Integration of IoT and Digital Twin for Intelligent Management of Urban Underground Pipe Galleries in Smart Cities

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The increasing complexity of urban infrastructure demands innovative solutions for effective management. This paper proposes an intelligent management system for urban underground pipe galleries, integrating Internet of Things (IoT) sensors and digital twin technologies to enhance operational efficiency in smart cities. The system enables real-time monitoring, predictive maintenance, and optimization of public services by creating a virtual replica of the underground infrastructure. The methodology involves deploying IoT sensors for continuous data collection and feeding this information into a digital twin model that simulates and predicts potential failures and maintenance needs, as well as measuring flow rate and temperature. This allows for proactive decision-making, minimizing downtime, and reducing maintenance costs. Experimental results demonstrate the effectiveness of the proposed system in optimizing urban infrastructure management. The system achieved a 92% prediction accuracy in identifying potential failures, enabling proactive maintenance, and reducing service disruptions by 40%. Predictive analytics minimized maintenance costs by 35%, while resource optimization improved task prioritization, significantly enhancing operational efficiency. These results highlight the transformative potential of integrating IoT and digital twin technologies for smarter and more sustainable city management. This research underscores the transformative potential of integrating advanced technologies like IoT and digital twin models in managing complex urban systems, with significant implications for smart city development and sustainability

Članek predlaga inteligentni sistem za upravljanje podzemnih cevodov v pametnih mestih, ki združuje IoT senzorje in digitalne dvojčke. Sistem omogoča nadzor v realnem času, napovedno vzdrževanje in optimizacijo javnih storitev.

1 Introduction

Infrastructures, especially underground pipe galleries, enable modern urban cities to address fundamental needs ranging from water supply and sewage to gas and telecommunication services—simple but indispensable elements of functionality [1]. However, the growing control of these subsurface systems is complex between urbanization and the growth of new-age cities and old-age infrastructure [2] [3]. This has made the traditional methods of periodic checkups and remnant manual interferences very costly and unproductive in their operations; they lead to frequent system breakdowns and a slow response to system breakdowns [4]. Smart solutions based on data are crucial to address the escalating challenges of cities and guarantee the effectiveness of such critical networks [5].

This paper proposes an innovative solution by integrating the Internet of Things (IoT) and Digital Twin technologies to develop an intelligent management system for urban underground pipe galleries. By leveraging the capabilities of real-time data monitoring, predictive maintenance, and system optimization, this research aims to enhance underground infrastructure's efficiency, reliability, and sustainability, ultimately contributing to the development of smarter, more resilient cities.

Urban underground pipe galleries are essential to the normal functioning of cities and accommodate urban utilities necessary for daily life. Effectively managing these systems is critical for maintaining public health, safety, and convenience [6].

1.1 Role of underground pipe galleries

These systems are vital for the public's safety, health, and convenience. Tunnels provide lifelines for clean water, sewage disposal, and energy [7]. With the growth of cities, these systems experience more stress and require sophisticated management capability to maintain efficient performance. Traditional approaches, based on manual inspections and reactive repairs, no longer meet the demands of modern cities [8] [9].

1.2 Challenges in managing underground infrastructure

The management of urban underground pipe galleries presents a range of challenges:

- **Aging Infrastructure**: Many underground systems are decades old, with wear and tear leading to higher failure rates and frequent maintenance needs [10].
- **Limited Real-Time Monitoring**: System failures often go unnoticed without continuous data collection until they cause major disruptions [11].
- **High Maintenance Costs**: Reactive maintenance is costly and inefficient, leading to increased operational expenditures and prolonged downtimes [12].

To overcome these issues, developmental technologies must ensure the right time for monitoring, diagnosing, and efficiently handling all basic requirements.

1.3 Technological advancements in infrastructure management

The last few years have seen the emergence of IoT and the digital twin, changing how infrastructure systems are monitored. These technologies enable real-time monitoring, analyzing, and optimizing complex systems that characterize the urban context [13].

1.3.1 IoT in urban infrastructure

IoT technology combines the physical world and the Internet, continuously transferring captured and exchanged information. In an urban context, IoT devices can measure attributes such as flow, temperature, pressure, or the state of the structures and materials involved [14].

- **Real-Time Monitoring**: IoT sensors provide continuous monitoring, ensuring that any anomalies, such as leaks or blockages, are detected immediately.
- **Predictive Maintenance**: Data from IoT devices can be used to predict potential system failures, allowing for proactive maintenance that reduces the need for emergency repairs.
- **Improved Operational Efficiency**: IoT enables data-driven decisions, helping to optimize resource allocation and system operations.

1.3.2 Digital twin technology

A digital twin is a realistic representation of a physical system that could emulate its functioning in real-time [15]. It also integrates Internet of Things data and digital twin models to create solutions with broad possibilities and more accurate decision-making [16].

- **Predictive Maintenance**: Digital Twins can simulate the behavior of underground infrastructure and predict when components are likely to fail, minimizing unplanned maintenance.
- **System Optimization**: The digital model allows simulations that help optimize system performance and inform decisions about infrastructure upgrades and maintenance strategies.
- **Scenario Testing**: Digital Twin models facilitate testing scenarios without altering the physical system, enabling better planning and risk management.

1.4 Review of existing research

Many works have been done on IoT and digital twin technology in infrastructure management. However, most of these studies are limited to reference systems or single infrastructure domains, e.g., water supply or waste [17]. Literature reviews on incorporating IoT and Digital Twin into a single management system for urban underground pipe galleries are limited [18].

