Proactive Infrastructure Management for Smart Cities

Client:	City of Columbus, Dept. of Public Service	**Industry:**	Municipal Government
Domain:	IoT & AI Infrastructure Monitoring	**Location:**	Columbus, Ohio, USA

A FORGE OS Deployment Case Study

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1 Executive Summary

577 Industries (577i) partnered with the City of Columbus Department of Public Service to design, deploy, and operationalize an AI-powered Integrated Infrastructure Monitoring System (IIMS) spanning bridges, roadways, water distribution mains, and sewer systems across the city. The system combines a network of 2,500+ ruggedized IoT sensors with a cloud-based predictive analytics engine and digital twin technology to deliver continuous, real-time condition assessment of critical public assets. Within two years of full operational deployment, the IIMS reduced infrastructure emergencies by 35%, decreased emergency maintenance costs by 25%, and achieved 89% prediction accuracy for infrastructure failures with an average advance warning of 21 days before major events. These results demonstrate that data-driven, condition-based maintenance can fundamentally replace reactive paradigms, yielding measurable gains in public safety, service reliability, and fiscal responsibility for municipal infrastructure programs. This deployment exercises two FORGE OS subsystems: **FORGE Core**'s ontology-grounded intelligence and continuous distillation power the AI analytics engine and digital twin platform, while **FORGE Memory**'s governance framework manages policy compliance, resource allocation decisions, and inter-agency data-sharing authorizations.

35%	**25%**	**89%**	**2,500+**
Reduction in Emergencies	Cost Decrease	Prediction Accuracy	IoT Sensors Deployed

2 Challenge

Columbus, the state capital of Ohio and a major Midwestern metropolitan center, manages a vast portfolio of public infrastructure essential to the daily lives and economic vitality of over 900,000 residents. The Department of Public Service is responsible for hundreds of bridges, thousands of lane-miles of roadways, extensive water distribution mains, and complex sewer systems [1]. As a growing city experiencing population increases and sustained economic development, Columbus faced escalating challenges common to established urban centers: managing the inevitable aging of its infrastructure while meeting increasing demands for service reliability and safety within the constraints of municipal budgets [2].

2.1 Reactive Maintenance Failures

Historically, maintenance interventions were predominantly triggered by acute events—outright failures such as water main bursts, bridge joint failures, and significant pothole formation—or based on fixed, time-based inspection schedules that did not accurately reflect the actual condition or rate of degradation of specific assets [5]. This reactive approach carried increasingly unsustainable consequences:

- **Emergency repair costs and budget volatility.** Sudden failures required unscheduled crew mobilization with overtime pay, urgent procurement at premium prices, and specialized equipment rental. These unforeseen expenditures created significant budget volatility and led to deferred maintenance on other assets [6].
- **Economic and social disruption.** Emergency road closures caused traffic congestion, delayed commutes, hindered emergency vehicle access, and disrupted logistics. Water service interruptions and sewer backups posed public health risks and forced temporary business closures [1].
- **Safety risks and liability.** Allowing infrastructure to degrade to failure inherently increased public safety risks—failing bridge components, collapsing sewer lines creating sinkholes, and major roadway defects could lead to serious accidents and significant legal liability [4].
- **Inefficiency of time-based inspections.** Biennial bridge inspections and similar fixed schedules wasted resources on assets in good condition while potentially missing rapidly developing issues between scheduled visits. They lacked the granularity to detect hidden degradation such as internal corrosion or underground pipe leaks before they became critical [5].

The Department of Public Service recognized that a fundamental paradigm shift toward proactive, data-driven, condition-based maintenance was essential. This initiative also aligned with the broader goals of the "Smart Columbus" program, which aimed to leverage technology and data to improve city services and quality of life [3].

3 Solution

The City of Columbus initiated a strategic partnership with 577 Industries Inc. (577i) to co-develop and implement a comprehensive Integrated Infrastructure Monitoring System (IIMS), specifically tailored to the diverse asset types and operational needs of the Department of Public Service. The core philosophy of the IIMS was the synergistic combination of a widespread IoT sensor network generating real-time condition data and a sophisticated AI-powered analytics engine capable of transforming raw data into actionable insights and predictive intelligence. Figure 1 illustrates the high-level system architecture.

