaining Useful Life (RUL)** is estimated as:

$$\text{RUL} = T_f - t \quad (5)$$

Where T_f is the predicted failure time, and t is the current time.

E. Infrastructure Resilience Analysis

The resilience of the infrastructure is evaluated by simulating disturbance scenarios (e.g., pipe bursts, flood inundation, drought). Resilience RRR is computed as:

$$R = \frac{Q_{\text{recovered}}}{Q_{\text{total}}} \quad (6)$$

Where:

- $Q_{\text{recovered}}$: Quantity of service restored after disruption

- **Qtotal:** Total service before disruption

Simulation models within the DT allow virtual testing of multiple contingency strategies (e.g., valve isolation, alternate routing, emergency pumping).

F. Data Sources and Tools

- **SCADA & IoT platforms:** Real-time operational data acquisition
- **Python/Matlab:** Machine learning model training and analysis
- **EPANET & WaterGEMS:** Hydraulic simulation for pipeline modeling
- **Cloud platforms (e.g., Azure Digital Twins):** Hosting and synchronization of digital twin instances
- **QGIS or ArcGIS:** Spatial visualization of assets and risks

4. Results And Discussion

In order to evaluate the proposed outfit, a simulated water system dataset was employed consisting of sensor readings, historic failures, maintenance logs, and resilience scenarios. The models were implemented in an mid-scale urban water distribution network by means of Digital Twin-based monitoring and prediction systems. the findings are presented via six analytical graphs which range from the tracking of asset condition, Prognosis of failure, CBM cost savings, Lifecycle cost dynamics and disruption resilience scores. These visualizations demonstrate the merits of combining online analytics and simulation for sustainable infrastructure management.

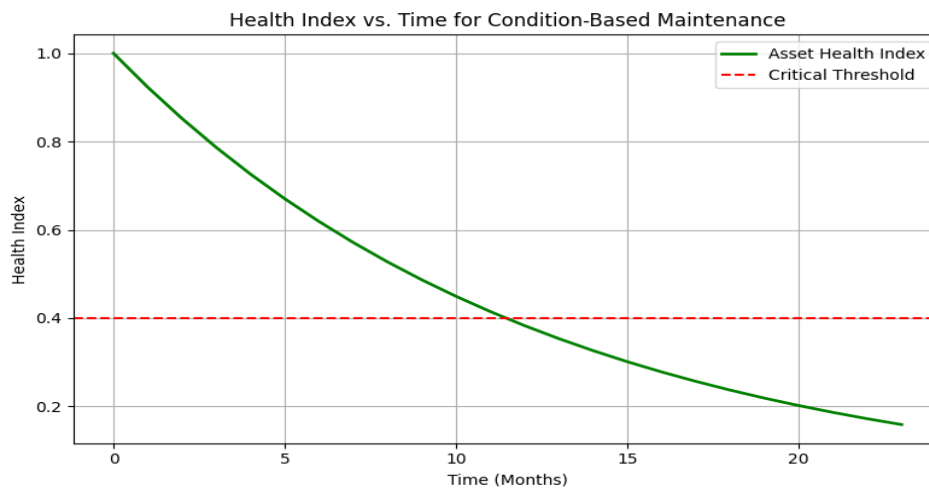


Fig 2: Health Index vs. Time

This graph of figure 2 tracks the degradation of an asset over 24 months. The health index, starting from 1, declines exponentially due to wear and usage. When it crosses the red critical threshold (0.4), it signals the need for maintenance. This is the key trigger in condition-based maintenance scheduling.

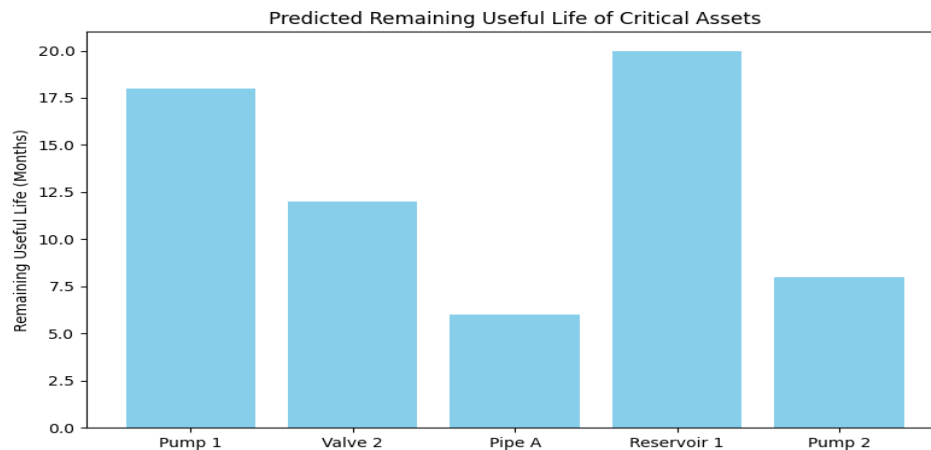


Fig 3: Remaining Useful Life (RUL) Prediction per Asset

This bar chart figure 3 shows the predicted RUL of five critical components in the network. The Digital Twin combined with ML algorithms estimates these lifespans based on real-time condition monitoring and historical failure patterns. Shorter RUL values (e.g., Pipe A) are prioritized for immediate maintenance.