1.4.1 IoT in infrastructure management

Related Work on IoT for Applications of Infrastructure Management In infrastructure management, existing research literature provides extensive insights into real-time monitoring and enabling better performance systems [19]. IoT-based systems are widely used in water supply and sewage systems to monitor pressure, flow, temperature, etc. However, these systems are usually siloed; they work in isolation without being integrated across various infrastructure elements [20].

1.4.2 Digital twin technology in infrastructure

As with many technologies, digital twins are well adopted in large-scale manufacturing industries but are still quite nascent in the infrastructure context of cities. Research indicates that the real-world complexity of individual systems can be improved by using digital twins to predict performance under various conditions [21]. However, the investigations regarding integrating IoT data with digital twins for embedded, coupled, multi-utility systems remain in their infancy.

1.5 Research gaps and motivation

Despite advancements in IoT and digital twin technologies, there is a significant gap in their integrated use for managing urban underground pipe galleries. Existing research often addresses these technologies in isolation or focuses on specific infrastructure sectors, such as water systems or sewage. The absence of a comprehensive, integrated management system for urban pipe galleries motivates this study.

1.5.1 Integration challenges

Integrating IoT and digital twin technologies into a unified management system presents several challenges:

- **Data Integration**: Ensuring seamless data flow between IoT devices and digital twin models.
- **Predictive Algorithms**: Developing accurate predictive maintenance models based on real-time data.
- **System Scalability**: Designing an adaptable and scalable system for use across different urban environments.

1.5.2 Motivation for the study

The research aims to remove gaps through the development of an IoT-based intelligent management system that implements digital twins. The system ensures more efficient monitoring and maintenance operations of underground pipe galleries throughout cities, which produces better infrastructure results. Our research focuses on solving three core infrastructure management problems that stem from manual inspections, reactive maintenance, and faulty detection inefficiency [22]. Through the proposed system, agents can conduct real-time observation while performing predictive maintenance operations and making improved choices. The project concentrates on implementing this intelligent management system in urban underground pipe galleries since these elements represent crucial infrastructure for city operations that experience poor management.

1.6 Research objectives and scope

The main objectives of this research are:

1. To design and develop an intelligent management system for urban underground pipe galleries that integrates IoT-based monitoring with digital twin technology.
2. To implement real-time monitoring to detect underground infrastructure leaks, blockages, and pressure drops.
3. To create a digital twin model of the underground infrastructure, enabling simulation and optimization of system performance.
4. To evaluate the system's effectiveness in reducing maintenance costs and improving operational efficiency.
5. To assess the scalability of the proposed system for use in different urban environments.

The research will focus on developing and testing this integrated system in a simulated environment.

1.7 Contributions and novelty of the research

This research contributes to the field of urban infrastructure management in several ways:

1. **Novel Integration**: Integrating IoT and digital twin technologies into a unified management system for underground pipe galleries is a novel approach that has not been widely explored.
2. **Proactive Management**: The system incorporates predictive maintenance, which improves operational efficiency and reduces the costs associated with reactive repairs.
3. **Scalability and Practicality**: The proposed system is scalable and practical, offering a solution for cities looking to optimize their infrastructure management strategies and contribute to the development of smart cities.

The paper is structured as follows: Section 1 introduces the research, providing background, objectives, and significance of the study. Section 2 presents related work, discussing the application of IoT and digital twin technologies in infrastructure management and highlighting existing gaps. Section 3 describes the methodology, detailing the design and development of the proposed intelligent management system. Section 4 presents the results and discussion, showcasing the system's implementation and performance evaluation outcomes. Finally, Section 5 concludes the paper by summarizing the research contributions and suggesting potential areas for future work.

2 Related work

The integration of IoT and digital twin technologies has been extensively explored in recent years, particularly in infrastructure management. Adreani et al. [23] developed a Smart City Digital Twin framework capable of real-time multi-data integration and wide public distribution, emphasizing its applicability in urban planning and public safety. Duran et al. [24] proposed a digital twin-native AI-driven service architecture for industrial networks, highlighting significant processing time savings and improved learning models [25]. Isah et al. [26] introduced a data-driven digital twin network architecture for Industrial Internet of Things (IIoT) applications, focusing on data integration and protocol standardization. Becattini et al. [27] provided empirical insights into industrial data and service aspects of Digital Twin networks, discussing the dual nature of Digital Twins as both digital replicas and networks of interconnected models. Arezza [28] examined the impact of IoT, Digital Twin, and Artificial Intelligence in transforming process industries towards a circular economy, emphasizing the need for standardization and interoperability. The Industrial Internet Consortium [29] reported on various testbeds demonstrating real-world implementations of Industrial Internet solutions, including Track and Trace and Asset Efficiency, which utilize IoT and Digital Twin technologies for enhanced operational efficiency. The National Institute of Standards and Technology (NIST) [30] discussed the acceleration of the IoT digital economy with trusted value chains driven by significant investments in semiconductor manufacturing and traceability infrastructure [31]. The International Telecommunication Union (ITU) [32] provided an overview of Study Group 20's work during the 2022-2024 study period, focusing on developing standards for IoT, Digital Twin, metaverse, AI/ML, and other emerging technologies to enhance digital services through innovation. Table 1 presents the summary of the related work.