3.1 IoT Sensor Network

A diverse array of 2,500+ ruggedized, industrial-grade sensors was deployed across strategically selected, high-priority infrastructure assets identified during the initial assessment phase based on age, criticality, traffic volume, and failure history [7, 8]:

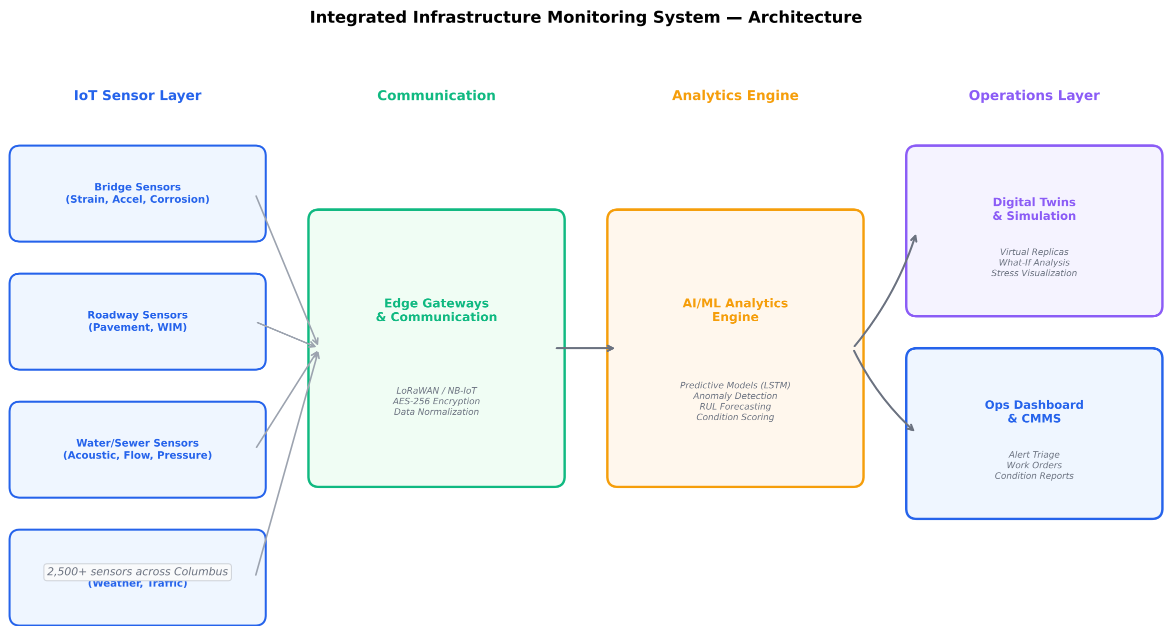

Figure 1. Integrated Infrastructure Monitoring System architecture. Sensor data flows from distributed IoT devices through edge gateways to cloud-based analytics, digital twins, and the operational dashboard.

- **Bridges** — High-sensitivity strain gauges on critical structural members to detect overstress or fatigue accumulation; accelerometers measuring vibrations and modal frequencies indicative of structural instability; embedded corrosion sensors near reinforcing steel monitoring electrochemical conditions; and tiltmeters on piers and abutments tracking settlement [9–11].
- **Roadways** — Embedded pavement sensors monitoring temperature gradients for freeze-thaw analysis and sub-base moisture levels; traffic flow and weigh-in-motion sensors providing granular axle load data for accurate pavement stress modeling [12, 13].
- **Water and sewer systems** — Advanced acoustic sensors detecting leak signatures with precise localization through signal correlation; vibration sensors monitoring pipe joints for abnormal stress patterns; and flow meters and pressure sensors enabling rapid detection of anomalies indicative of leaks, bursts, or blockages [14, 15].

Sensor deployment considerations included long-life batteries and solar power, robust environmental sealing (IP-rated enclosures), and physical protection against vandalism.

3.2 AI-Powered Analytics Platform

Continuous, high-velocity data streams from the sensor network were transmitted via a Low-Power Wide-Area Network (LPWAN) using LoRaWAN technology, with cellular backup (NB-IoT) in critical locations, to a centralized cloud-based analytics platform [21]. All data channels employed AES-256 encryption and end-to-end cybersecurity protocols [22, 25]. The platform employed a suite of advanced AI techniques:

- **Predictive modeling and remaining useful life (RUL) forecasting.** Time-series forecasting models (ARIMA, LSTMs), survival analysis models, and physics-based degradation models continuously estimated the probability and timeframe of potential component failures [16].
- **Anomaly detection.** Machine learning algorithms including Isolation Forests, One-Class SVMs, and autoencoders established dynamic, multivariate operational baselines for each monitored asset, automatically flagging statistically significant deviations [10, 17].

- **Digital twin integration.** High-fidelity virtual replicas of critical assets fused real-time sensor data with environmental forecasts, traffic patterns, and maintenance history to generate dynamic health scores. Engineers could visualize current state, simulate future load conditions, and perform "what-if" analysis for proposed interventions [18, 20].

