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AI-Driven Decision Support Using CIRx for Smart Urban Water Infrastructure

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Abstract

Smart urban water infrastructure spans drinking water distribution, stormwater conveyance, and wastewater collection systems, each generating growing volumes of sensor, inspection, and operational data as utilities adopt SCADA telemetry, smart metering, and IoT-based condition monitoring. Translating this data into timely, defensible capital and operational decisions remains difficult, particularly for resource-constrained municipal utilities that must prioritize a limited rehabilitation budget across a large and heterogeneous asset base. This paper presents an artificial intelligence (AI) driven decision support framework built around the Condition-Index Rx (CIRx) methodology, a composite scoring approach that fuses structural condition, hydraulic or hydraulic-equivalent performance, consequence of failure, and machine-learning-forecast deterioration risk into a single, prescriptive rehabilitation recommendation. We describe how CIRx extends naturally across the three principal urban water subsystems, and we present a decision-support architecture that couples AI/ML predictive models with an interactive prioritization layer intended for use by utility engineers and capital planners. The paper discusses model selection considerations for heterogeneous urban water asset types, human-in-the-loop decision workflows, integration with geographic information systems and asset management platforms, and the governance considerations relevant to using AI-generated prescriptions to inform public infrastructure spending. We conclude with a discussion of adoption barriers among small and mid-sized utilities and directions for future research, including transferable deterioration models and explainability requirements for public-sector AI decision support.

Keywords: CIRx; artificial intelligence; machine learning; decision support system; smart water infrastructure; urban water management; asset management; predictive maintenance; stormwater; wastewater; drinking water distribution.

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Introduction

Urban water infrastructure — the combined network of drinking water distribution mains, stormwater conveyance systems, and wastewater collection pipes that keep a city functioning — is aging in most developed economies at a pace that outstrips available rehabilitation funding. Utilities are increasingly instrumented with SCADA telemetry, smart water meters, acoustic leak-detection sensors, and CCTV-based inspection technologies, generating far more condition and performance data than most engineering teams can manually synthesize into a defensible capital plan. The central challenge is therefore not a lack of data but a lack of decision support capable of converting heterogeneous, multi-subsystem data into prioritized, actionable recommendations at the pace utilities need to keep up with deteriorating infrastructure.

The Condition-Index Rx (CIRx) methodology offers a structured answer to this challenge for pipe-based infrastructure by combining several weighted inputs — observed structural condition, hydraulic or operational performance, consequence of failure, and forecast deterioration risk — into a single composite score that is explicitly framed as a prescription for action rather than a passive numerical rating. This paper extends the CIRx approach into a broader AI-driven decision support framework applicable across the three principal urban water subsystems, and examines how artificial intelligence and machine learning can be embedded throughout the framework, from raw sensor and inspection data through to an interactive decision-support interface used directly by utility engineers.

The remainder of this paper is organized as follows. Section 2 provides background on decision support in urban

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water asset management and reviews the CIRx methodology. Section 3 presents the proposed AI-driven decision support framework and its extension across drinking water, stormwater, and wastewater subsystems. Section 4 discusses the AI/ML components underlying the framework. Section 5 addresses the human-in-the-loop decision workflow and system integration. Section 6 discusses governance and adoption considerations, and Section 7 concludes with directions for future work.

BACKGROUND

Decision Support in Urban Water Asset Management

Decision support systems for urban water infrastructure have historically ranged from simple spreadsheet-based prioritization tools to dedicated asset management software integrated with geographic information systems (GIS) and computerized maintenance management systems (CMMS). Most such systems rely on relatively static condition scoring, updated only when new inspection data becomes available, and generally treat each subsystem — drinking water, stormwater, wastewater — as a separate planning exercise with its own scoring methodology, which can obscure opportunities for coordinated capital planning, such as scheduling wastewater and drinking water main replacement together on the same street to reduce combined excavation cost.

The CIRx Methodology

CIRx synthesizes multiple weighted components into a single composite score for each infrastructure segment: structural condition drawn from inspection data, a performance component capturing hydraulic capacity or operational stress, a consequence-of-failure component reflecting population served and criticality of location, and a predicted deterioration component derived from machine learning forecasts of future condition. The output of a CIRx evaluation is not merely a numerical ranking but a specific rehabilitation prescription, mapped from the composite score and its dominant contributing factors to a standard intervention type and recommended timeframe, intended to be directly actionable by capital planning staff without requiring further interpretation.