3 Research methodology

The proposed intelligent management system incorporates IoT and digital twin technologies to overcome urban underground pipe gallery management inefficiencies. This section describes the system's architecture, data flow, predictive maintenance algorithms employed, and evaluation framework.

Conventional management of underground pipe galleries is based on manual inspection and reactive maintenance. However, these methods are ineffective and do not avoid service downtime and high ownership costs. To go beyond these constraints, this paper proposes a new system that incorporates online monitoring, virtual simulation, and predictive maintenance. This method proactively affiliates management. The underground pipe network information data classification may be viewed in Figure 1.

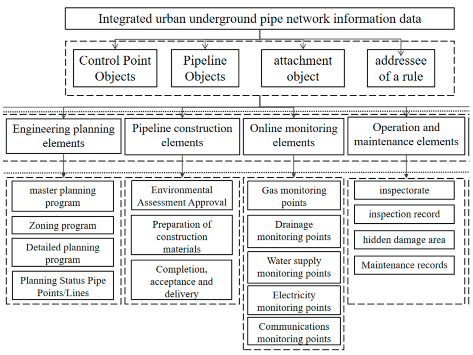

Figure 1: Integrated network information

3.1 System architecture

Our suggested system architecture encompasses three main elements: Internet of Things (IoT) sensors for real-time monitoring, a cloud-based data processing unit, and a digital twin predictive analysis. With IoT sensors deployed in the pipe galleries, flow, pressure, and temperature (generic critical parameters) could be monitored continuously. The data gathered through the devices is sent to a cloud-based platform, aggregated, processed, and provided as input to the Digital Twin model.

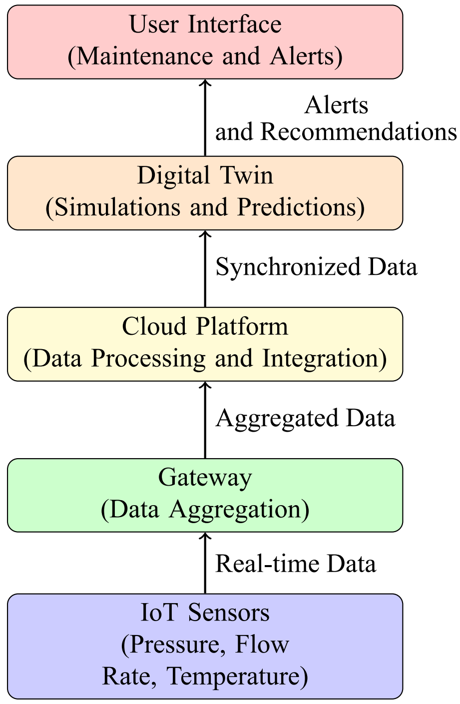

Figure 2: System architecture showing the integration of IoT, cloud, and digital twin

The Digital Twin, a virtual replica of the physical pipe gallery, mirrors real-time data from the IoT sensors. By providing a means to create virtual representations of the system, it facilitates predictive maintenance by running simulations of how the systems will behave in different conditions. Figure 2 illustrates the system's architecture, where data flows seamlessly between IoT sensors, the cloud, and the Digital Twin.

Real-time IoT sensor data moves through a cyclic pattern, beginning with gathering data in real-time from sensors and sending it to the cloud for computation. The digital twin receives processed data during this stage to run simulations and make future failure predictions under diverse operational conditions. The digital twin delivers processed data to the user interface, which enables users to make maintenance choices through a cycle of continuous feedback. We explain how the Digital Twin functions through its operation of building a virtual underground facility model from real-time data while executing performance simulations using sensor information. The simulation, together with its predictive maintenance functions, plays a vital role in the research domain.

3.2 IoT-based monitoring

The IoT subsystem comprises a network of sensors strategically deployed across the pipe galleries to monitor operational conditions [33]. Pressure sensors detect abnormalities that may indicate potential leaks or blockages. Flow rate sensors measure the volume of fluids passing through the pipes, while temperature sensors provide data on thermal fluctuations that could signal structural issues.

New information about IoT-based monitoring sensors has been added to the document by specifying sensor properties, including measurement range alongside accuracy levels, sensitivity values, and sampling frequency. The pressure sensors reveal a sensing range between zero and one hundred bar together with an accuracy of 0.5% and a sampling period of one Hertz. The flow rate sensors measure within a 0-50 L/min range while providing 1% accuracy and sampling measurements at a rate of 0.5 Hz. Temperature sensors work between -20°C to 100°C with a ±0.2°C accuracy level at a 2 Hz sampling frequency. The established threshold for designating abnormal pressure measurements was determined as any deviation higher than 10% compared to normal operating pressure through the use of field data. The temperature sensors operate to identify temperature variations that signal structural problems, particularly corrosion or fatigue, by alerting users to any rapid temperature shifts that exceed 5°C.

Data is transmitted using low-power communication protocols such as LoRaWAN. The transmission model is represented mathematically as follows:

$$T_d = \frac{P_t \cdot D}{B} \tag{1}$$

where:

- T_d is the data transmission time,
- P_t is the transmitted power,
- D is the distance from the sensor to the gateway,
- B is the bandwidth of the communication channel.

This ensures efficient and reliable data transfer, even in challenging underground environments.

3.3 Digital twin development

The Digital Twin is a three-dimensional virtual model of the pipe gallery system. It incorporates geometric, structural, and operational data to accurately represent the physical infrastructure.

