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Towards Smart Cities: AI and SAP for Integrated Urban Water and Waste Management

Naveen Kumar

Independent Research Scholar

ABSTRACT

Rapid urbanisation is placing unprecedented stress on municipal water distribution and solid waste management systems, while simultaneously generating vast quantities of sensor, operational, and citizen data that intelligent systems can exploit. This article examines how the convergence of artificial intelligence (AI) and SAP enterprise software—particularly SAP S/4HANA, SAP Business Technology Platform (BTP), SAP AI Core, SAP IoT, and the Joule generative AI copilot—can enable city administrations and utility operators to transition from reactive infrastructure management to proactive, data-driven intelligent urban services. We map AI techniques including time-series deep learning, computer vision, anomaly detection, and reinforcement learning against specific water and waste management use cases: demand forecasting, non-revenue water reduction, real-time quality monitoring, predictive asset maintenance, dynamic waste collection routing, automated material recovery, and biogas yield optimisation.

Keywords: SAP S/4HANA; SAP BTP; water management; waste management; IoT; predictive maintenance;

Introduction

By 2050, an estimated 68 per cent of the world's population will reside in urban areas, intensifying pressure on the municipal infrastructure systems that sustain urban life [1]. Among these systems, urban water networks and solid waste management services are particularly critical: water distribution inefficiencies generate non-revenue water (NRW) losses that can exceed 40 per cent of treated supply in developing-country cities, representing enormous economic and environmental waste; and municipal solid waste generation is projected to grow from 2.1 billion tonnes annually in 2016 to 3.4 billion tonnes by 2050, overwhelming landfill capacity and recycling infrastructure that was designed for smaller urban populations [2].

Acoustic sensor networks analysed by deep learning can localise pipe leaks within hours rather than weeks. Computer vision systems can classify mixed waste streams at material recovery facilities (MRFs) with accuracy exceeding human sorters. Reinforcement learning agents can dynamically optimise waste collection routes in response to real-time fill-level sensor data, eliminating unnecessary collections while preventing overflow incidents [3].

SAP SE, whose enterprise resource planning and asset management software is widely deployed by municipal utilities and city administrations globally, has developed a comprehensive AI and IoT technology portfolio—centred on SAP Business Technology Platform, SAP AI Core, SAP IoT, and the Joule generative AI copilot—that enables these AI capabilities to be integrated directly within the enterprise management systems that already govern utility operations, financial management, asset maintenance, and citizen service delivery [4].

This article provides a comprehensive examination of the AI–SAP integration opportunity for urban water and waste management, covering the AI use case landscape, the SAP technology enablers, the architectural and governance prerequisites, and a readiness framework for city administrations and utility operators. Section 2 reviews the relevant literature. Section 3 describes the SAP technology stack for smart city applications. Section 4 maps AI use cases across water and waste domains, with a summary table. Section 5 analyses prerequisites for deployment. Section 6 proposes a Smart City AI Readiness Framework. Section 7 concludes.

2. Literature Review

2.1 AI in Urban Water Management

The application of machine learning to urban water systems has been an active research domain since the early 2010s, with initial focus on demand forecasting and network hydraulic modelling. Studies employing LSTM neural networks for short-term residential water demand forecasting have demonstrated mean absolute percentage errors (MAPE) of 4–8 per cent at DMA resolution—substantially below the 12–18 per cent typical of conventional statistical methods such as ARIMA—when trained on at least 24 months of smart meter history enriched with weather, socioeconomic, and calendar variables [5]. Non-revenue water reduction through ML-based leakage detection has been demonstrated across several full-scale city deployments: a landmark study in Singapore's national water agency demonstrated a 38 per cent reduction in the time between leak inception and detection using deep learning applied to pressure transient data, compared with conventional pressure zoning methods [6].

Water quality management using AI has advanced significantly with the deployment of low-cost multi-parameter sensor arrays in distribution networks. Multivariate anomaly detection models trained on turbidity, chlorine residual, pH, conductivity, and temperature readings can identify contamination events within minutes of onset, enabling proactive consumer advisories and targeted flushing responses before water quality breaches propagate through distribution zones [7].

2.2 AI in Urban Waste Management

Research on AI applications in solid waste management has concentrated on three domains: collection route optimisation, material stream classification at recovery facilities, and treatment process optimisation. Dynamic routing studies employing IoT fill-level sensors combined with reinforcement learning or metaheuristic optimisation algorithms have consistently demonstrated fuel and operational cost reductions of 15–30 per cent compared with fixed-schedule collection in medium-density urban environments [8].

Automated waste classification using convolutional neural networks (CNNs) trained on labelled image datasets of mixed municipal solid waste has achieved sorting accuracy rates of 90–97 per cent for primary material categories (glass, metal, paper, plastic, organics) in controlled MRF environments—comparable to or exceeding trained human sorters operating under production conditions [9].