AI and Machine Learning in Smart Water Systems

Machine learning has been applied across urban water management for tasks including leak detection from acoustic and pressure sensor data, water quality anomaly detection, demand forecasting for drinking water distribution, and deterioration forecasting for buried pipe assets, generally outperforming static or rule-based approaches by learning patterns from historical sensor and inspection data that are difficult to encode manually. Applying these techniques consistently across drinking water, stormwater, and wastewater subsystems, however, requires accommodating substantially different sensor types, failure modes, and consequence considerations specific to each subsystem, which is a central design consideration for the framework proposed in this paper.

AI-Driven CIRx Decision Support Framework

Framework Overview

The proposed framework organizes decision support around four functional stages. A data integration stage ingests and normalizes telemetry and inspection data from each subsystem into a common asset-referenced data model. An AI/ML prediction stage applies subsystem-appropriate models to forecast deterioration, leak risk, or capacity exceedance for each asset. A CIRx scoring stage computes the composite prescription score for each asset using both current condition and forecast risk. A decision-support interface stage presents ranked, prescriptive recommendations to utility engineers, along with the ability to explore alternative budget scenarios and cross-subsystem coordination opportunities.

Extending CIRx Across Subsystems

For wastewater and stormwater pipe networks, CIRx components map naturally onto CCTV-based structural condition coding, hydraulic capacity utilization, and consequence factors such as proximity to sensitive receiving waters or critical infrastructure. For drinking water distribution mains, the structural condition component instead draws on pipe age, material, break history, and where available, acoustic or fiber-optic leak-detection signals, while the performance component reflects pressure stability and water quality parameters such as chlorine residual decay, and the consequence component reflects population served and proximity to critical facilities such as hospitals. This subsystem-specific mapping allows a single underlying CIRx scoring logic to be applied consistently across the utility's full asset base, while still respecting the distinct data sources and failure modes relevant to each subsystem.

Cross-Subsystem Coordination

Because the framework maintains a common, geographically referenced asset model across subsystems, the decision-support interface can surface coordination opportunities that subsystem-specific planning tools typically miss, such as identifying street segments where both a wastewater main and an overlapping drinking water main carry elevated CIRx scores within the same planning horizon, allowing capital planners to bundle replacement work and reduce combined construction disruption and cost. This cross-subsystem view is one of the more distinctive practical benefits of extending CIRx beyond a single infrastructure type.

AI and ML Components

Deterioration and Failure-Risk Forecasting

Deterioration and failure-risk forecasting models, typically gradient-boosted tree ensembles or survival-analysis models, are trained separately for each subsystem's characteristic asset types, using features that include material, age, diameter, soil and environmental context, and prior maintenance and inspection history. Separate model training by subsystem and asset cohort is generally preferred over a single unified model, since failure mechanisms differ substantially between, for example, a corroding cast-iron water main and a root-intruded vitrified clay sewer segment.

Sensor-Based Anomaly Detection

For subsystems with continuous telemetry, including SCADA-monitored pump stations, smart water meters, and pressure sensors on drinking water distribution networks, unsupervised anomaly detection models identify early indicators of leaks, blockages, or capacity stress from streaming sensor data, often providing earlier warning than periodic inspection alone. These models are typically retrained or recalibrated periodically to accommodate seasonal demand patterns and gradual sensor drift, which if left unaddressed can otherwise degrade detection accuracy over time.

Natural Language Processing for Inspection and Complaint Records

Many utilities maintain substantial unstructured data in the form of free-text CCTV inspection notes, customer complaint records, and maintenance logs, which contain relevant condition and performance signals not always captured in structured defect coding. Natural language processing techniques can extract structured signals from this unstructured text, supplementing structured inspection and sensor data and improving the completeness of the feature set available to downstream deterioration and prioritization models, particularly for older assets with limited structured inspection history.

Human-in-the-Loop Decision Workflow

Interactive Prioritization and Scenario Analysis

The decision-support interface presents CIRx-ranked assets alongside their component scores and underlying model confidence, allowing capital planners to interrogate why a given asset received a particular score rather than treating the output as an opaque ranking. Planners can adjust budget constraints and component weightings interactively to explore how different funding levels or risk priorities change the resulting prioritized rehabilitation list, supporting scenario-based capital planning discussions with utility leadership and governing boards.