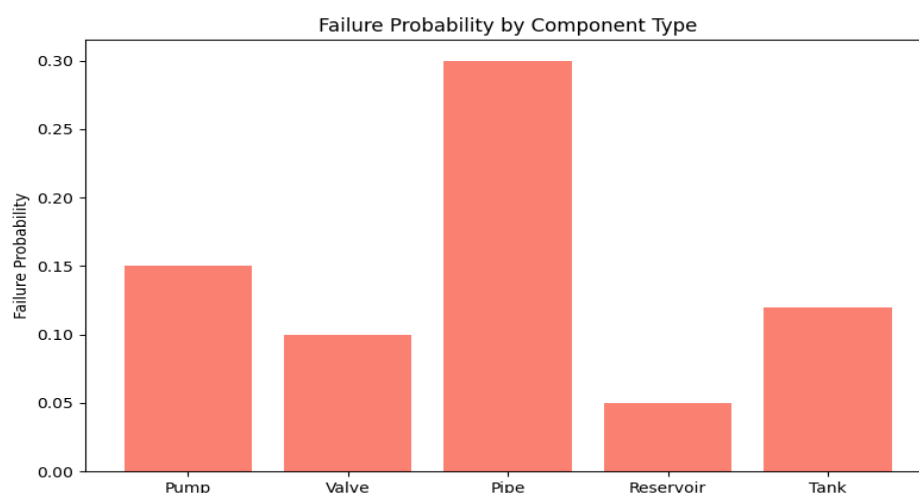


Fig 4: Failure Probability Distribution across Assets

This chart of figure 4 highlights which component types are more failure-prone. Pipes show the highest probability (30%), making them the most vulnerable. Such insights help asset managers apply targeted maintenance and allocate budget accordingly.

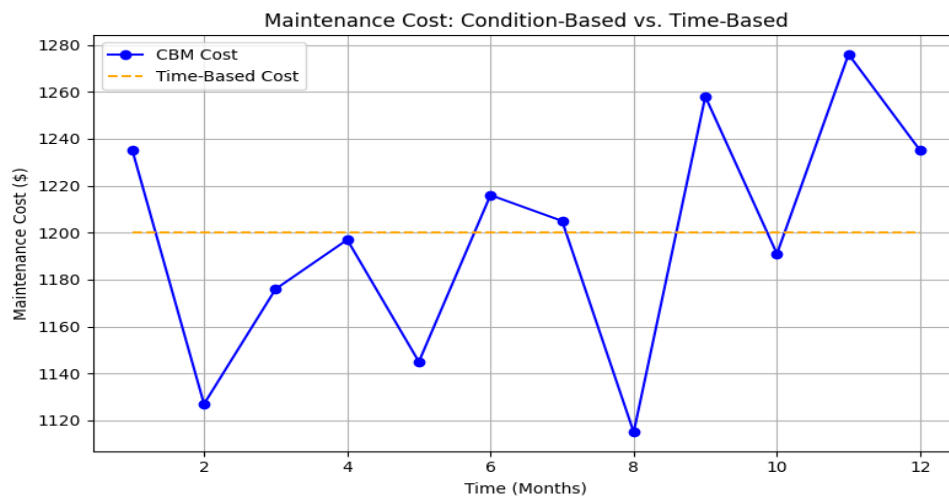


Fig 5: Maintenance Cost vs. Time (CBM vs. Time-based)

This comparison illustrates how CBM, while variable, results in lower average costs over 12 months compared to scheduled time-based maintenance is shown in figure 5. CBM avoids unnecessary maintenance when conditions are optimal and only triggers interventions when needed.