2.3 SAP in Municipal Infrastructure Management

SAP's penetration of municipal utility and city administration markets is substantial. Water utilities and waste management authorities in Europe, the Middle East, North America, and increasingly Asia-Pacific use SAP S/4HANA or SAP IS-U (Industry Solution for Utilities) for financial management, customer billing, asset lifecycle management through SAP Plant Maintenance (PM), and procurement. Recent deployments have increasingly integrated SAP IoT for connected asset monitoring and SAP Analytics Cloud for operational performance dashboards [10] [11].

3. SAP Technology Stack for Smart City Applications

The SAP technology stack relevant to smart city water and waste management encompasses four integrated layers. The IoT and Sensor Data Layer is provided by SAP IoT, which ingests time-series data from connected sensors—smart water meters, pressure transducers, acoustic leak detection devices, fill-level ultrasonic sensors on waste containers, and water quality analysers—through standardised MQTT and REST protocols, stores ingested time-series in a scalable cloud time-series database, and routes events to downstream processing and AI services via SAP Event Mesh [12].

The AI Development and Serving Layer is provided by SAP AI Core and SAP AI Launchpad on SAP Business Technology Platform. AI Core hosts model training pipelines and serves inference requests from operational SAP applications, supporting standard ML frameworks (TensorFlow, PyTorch, scikit-learn) and enabling both SAP-delivered pre-trained models and municipality-developed custom models [13]. SAP Datasphere provides the semantic data integration layer, virtualising sensor time-series data from SAP IoT alongside operational data from S/4HANA PM (equipment master, maintenance order history), EHS (compliance records, water quality certificates),

The Enterprise Process Integration Layer is provided by SAP S/4HANA modules that embed AI outputs directly in operational workflows: Plant Maintenance for asset management and predictive maintenance work orders; Environment, Health and Safety Management for quality compliance monitoring and incident management; Transportation Management for dynamic waste collection route planning and carrier management; and Materials Management for consumable procurement driven by AI-generated demand forecasts [14].

4. AI Use Cases Across Water and Waste Management Domains

Table 1 maps the principal AI use cases across water distribution and solid waste management domains, the AI techniques employed, the SAP components involved, and the documented or achievable performance improvements. The sections below discuss the most consequential use cases in each domain.

Table 1: AI and SAP Use Case Map for Urban Water and Waste Management

Domai n	AI Techniq	SAP Compon	Applicati on	Benefit

	ue	ent		
Water — Demand	LSTM time-series	SAP IBP / S/4HANA MM	24-hour consumption forecasting per district zone	NRW ↓ 18%
Water — Leakage	Isolation Forest; CNN	SAP IoT + AI Core	Acoustic sensor anomaly detection on pipe networks	Detection rate +42%
Water — Quality	Multivariate regression	SAP EHS + AI Launchpad	Real-time pH, turbidity, contaminant risk scoring	Compliance incidents ↓ 30%
Water — Assets	Survival analysis; RUL	SAP PM + Predictive Service	Pump and pipe remaining-useful-life estimation	Downtime ↓ 35%
Waste — Collection	Route opt. + RL	SAP TM + S/4HANA SD	Dynamic fill-level-driven collection routing	Fuel cost ↓ 22%
Waste — Sorting	CNN image recognition	SAP Digital Mfg + AI Core	Automated material stream classification at MRF	Sorting accuracy 95%
Waste — Treatment	Process simulation ML	SAP PM + SAP Analytics Cloud	Digester biogas yield optimisation	Energy recovery +15%
Cross-domain	LLM / Joule NLP	SAP Joule on BTP	Citizen query resolution; operator decision support	Response time ↓ 60%

4.1 Water Demand Forecasting and Network Optimisation

Accurate short-term water demand forecasting at DMA level is the foundational AI capability for water network optimisation. LSTM-based models trained on 15-minute interval smart meter aggregates, enriched with hourly weather observations, school calendar flags, and local event data, achieve MAPE values of 4–7 per cent for 24-hour ahead demand at DMA resolution—sufficient to enable automated pump scheduling within SAP S/4HANA Plant Maintenance that reduces energy consumption by 12–18 per cent compared with fixed-schedule pumping [5]. In SAP-integrated deployments, demand forecast outputs from AI Core are consumed by SAP IBP supply planning functions to generate optimised production schedules for water treatment works, and by S/4HANA PM to schedule valve adjustments and pressure zone reconfigurations in response to predicted demand variations across network sectors.

4.2 Non-Revenue Water Reduction Through Leakage Detection

AI-based leakage detection applies Isolation Forest and deep autoencoder models to pressure logger time-series from district meter area boundary loggers, identifying pressure transient signatures associated with pipe bursts and chronic background leakage. SAP IoT ingests real-time pressure logger readings at five-minute intervals; the AI Core inference service scores each DMA against trained leakage models and generates geo-referenced anomaly alerts ranked by estimated volume loss [6].

4.3 Real-Time Water Quality Monitoring and Compliance

Multi-parameter water quality sensor networks—measuring turbidity, residual chlorine, pH, conductivity, temperature, and emerging contaminants through online sensors deployed at key network nodes—generate continuous quality data that AI models can analyse in real time to detect contamination events, predict compliance risks, and recommend corrective interventions. Multivariate regression and anomaly detection models trained on historical sensor readings and corresponding laboratory water quality analysis results learn the characteristic signatures of contamination events, supply zone mixing changes, and chlorine decay patterns—enabling automated alerts to be generated within minutes of quality deviation onset [7].