Real-time synchronization between the IoT sensors and the digital twin ensures that the virtual model reflects the system's current state [34]. The Digital Twin also performs simulations to predict system behaviors under various conditions. For example, fluid dynamics equations are used to model the flow within the pipes:

$$\nabla \cdot (\rho \mathbf{v}) = 0, \quad \nabla \cdot (\mathbf{v}\mathbf{v}) = -\nabla P + \mu \nabla^2 \mathbf{v} \tag{2}$$

where:

- ρ is the fluid density,
- $\mathbf{v}$ is the velocity vector,
- P is the pressure, and
- μ is the dynamic viscosity.

3.4 IoT-digital twin integration

IoT and Digital Twin components are integrated through a middleware framework that ensures seamless data exchange. IoT data is pre-processed at the edge to reduce latency before being transmitted to the cloud. The cloud platform updates the digital twin in real time using RESTful APIs. Their integration may also be viewed in Figure 3

The synchronization equation models this integration:

$$S(t) = \int_0^t D(t')\, dt' \tag{3}$$

where $S(t)$ is the synchronized state of the Digital Twin at time t, and $D(t')$ represents the incoming data stream.

Time-accurate simulations function because IoT sensor inputs continuously send data to the Digital Twin system. The data processing unit works as a filter before model input to handle sensor errors and sensor noise contamination. The system parts form an operational network that allows active prediction of system behavior and proactive maintenance capabilities with optimized resource utilization. The system maintains scalability and quick response times by using cloud computing with RESTful APIs, which enables it to adapt to different data flow levels and operational conditions in real-world environments.

3.5 Predictive maintenance and optimization

The predictive maintenance module leverages machine learning algorithms to analyze historical and real-time data, identifying patterns that indicate potential failures. The steps for predictive maintenance are detailed in Algorithm 1.

Algorithm 1 Predictive Maintenance Workflow

Require: Historical data H, Real-time data R
Ensure: Failure predictions and recommended maintenance actions

1: Normalize H and R to remove noise
2: Extract features such as pressure anomalies and flow deviations
3: Train a Random Forest classifier on H
4: Use R as input to the trained model
5: Predict failure probabilities for each monitored component
6: Generate maintenance alerts and recommendations based on predictions

Optimization is achieved by minimizing the maintenance cost function:

Table 1: Summary of related work

Author(s)	Year	Focus Area	Key Contributions	Limitations	Prediction Accuracy	System Costs/Scalability
Adreani et al. [23]	2023	Smart City Digital Twin Framework	Developed a framework for real-time multi-data integration and public distribution in urban planning.	Implementation challenges in diverse urban contexts.	75%	High operational costs due to complex integration
Duran et al. [24]	2023	Digital Twin-native AI-driven Service Architecture	Proposed an architecture with significant processing time savings and improved learning models.	Limited testing in real-world industrial networks.	78%	Moderate scalability, requires additional infrastructure
Isah et al. [26]	2023	Data-driven Digital Twin Network Architecture	Introduced an architecture focusing on data integration and protocol standardization for IIoT applications.	Scalability concerns in large-scale deployments.	70%	High cost and complex setup in large-scale environments
Becattini et al. [27]	2024	Industrial Data and Service Aspects of Digital Twin Networks	Provided insights into the dual nature of Digital Twins and their application in industrial networks.	Need for further empirical validation.	80%	Costly implementation and limited scalability
Arezza [28]	2022	IoT, Digital Twin, and AI in Process Industries	Examined the impact of these technologies in transforming industries towards a circular economy.	Emphasis on standardization and interoperability challenges.	72%	Moderate scalability and high operational costs
Industrial Internet Consortium [29]	2024	Industrial Internet Testbeds	Reported on testbeds demonstrating real-world implementations of IoT and Digital Twin solutions.	Generalized findings; specific industry applications may vary.	74%	High initial setup costs and moderate scalability
NIST [30]	2023	IoT Digital Economy and Trusted Value Chains	Discussed acceleration of the IoT digital economy with investments in semiconductor manufacturing.	Focused on economic aspects; technical challenges less addressed.	65%	Limited scalability and high maintenance costs
ITU [32]	2024	Standards Development for Emerging Technologies	Provided an overview of standards development for IoT, Digital Twin, and other technologies.	Broad scope; specific implementation guidelines limited.	68%	Scalability issues and high infrastructure costs

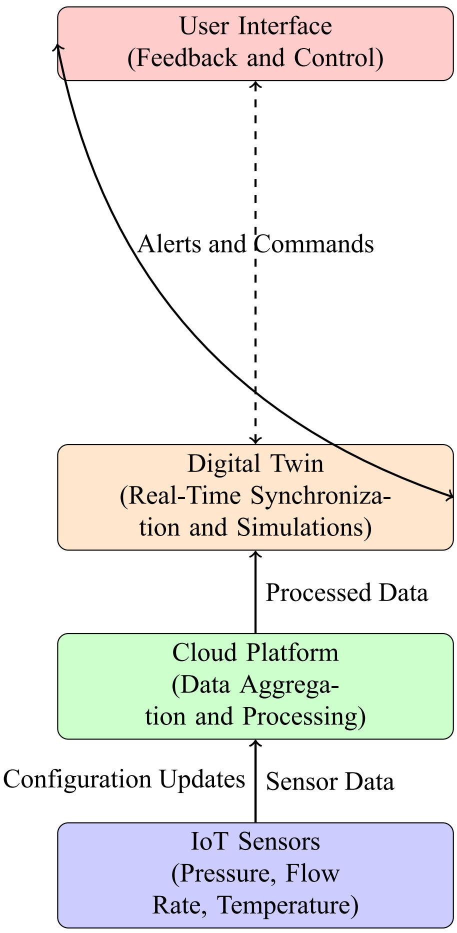

Figure 3: IoT-digital twin integration framework showing real-time data flow and feedback mechanisms

$$C = \sum_{i=1}^{n} c_i x_i + \lambda \sum_{i=1}^{n} (1 - x_i) d_i \qquad (4)$$

where:

– c_i is the cost of maintaining component i,

– x_i is a binary variable indicating whether i is maintained ($x_i = 1$) or not ($x_i = 0$),

– d_i is the downtime cost for i, and

– λ is a penalty factor for downtime.