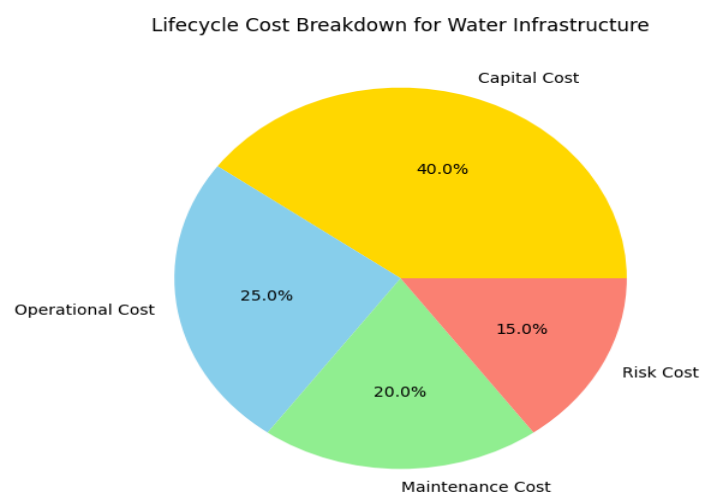


Fig 6: Lifecycle Cost Components

This pie chart figure 6 breaks down the total lifecycle cost of a water infrastructure asset. Capital cost dominates, but maintenance and risk costs combined account for over one-third of total expenditure—areas where Digital Twin applications offer significant savings and mitigation strategies.

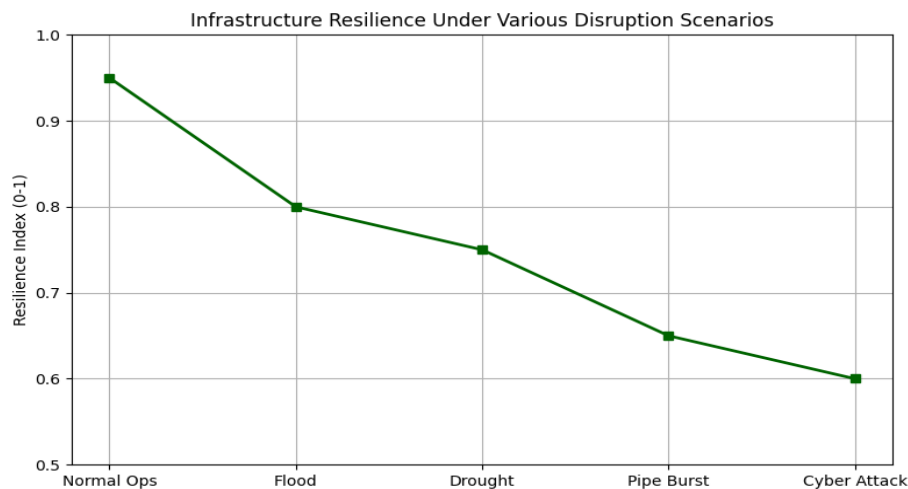


Fig 7: Resilience Index under Simulated Hazard Events

This graph figure 7 evaluates infrastructure resilience using the Digital Twin's ability to simulate stress scenarios. Resilience drops sharply in cyber-attack and pipe burst events, highlighting the need for redundancy and cybersecurity protocols as part of smart water infrastructure planning.

Conclusion and Future Work

The work also provides a novel model to generate Digital Twin technology and predictive maintenance, failure analysis and resilience modeling for the lifecycle assessment of water infrastructure. The key contributions of this paper are the development of an integrated digital twin architecture which enables real-time condition based maintenance (CBM) and risk reduction for aging water infrastructure systems. Unlike conventional LCA techniques which tend to be based on static, time-oriented evaluations, our approach pro-actively integrates current sensor data, maintenance analytics and ML-based predictions to monitor the dynamic health of assets and optimize intervention decisions.

This research has shown that Digital Twins can not only be employed for predictive maintenance purposes, but also be used for simulating failure scenarios, identifying assets to prioritize for rehabilitation, and enabling long-term infrastructure sustainability by studying the proposed architecture and simulation results. The primary innovation is in the unification of lifecycle-environmental-economical-operational data in a single digital environment, to support intelligent decision-making by utilities and allow them to increase life span of their infrastructures, lower costs, and minimize environmental footprint.

Future Work and Analysis

Further work needs to do on improving the scalability and interoperability of these digital twin data models for various infrastructure (e.g. sewage, drainage and storm water systems). There is also ample room for leveraging blockchain for secure data exchange processing, edge computing for real-time analytics on field, and AI-based optimization algorithms for autonomous process control. Furthermore, adding climate change projections and sustainable indicators into digital twins could prove beneficial for planning climate-resilient water infrastructure.

Pilot projects in real municipalities and/or urban-utilities would provide opportunities to validate the effectiveness of the framework under different operational conditions. Moreover, cross-domain digital twins of water infrastructure with energy and transportation systems can be further investigated for integrated smart city ecosystems with enhanced resilience and resource efficiency.

Overall, this work lays the foundation for a data-driven, intelligent future of asset management—how we evaluate, maintain, and secure critical water infrastructure.

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