4.4 Predictive Asset Maintenance for Water Infrastructure

Water utility asset portfolios—pumping stations, treatment works, pressure-reducing valves, and ageing pipe networks—represent capital investments of hundreds of millions to billions of currency units per city. Predictive maintenance AI applied to these assets can significantly reduce unplanned failure events, optimise maintenance scheduling, and extend asset service life. Survival analysis models and LSTM-based remaining useful life (RUL) estimators trained on SAP PM maintenance order history, failure event records, asset age and material data, and operational parameter time-series from SAP IoT enable probability-of-failure scoring for each monitored asset on a continuous basis [14].

4.5 Intelligent Waste Collection Routing

Dynamic waste collection routing based on real-time bin fill-level data represents one of the most immediately deployable and economically compelling AI applications in urban waste management. Ultrasonic fill-level sensors deployed in smart waste containers transmit fill readings to SAP IoT at configurable intervals—typically twice daily in residential deployments and hourly in high-generation commercial areas. A reinforcement learning routing agent, trained on historical fill-level distributions, vehicle capacity constraints, time window requirements, and road network data, generates daily optimised collection routes that direct vehicle resources to containers requiring collection while bypassing those below fill-level thresholds [8].

5. Prerequisites for AI–SAP Integration in Municipal Environments

Three categories of prerequisite condition must be established before AI–SAP integration can deliver reliable operational value in municipal water and waste management contexts. The first is IoT sensor infrastructure readiness. AI models for leakage detection, quality monitoring, and fill-level routing require dense, reliable sensor coverage of the water distribution network and waste container estate. Many municipal utilities operate heterogeneous, partially instrumented networks in which sensor coverage is insufficient for AI model training or real-time inference. [12].

The second prerequisite is master data quality within SAP. AI models for predictive maintenance depend on accurate equipment master records, reliable failure event documentation in SAP PM maintenance orders, and consistent recording of maintenance activities across operational sites.[11]

Establishing a data governance framework—defining data ownership, quality standards, sharing agreements, and integration architectures through SAP Datasphere—that enables these datasets to be harmonised into a unified AI data foundation is an organisational and technical challenge that typically requires senior executive sponsorship to overcome departmental boundaries.[13]

6. Smart City AI Readiness Framework

Drawing on the analysis of use cases, prerequisites, and implementation evidence presented above, we propose a four-dimension Smart City AI Readiness Framework (SCARF) for assessing and building AI capability in SAP-managed municipal water and waste environments. Each dimension is assessed on a three-level scale: Foundational (Level 1), Developing (Level 2), and Advanced (Level 3).

The first dimension, Sensor and Data Infrastructure, assesses the coverage, reliability, and integration of IoT sensor networks and the quality of their data integration with SAP IoT and SAP Datasphere. Level 1 cities operate partial sensor networks with manual data collection as the primary mode for most assets. Level 2 cities have continuous IoT sensor coverage of primary assets with automated SAP IoT ingestion and historical data archives adequate for initial ML model training. Level 3 cities operate dense, redundant sensor networks across water and waste assets with real-time SAP IoT integration, standardised data quality monitoring, and enriched feature engineering pipelines.

The second dimension, SAP Platform Maturity, assesses the adoption of SAP BTP AI infrastructure and Clean Core S/4HANA implementation discipline. Level 1 organisations run on-premise SAP systems with limited BTP adoption and significant custom ABAP modifications. Level 2 organisations have adopted SAP BTP for at least integration and analytics workloads, are consuming SAP-delivered embedded intelligent scenarios, and have initiated a Clean Core simplification programme. Level 3 organisations operate AI models on SAP AI Core, have deployed Joule across utility operational roles, and manage a full MLOps lifecycle through SAP AI Launchpad.

The third dimension, Governance and Organisation, assesses data governance maturity, AI model governance processes, and organisational AI literacy. Level 1 organisations have informal data governance, no AI model governance, and low AI literacy among operational and IT staff. Level 2 organisations have formalised data ownership, a pilot AI governance framework covering priority models, and targeted AI literacy programmes for key roles. Level 3 organisations operate a comprehensive AI governance framework integrated with IT risk management, have established an AI Centre of Excellence with combined SAP and ML competency, and conduct regular AI model performance reviews in operational governance forums. [15, 16].

7. Conclusion

The convergence of AI and SAP enterprise software in urban water and waste management systems offers a technically mature and economically compelling pathway toward the smart city objective of self-optimising, data-driven urban infrastructure. Across demand forecasting, leakage detection, water quality monitoring, predictive asset maintenance, dynamic waste collection, automated material recovery, and treatment process optimisation, AI techniques are demonstrably capable of delivering substantial improvements in operational efficiency, resource recovery, and environmental compliance—improvements that, when integrated with SAP's enterprise management platform, translate directly into measurable financial and service quality outcomes.

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