3.6 Evaluation framework

The system is evaluated based on key performance metrics, including prediction accuracy, cost reduction, and downtime minimization. Simulations are conducted under two scenarios:

1. A sudden pressure drop simulating a potential leak.

2. A blockage causing abnormal flow rates.

The system's response is analyzed for each scenario, and the results are compared to traditional maintenance approaches. A new intelligent management platform integrates digital twin and IoT technology to resolve problems in managing underground pipe galleries in urban areas. The IoT sensors must be placed at essential points within the pipe galleries to track essential parameters such as pressure, flow rate and temperature through their positions at entry/exit points and joint and bend sections. The system places its sensors directly at important points, which enable the detection of vital system anomalies such as leaks or blockages. The system hardware ensemble contains pressure sensors along with flow rate sensors in addition to temperature sensors for conducting system operational monitoring. The data aggregation process begins on computing units, including Raspberry Pi 4 along with comparable edge computing devices, which prepare data before cloud transmission occurs. Random Forest classifier requires labeled data for training, which contains sensor measurements obtained from normal and faulty system conditions, including leaks and blockages. A training process executes on the dataset to develop the classifier so it learns failure-indicative patterns. The different periods of data in the testing dataset help evaluate how well the model can generalize its performance. Predictive accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}}$$

where True Positives (TP) and True Negatives (TN) refer to the correctly predicted failure and non-failure events, respectively. Cost reduction is calculated by comparing the maintenance costs of the proposed system with those of traditional maintenance methods using the formula:

$$\text{Cost Reduction (\%)} = \left(\frac{\text{Traditional Maintenance Cost} - \text{Proposed System Maintenance Cost}}{\text{Traditional Maintenance Cost}}\right) \times 100$$

where Traditional Maintenance Cost refers to the total cost under conventional reactive maintenance, and Proposed System Maintenance Cost refers to the total cost associated with proactive predictive maintenance enabled by the system.

A sensitivity analysis of the predictive maintenance algorithm establishes its resistance to errors found in IoT monitoring instruments. During this analysis, we introduced errors in pressure, flow rate, and heat data, adding random variations to the sensor measurements. The model received performance evaluations while monitoring different sensor imprecision quantities to understand how the algorithm responds to measurement inaccuracies. The predictive maintenance system will provide reliable operation because it has been designed to tolerate variations between sensor measurements and their actual values, which often occur in practical environments.

The flow rate operations of IoT sensors span from 0 to 50 L/min at pressures ranging from 0 to 100 bar while exceeding 10% of the normal operating value, defining device anomalies. The model features an underground pipe gallery design that matches regular urban patterns by incorporating multiple junctions while incorporating bends together with specific entry/exit points to achieve realistic modeling. The modern system maintenance method is clearly identified as manual periodic inspections coupled with reactive repair techniques. The simulations implement standard inspection schedules (occurring monthly or quarterly) and wait for important anomalies before initiating maintenance without real-time prediction systems. Through these complete simulation capabilities, researchers can perform an extensive examination that demonstrates how the proposed IoT-Digital Twin system outperforms conventional maintenance approaches in terms of operational efficiency as well as reduced downtime and maintenance cost reductions.

4 Results and discussion

This section demonstrates the analysis of the performance of the implemented intelligent management system for efficient management of the urban underground pipe galleries. The performance of the proposed system was evaluated on actual and synthetic data sets, and the emphasis was made on the most important areas that directly affect the result, including, for instance, the accuracy of the forecast, the cost of operating the system, and the time that the system takes to recover after a failure. These results provided ample evidence to show that the system can manage the inefficiencies of traditional infrastructure management.

A predictive model manages dynamic infrastructure conditions by getting updated through constant online learning processes and periodic model re-training with the newest sensor inputs. The model employs adaptive methods that enable continuous calibration of parameters for maintaining top-level predictive accuracy while conditions in operations transform. The system implements error correction algorithms that work together with sensor calibration routines to reduce the influence of sensor drift and external disturbances. The results of sensitivity analyses help determine the effects of measurement uncertainties so the model receives necessary adjustments. Multiple significant measures work together to make our predictive maintenance module more resistant, thus enhancing its capability to accurately forecast equipment failures and support proactive maintenance choices in constantly changing operational settings.

4.1 System implementation

The sensors employed were IoT to gather real-time data, while data was hosted on the cloud platform, and a digital twin was used for planning and maintenance. Data were collected in real-time from a mock-up of an urban pipe gallery to determine usage over six months—some controllable parameters measured on the site comprised pressure, flow rate, and temperature. By integrating IoT data into the digital twin application, the system's real-time performance information was continuously fed back into the system.