Review and Override Mechanisms

Because AI-generated prescriptions inform public capital spending, the framework preserves an explicit human review step before any prescription is finalized into a capital work order, and records any manual override of a system-generated prescription along with the reviewing engineer's rationale, both to maintain accountability and to provide a feedback signal that can be used to refine model calibration over time.

Integration with GIS and Asset Management Platforms

The framework is designed to integrate with, rather than replace, the GIS and CMMS platforms most utilities already operate, exporting CIRx scores and prescriptions as attributes on existing asset records and generating draft work orders within the utility's existing maintenance management system rather than requiring engineers to work in a separate, disconnected tool.

Governance and Adoption Considerations

Explainability for Public Accountability

Because municipal capital spending decisions are subject to public accountability and, in many jurisdictions, formal procurement and budget approval processes, the AI/ML components underlying CIRx scoring favor model classes that support clear component-level explanation over marginally more accurate but less interpretable alternatives, consistent with the broader need for defensible, auditable public-sector decision-making.

Barriers for Small and Mid-Sized Utilities

Smaller utilities often lack both the historical data volume needed to train robust deterioration models independently and the in-house technical capacity to operate a decision-support system of this kind, suggesting a role for shared regional deployments, vendor-hosted platforms, or transferable pre-trained models calibrated to local conditions with a smaller quantity of local data, an approach sometimes referred to as model transfer or fine-tuning in the broader machine learning literature.

Data Privacy and Security

Smart metering and SCADA telemetry can incidentally reveal sensitive information about individual customer water usage patterns or critical infrastructure vulnerabilities, requiring the decision-support platform to apply appropriate access controls and data minimization practices, particularly where telemetry data is aggregated or shared beyond the utility's own operational staff.

Illustrative Scenario: Coordinated Capital Planning

Consider a mid-sized utility applying the framework across a downtown corridor served by a cast-iron drinking water main installed several decades ago and a parallel vitrified clay sanitary sewer of similar age. Independently, the drinking water deterioration model flags the water main with a moderate-to-elevated CIRx score driven primarily by break history and predicted corrosion progression, while the wastewater deterioration model flags the sewer segment with a similarly elevated score driven by root intrusion patterns identified in recent CCTV inspection. Under a conventional, subsystem-siloed planning process, these two findings would likely surface in separate departmental planning cycles, potentially resulting in two disruptive excavation projects on the same street within a few years of one another.

Because the proposed framework maintains both assets within a common, geographically referenced data model, the decision-support interface surfaces this overlap directly to capital planners, along with each asset's individual CIRx prescription and projected intervention timeframe. Planners reviewing the corridor can then evaluate a bundled replacement scenario, comparing the combined cost and disruption of coordinated excavation against the cost of proceeding with each subsystem's rehabilitation independently on its own schedule. In this illustrative scenario, the bundled option offers a meaningful reduction in total excavation and traffic-disruption cost relative to two separate projects, illustrating the practical value of extending CIRx-based decision support across subsystems rather than confining it to a single infrastructure type. This kind of coordination opportunity is difficult to surface reliably through manual cross-referencing of separate departmental spreadsheets, particularly for utilities managing thousands of individual asset segments, and represents one of the more concrete operational benefits utility staff report valuing when evaluating cross-subsystem decision-support tools of this kind.

Conclusion

This paper has presented an AI-driven decision support framework built around the CIRx methodology, extended across drinking water, stormwater, and wastewater subsystems to support coordinated, defensible capital prioritization for smart urban water infrastructure. By combining subsystem-appropriate machine learning models for deterioration forecasting and anomaly detection with a composite, prescriptive CIRx scoring layer and an interactive, human-in-the-loop decision-support interface, the framework offers municipal utilities a path toward more proactive and better-coordinated infrastructure investment than subsystem-siloed, condition-only approaches typically allow. Realizing this potential across the full range of municipal utilities, including smaller and less technically resourced ones, will require continued attention to explainability, data governance, and transferable modeling approaches that lower the data and technical barriers to adoption, and these areas represent promising directions for continued research and practical development.

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