3.3 Implementation: Phased Rollout

Deployment followed a structured, collaborative approach:

1. **Pilot program (6 months).** Three aging bridges and a section of the water distribution network known for historical leak issues were instrumented. This phase validated sensor performance in field conditions, calibrated AI models to Columbus-specific assets, and gathered user feedback from city engineers [19].
2. **Phased sensor deployment.** Physical installation across hundreds of designated locations proceeded in priority-ordered phases, with close collaboration between 577i technicians and experienced city maintenance crews.
3. **Platform integration.** Standardized APIs connected IIMS outputs to the Department's existing Computerized Maintenance Management System (CMMS), automating condition-based work order generation. Role-based dashboards were developed for management, engineering, and maintenance planning staff [23, 24].
4. **Training and adoption.** Comprehensive programs trained all relevant city staff on system operation, data interpretation, alert validation, and adapted maintenance procedures.

4 Results

The IIMS delivered substantial, measurable benefits within two years of full operational deployment across all monitored asset classes.

4.1 Prediction Accuracy

The AI analytics engine achieved an overall 89% prediction accuracy for infrastructure failures across all asset types, measured against verified ground-truth events. Figure 2 presents accuracy by infrastructure category.

Performance was highest for water mains (93%), where acoustic and pressure sensor data provided strong predictive signals for leak and burst events. Bridge structural monitoring achieved 91% accuracy through strain, vibration, and corrosion sensor fusion. Sewer systems reached 87% accuracy, and roadway pavement prediction achieved 84%, the most challenging category due to the complex interplay of freeze-thaw cycles, traffic loading, and sub-base conditions. The system provided an average advance warning of 21 days before major failure events, enabling planned maintenance interventions during low-impact windows.

4.2 Emergency Reduction and Cost Savings

The predictive maintenance capability drove a 35% reduction in unplanned, emergency maintenance interventions and a 25% decrease in direct emergency repair expenditures. Figure 3 breaks down the cost savings by category.

Table 1 summarizes the key quantitative outcomes.

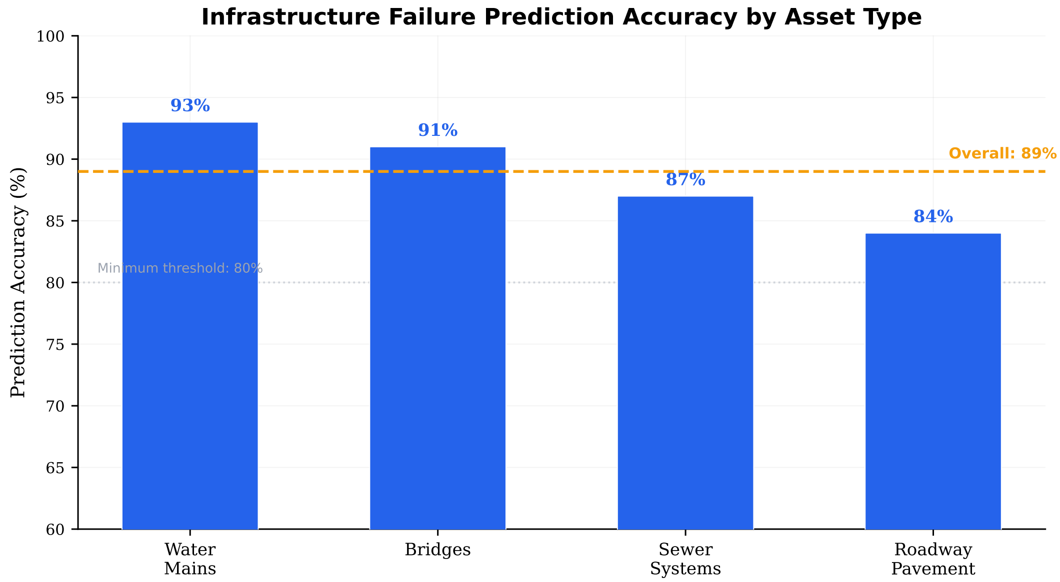

Figure 2. Infrastructure failure prediction accuracy by asset type. The dashed line indicates the overall 89% weighted accuracy.

Table 1. Key performance metrics: pre-deployment versus post-deployment.

Metric	Before	After (577i IIMS)
Emergency interventions (annual)	Baseline	−35%
Emergency repair costs	Baseline	−25%
Failure prediction accuracy	N/A	89%
Average advance warning	N/A	21 days
Resource allocation efficiency	Baseline	+30%
IoT sensors deployed	0	2,500+

4.3 Response Time Improvement

By shifting from reactive to predictive operations, the Department achieved significant improvements in how quickly infrastructure issues were identified, assessed, and resolved. Figure 4 compares response workflows before and after IIMS deployment.