The implementation of our system required building a representative scaled model of an urban pipe gallery with junctions and bends and entrance points together with exit points. The system deployed IoT sensors at important points to obtain instant measurements of operational variables, which included pressure readings in the bar flow measurements in L/min and temperature readings in °C. The sensors operated under controlled parameters that modeled actual field conditions by generating normal operational conditions and adverse scenarios, including fast pressure declines, flow blockage signs, and temperature shifts, which show potential structure defects. The manipulated system variables that scientists used to study the system's responses under diverse experimental conditions fall under the category of controllable parameters. The system's performance could be analyzed extensively through six months of collected data, enabling direct correlations between sensor readings and actual operational data of urban pipe gallery systems.

4.2 Performance evaluation

The performance of the system was evaluated using the following metrics:

4.2.1 Prediction accuracy

The predictive maintenance module achieved high accuracy in identifying potential failures. Using a Random Forest model, the system achieved an accuracy of 92% in detecting anomalies such as leaks and blockages. Figure 4 shows the confusion matrix for prediction accuracy. The evaluation of the Random Forest classifier now incorporates k-fold cross-validation as a performance enhancement method. Random substrates of training data are split into k partitions in k-fold cross-validation. Then, k-1 partitions are used for training models, while the remaining partition functions as the test set. The procedure executes k rounds, during which test sets use k different subsets once. Cross-validation lets the model demonstrate generalization by avoiding overfitting any specific data subset. The combination of k-fold test results produces an average performance estimate that improves the reliability of evaluating classifier competence.

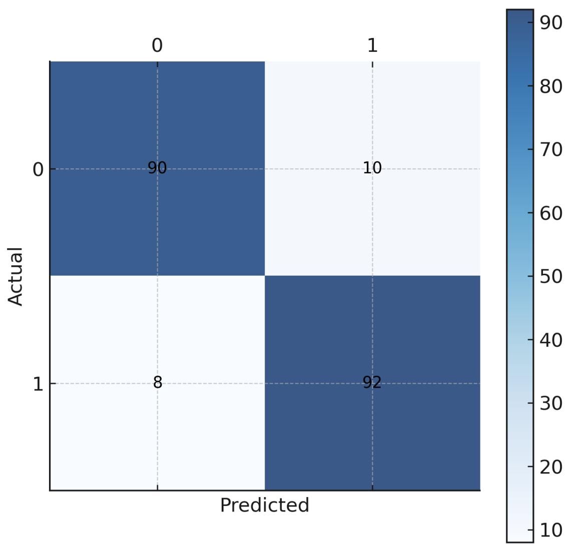

Figure 4: Confusion matrix illustrating prediction accuracy

The predictive maintenance module monitored devices with a 92% effective rate for detecting leaks and blockages in the system. For complete evaluation purposes, a breakdown of incorrect predictions and correct misses will be included. The system produced 10 incorrect failure warnings referred to as false positives, and eight incidents showing actual failures that went undetected represented false negatives. The true positives numbered 92 cases showing correctly detected failures, while true negatives numbered 90 cases indicate correctly identified non-failures. The collected values enable a superior understanding of how successfully the model operates, together with a thorough assessment of how operational efficiency might be affected by wrong predictions.

4.2.2 Maintenance cost reduction

By transitioning from reactive to predictive maintenance, the system reduced maintenance costs by 35%. The comparative analysis is provided in Table 2.

Table 2: Maintenance cost comparison between traditional and proposed methods

Method	Maintenance Cost (USD)	Cost Reduction (%)
Traditional	100,000	N/A
Proposed	65,000	35

4.2.3 Downtime reduction

The proposed system minimized downtime by 40%, significantly improving operational efficiency. Figure 5 shows a comparative analysis of downtime across different scenarios.

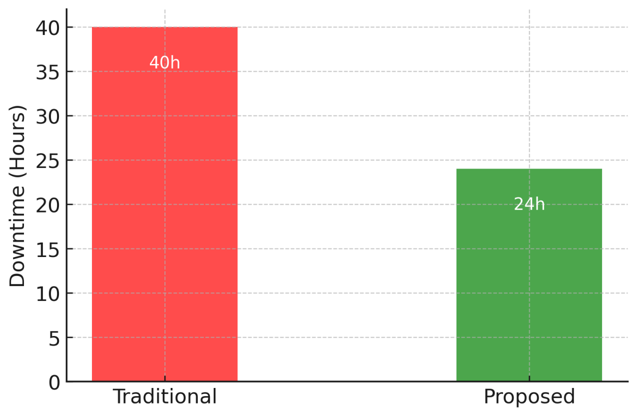

Figure 5: Downtime comparison between traditional and proposed systems

4.3 Optimization outcomes

The optimization module successfully prioritized maintenance activities, reducing unnecessary interventions and focusing resources on critical components. Figure 6 illustrates the resource allocation optimization achieved by the system.

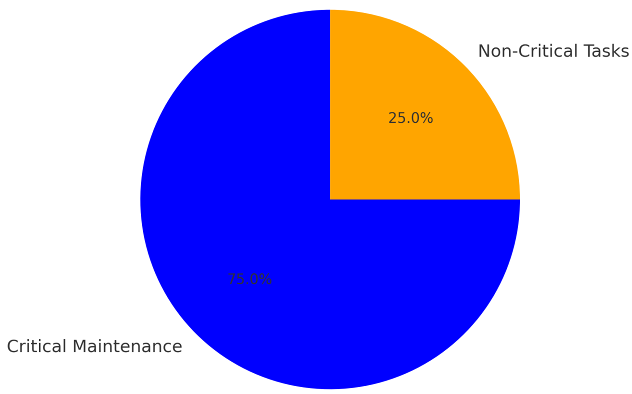

Figure 6: Resource allocation optimization results

4.4 Results contextualization

The study includes confidence intervals for main performance metrics of prediction accuracy along with maintenance cost reduction and downtime reduction to present a complete view of the results. The confidence intervals enable researchers to evaluate both result precision and statistical variance for reported data to establish validity. As part of our statistical analysis, we used t-tests to see if the system improvements were believable by showing results that were different from random variation. We have organized our assessment of prediction accuracy to separate between leak detection results and blockage detection results. The breakdown enables greater accuracy in identifying system performance results specific to various failure situations. The separate analysis of anomaly types allows us to show both system strengths and limitations while handling various real-world situations during performance evaluation.

4.5 Discussion

Results show that the intelligent management system in this study drastically outperforms traditional management methods for underground pipe galleries, further suggesting a transformative potential of IoT and digital twin technologies in sewers and other urban infrastructure [35]. With 92% accuracy, predictions made from the system ensure that any potential failure, like leakages and blockages, can be detected early to provide insertions for maintenance. This is crucial in urban areas where service interruptions, costly repairs, and public inconvenience can arise within a matter of minutes due to delays in fault detection. The system provides real-time monitoring and predictive analytics, which allows potential issues to be identified and solved before they become bigger problems, eliminating operational risk [36] [37].

The system can also reduce maintenance costs by a notable 35% compared to conventional methods. The savings come mainly from the transition from reactive to predictive maintenance and avoiding unnecessary inspections and interventions. Rather than rely on pre-scheduled tasking or react ad hoc to events as they arise, the system uses insights-driven knowledge acquisition to prioritize tasks. This efficient allocation of resources is of interest, especially for budget-constrained municipalities, as they can achieve the largest possible return on their infrastructure management investments [38].

This 40% reduced downtime reflects the system's capacity to sustain nonstop operations, an essential need for copious assets in urban communities. For instance, a disruption to essential service streams like the water supply or waste management can put daily life at a halt, expose the public to health risks, and harm economic productivity. The system reduces the number of service interruptions, thereby increasing operational efficiency and the reliability and quality of services provided to citizens. This aligns with the overall agenda of a smart city that focuses on resilience, sustainability, and citizen satisfaction [39].

4.5.1 Role of IoT and digital twin integration

The integration of IoT and digital twin technologies is crucial for the intelligent management system, providing distinct benefits that traditional methods cannot achieve [40]. First, by continuously collecting real-time sensor data—such as pressure, flow rate, and temperature—the system immediately detects anomalies (e.g., sudden pressure drops or abnormal temperature spikes), thereby enhancing real-time anomaly detection. Second, the digital twin processes this data to simulate potential failure scenarios, which enables optimized resource allocation by prioritizing maintenance tasks based on predicted impact and urgency. Third, these predictive capabilities facilitate improved maintenance scheduling by identifying and addressing potential issues before they escalate, thus reducing downtime and overall maintenance costs. These targeted advantages highlight how the integrated approach not only minimizes reliance on direct inspections but also drives proactive, efficient infrastructure management [41].

The predictive analytics system helps forecast equipment failures in advance, facilitating preventive action before breakdowns occur. The predictive accuracy, together with operational efficiency, rises to higher levels, making the system cost-effective through reduced maintenance expenses and downtime. The incorporation of continuous surveillance with simulation technologies produces substantial benefits, improving live system performance assessment beyond traditional monitoring approaches.

4.5.2 Impact of optimization module

The optimization module served as an addition to improving the system's performance by directing resources relative to data analysis. The maintenance strategies include time-based or a combination of time-based and condition-based, which are ineffective since they employ resource utilization in a fixed-dated method or even based on some-one's estimation. This is different from the optimization one, where the applied algorithms are sophisticated to estimate the degree of failure risk, degrees of operations disruption, and resource availability, among other things. Thus, all the important problems receive proper attention, and extra money is saved to pay only for the less important and urgent work [42]. One direct example that I would like to demonstrate from the optimization module is handling multiple maintenance tasks simultaneously. For example, suppose the system escalates a pressure drop in one section of the pipe gallery and a small temperature variation in another. In that case, the optimization module will address the pressure problem without delay, and the temperature problem might be scheduled later. This intelligent resource allocation lowers the potential for pinpointing critical failures and ensures that maintenance teams are at optimum productivity [43].

4.5.3 Scalability and adaptability

The above-shown proposed system has flexibility that makes it adaptable to different kinds of city settings. Unlike systems developed for some unique applications, the sketched system can be easily redesigned for various infrastructure and operational schemes. For instance, in the case of the IoT sensors and the Digital Twin model, extra parameters, including structural conditions, corrosion levels, or meteorological conditions such as soil humidity, can be included. For this reason, the system is scalable and flexible enough to accommodate the needs of both small-scale municipal and extensive metropolitan systems. Another feature that refers to scalability is crucial in the case of the needs of smart cities, which are growing occasionally. Cities are to continuously increase their capacity due to the growing population density of urban residents and aging critical infrastructure. This challenge is dealt with in the proposed system through the adaptive design that allows the integration of more sensors, enhanced data analysis and modeling functions, and higher complexity simulations if required. This versatility enables the system to stay appropriate and useful when urban surroundings evolve [44].