Under the reactive model, issue detection relied on citizen reports or scheduled inspections, assessment required dispatching field crews, and repair scheduling was constrained by emergency availability. Under the IIMS, continuous sensor monitoring provides automated detection, the analytics platform delivers instant diagnostic context, and maintenance teams schedule proactive interventions during optimal windows.

21 days	30%	89%
Avg. Advance Warning	Resource Allocation Improvement	Prediction Accuracy

5 Impact & Operational Benefits

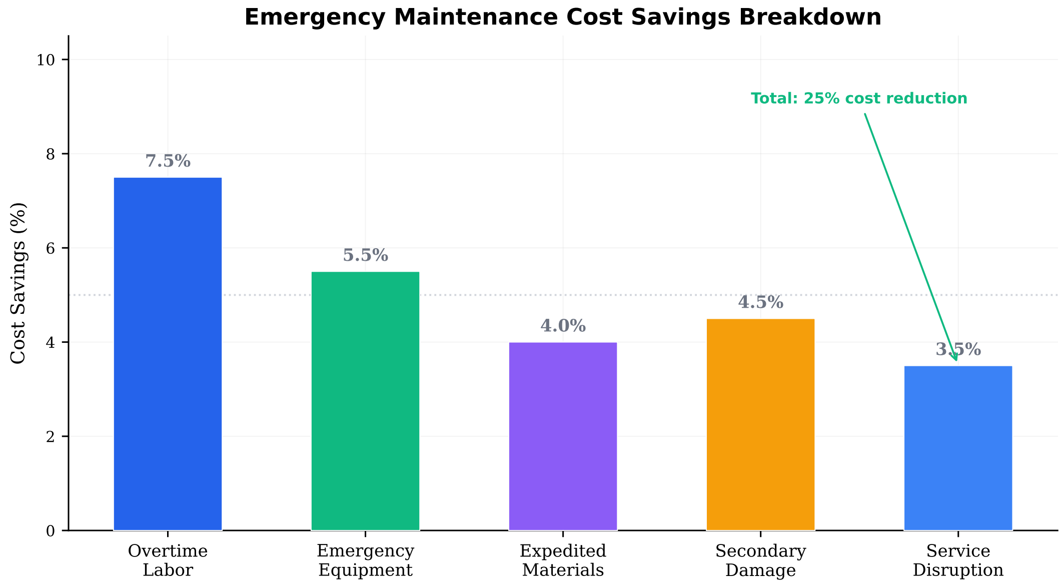

Figure 3. Annual cost savings breakdown by maintenance category after IIMS deployment.

5.1 Enhanced Public Safety

The IIMS directly enhanced public safety by identifying hidden risks before they could manifest as dangerous incidents. Abnormal stress patterns detected by strain gauges on heavily trafficked bridge girders prompted detailed inspections that revealed internal fatigue cracking requiring urgent reinforcement [9, 10]. Early detection of ground subsidence precursors near aging sewer lines and localized corrosion on bridge rebar enabled targeted, timely interventions that mitigated significant safety risks.

5.2 Extended Infrastructure Lifespan

Condition-based interventions—applying cathodic protection to address localized corrosion, repairing specific pipe joints showing stress before failure, resurfacing roadway sections exhibiting early sub-base moisture damage—demonstrably extended the functional lifespan of critical assets [4, 11]. This deferred the need for costly full replacements, maximizing the return on original infrastructure investments. RUL data also provided objective inputs for long-range capital budgeting.

5.3 Optimized Resource Allocation

The objective condition scores and risk assessments from the IIMS enabled a 30% improvement in resource allocation efficiency. Limited maintenance budgets and personnel were directed toward assets demonstrably in greatest need or posing the highest quantitative risk, calculated as the product of failure probability and consequence severity [5, 24]. Data-driven prioritization replaced age-based scheduling, and maintenance teams could bundle nearby proactive tasks identified by the system for further efficiency gains.