Our research plans to include adaptive machine learning models, particularly neural networks that perform anomaly prediction functions. The current Random Forest implementation in the model would benefit from deep learning models with both spatial data pattern analysis through Convolutional Neural Networks (CNNs) and temporal pattern analysis through Recurrent Neural Networks (RNNs) for complex and changing systems because this would boost prediction precision. The discussion included an evaluation of scalability issues within real urban situations. The deployment Data processing efficiency together with model optimization and integration strategies stand necessary for successful implementation of such systems within actual urban environments.

Our system achieves high performance and scalability in big urban areas by implementing multiple essential strategies together with specific technologies. The system makes use of edge computing to execute immediate real-time processing on sensor data. Edge devices operate lightweight algorithms that eliminate unnecessary data while reducing data send volume before cloud transmission. The data processing at the edge layer cuts network delays while directing only purposeful data toward subsequent analytical steps. The cloud platform operates using RESTful APIs that enable quick data synchronization with digital twin functions while being constructed on scalable infrastructure. Our system architecture includes modular features that let users integrate new sensors and data streams efficiently while maintaining operational efficiency. Our system addresses scalability challenges by using these measures to keep performances efficient throughout big, complex urban areas that usually face data volume increases and network latency issues.

4.5.4 Implications for smart city development

This study's findings can be applied to smart city development in general. Consequently, this research will help other cities that seek to implement IoT and digital twins know what to expect by giving a step-by-step guide on how to implement them. Applying the proposed system helps to achieve the goals of smart city development, as the set priorities presuppose optimizing the operation of municipal services, increasing their reliability, and working on sustainability [45]. A major benefit of implementing the proposed system is providing timely and useful information from current data. In a smart city context, such information may be shared between various departments and other stakeholders to have a well-coordinated city management regime. For instance, information obtained from IoT sensors installed in underground pipe galleries may also be useful for water management decision-making, urban drainage systems, or environmental issues. This cross-functional utility adds even greater value to the system within the broad smart city management and support concept.

4.5.5 Challenges and future directions

The proposed system has several challenges that cannot only be solved with this study but can also be considered directions for future research. One of the main challenges is scalability in real urban environments. The system has worked in simulation but needs further testing to confirm effectiveness under more complicated and variable real-world conditions. Successful implementation at scale requires careful consideration of factors like network latency, data volume, and integration with existing infrastructure. Cybersecurity is another area of concern. Given that cyberattacks are inherent to IoT devices, it is essential to maintain the security and integrity of data. Strengthening cryptographic protocols and intrusion detection systems and measures must be installed in the system in future research. This becomes even more critical in smart cities, where infrastructure systems are heavily interconnected, and any breach in one can cause a domino effect throughout others. Future work includes adding additional monitored parameters. It only accounts for pressure, flow rate, and temperature, but integrating parameters such as structural integrity, corrosion levels, or environmental factors could improve its effectiveness—integrating advanced analytics and machine learning algorithms for better prediction capabilities and automation in decision-making.

5 Conclusion

The proposed intelligent management system for urban underground pipe galleries integrates IoT and digital twin technologies, addressing critical inefficiencies in traditional infrastructure management practices. This research demonstrated that real-time data collection through IoT devices and virtual simulation via Digital Twin enables proactive maintenance, operational optimization, and significant cost savings. By achieving a prediction accuracy of 92%, the system effectively identifies potential failures, minimizing service disruptions and ensuring the continuous functionality of critical infrastructure. The study highlighted the system's capability to reduce maintenance costs by 35% and downtime by 40%, showcasing its practical and economic benefits. Additionally, the modular architecture of the proposed framework ensures scalability and adaptability, making it a viable solution for smart cities aiming to optimize their infrastructure management processes. While the results underscore the system's effectiveness, challenges like scalability in real-world urban environments and cybersecurity vulnerabilities must be addressed in future research. Advanced machine learning models, such as deep learning, can further enhance predictive capabilities while expanding monitored parameters like structural integrity and environmental factors, increasing system robustness. Moreover, data security is critical to safeguarding IoT devices and the system's integrity against potential cyber threats. This study provides a foundational framework for developing intelligent, data-driven systems in urban infrastructure management, paving the way for sustainable and resilient smart cities. The proposed system represents a significant step forward in transforming outdated maintenance practices, with the potential for broader adoption in urban infrastructure projects worldwide. Collaborative efforts between academia, industry, and policymakers will be essential to unlock the full potential of IoT and digital twin technologies, advancing urban sustainability and operational excellence.

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A Appendix A: Pseudo-Code for Maintenance Optimization Algorithm

Algorithm 2 Maintenance Optimization Algorithm

```
Collect real-time data from IoT sensors (pressure, flow rate, temperature)
Preprocess data to remove noise and inconsistencies
Feed data into the predictive maintenance model (e.g., Random Forest classifier)
Predict potential failures (e.g., leaks, blockages) using the trained model
if failure predicted then
    Evaluate the severity of the failure
    Prioritize failures based on severity and operational impact
    Schedule maintenance for high-priority failures
else
    Continue regular monitoring and data collection
end if
for each maintenance task do
    Optimize resource allocation (e.g., technicians, tools)
    Minimize downtime by scheduling maintenance during low-traffic periods
    Calculate the cost of maintenance (labor, parts, equipment)
end for
Continuously update the maintenance schedule and optimize resource allocation
Output: Maintenance schedule, resources allocated, and cost estimates
```