5.4 Service Reliability and Citizen Satisfaction

Fewer unexpected infrastructure failures translated directly into more dependable city services. Citizens experienced fewer disruptions from emergency road closures, fewer unexpected water service interruptions, and fewer sewer-related incidents. This increased reliability led to higher

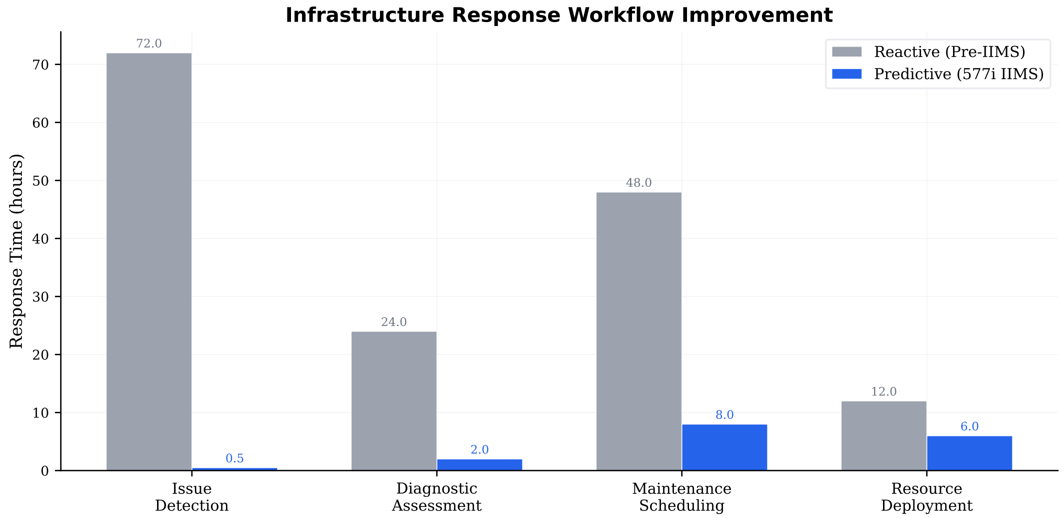

Figure 4. Infrastructure response workflow comparison: reactive (pre-IIMS) versus predictive (post-IIMS) across key operational phases.

citizen satisfaction levels and reduced complaint volumes, fostering greater public trust in the city's management of its vital infrastructure [1, 2].

5.5 Framework for Scalable Deployment

The modular IIMS architecture—with its sensor-agnostic ingestion layer, configurable analytics engine, and standards-based API integrations—provides a replicable framework for extending smart infrastructure monitoring to additional asset classes and other municipalities. The digital twin platform and predictive models can be retrained for new infrastructure types with minimal architectural changes, establishing Columbus as a national benchmark for data-driven urban infrastructure management [19, 20, 25].

6 FORGE OS Integration

The Columbus Smart Cities IIMS deployment demonstrates the operational integration of two FORGE OS subsystems within a municipal infrastructure intelligence platform.

6.1 FORGE Core — Ontology-Grounded Urban Analytics

FORGE Core's intelligence pipeline powers the AI analytics engine across all four infrastructure asset classes. The zero-shot ontology extraction capability automatically maps the diverse sensor modalities—strain gauges, accelerometers, corrosion sensors, acoustic leak detectors, pavement monitors—into a unified analytical ontology without manual feature engineering per asset type. FORGE Core's causal model routing engine dynamically selects the optimal prediction pathway: ARIMA and LSTM time-series forecasting for gradual degradation, Isolation Forest and One-Class SVM anomaly detection for sudden deviations, and physics-based degradation models for structural health assessment. The continuous online distillation framework enables closed-loop model refinement as maintenance outcomes feed back into the platform, sustaining the 89% prediction accuracy and 21-day average advance warning across evolving infrastructure conditions.

6.2 FORGE Memory — Municipal Governance Framework

FORGE Memory's Information Governance & Oversight Module (IGOM) manages the policy compliance and resource allocation decisions that govern municipal infrastructure maintenance. When the analytics engine generates a predictive alert, FORGE Memory's HITL gates route the recommendation through role-based approval workflows—engineering assessment, budget authorization, and scheduling coordination—before condition-based work orders are generated in the CMMS. The deterministic citation framework ensures that every maintenance decision can be traced back to its originating sensor data, model confidence scores, and predicted failure timeline, supporting municipal audit requirements and citizen transparency obligations. The 30% improvement in resource allocation efficiency reflects FORGE Memory's ability to enforce data-driven prioritization over time-based scheduling heuristics.

6.3 ForgeEvent Integration

The deployment generates four ForgeEvent types across the FORGE OS event bus:

- `INFERENCE` — Predictive failure assessments and RUL forecasts across all asset classes
- `SENSOR` — Real-time IoT sensor readings from 2,500+ deployed devices
- `GOVERNANCE` — Work order approvals, budget authorizations, and scheduling decisions
- `AUDIT` — Immutable records linking predictions to maintenance outcomes for model retraining

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