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A Survey on Recent Research Trends Towards Smart Water Grid System for Sustainable Urban Water Management and Leakage Localization.

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Abstract: Rapid urbanization, increasing water demand, aging distribution infrastructure and climate variability have intensified the need for sustainable urban water management. Conventional water distribution systems rely heavily on inspection and reactive maintenance making it difficult to detect and localize small leaks before they become major failures. Smart Water Grid systems address this challenge by integrating Internet of Things sensors, smart meters, wireless communication, hydraulic modelling, cloud and edge computing, machine learning, graph-based learning and Digital Twin technologies. This literature review examines research on smart water distribution systems, with particular emphasis on leakage detection and localization. Recent studies show a transition from pressure- and flow-based approaches toward data-driven and hybrid physics-informed techniques. Three-dimensional convolutional neural networks, graph networks, machine-learning classifiers, wavelet-based signal processing, acoustic localization and mixture-of-experts architectures have demonstrated promising results. However reported studies remain dependent on simulated or laboratory data and performance can degrade when network topology, sensor availability, demand patterns or hydraulic-model assumptions change. The review identifies research gaps in real-world validation, sensor placement, uncertainty quantification, explainable AI, cybersecurity, interoperability and scalable edge implementation. Finally, a research framework is proposed for a Smart Water Grid combining distributed sensing, topology-aware AI, hydraulic constraints, real-time communication and Digital Twin-assisted decision support.

Keywords: Smart Water Grid, Smart Water Distribution Network, Sustainable Urban Water Management, Water Leakage Detection, Leakage Localization, Internet of Things Machine Learning, Graph Neural Networks, Digital Twin, Smart Metering.

1. INTRODUCTION

Urban water distribution networks are infrastructure systems that must deliver safe water continuously while operating under constraints imposed by limited resources, energy consumption, aging assets and uncertain demand. Water losses caused by leakage represent both an environmental problem because treated water has already consumed energy and treatment resources before it is lost. The increasing availability of meters and IoT-enabled sensing has created an opportunity to transform conventional water networks into data-rich cyber-physical systems.

Recent literature indicates that machine learning is becoming a component of smart water distribution systems. A 2025 review by Taloma et al. Organizes applications into infrastructure analysis user-demand analysis and water-quality monitoring. Identifies leakage detection/localization, state estimation and asset management as major infrastructure applications. The review also highlights the tension between data-driven models and the physical laws governing networks.

The purpose of this paper is to synthesize developments relevant to a Smart Water Grid for sustainable urban water management and leakage localization. Particular attention is given to research published during 2024–2025 while earlier influential studies are included to establish the evolution of the field.

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II. SMART WATER GRID and ARCHITECTURE

A Smart Water Grid can be regarded as a cyber- water infrastructure in which physical water assets are continuously observed through sensors connected through communication networks analyzed using computational intelligence and used to support operational decisions. A practical architecture can be organized into five interacting layers: sensing, communication, data and computing, intelligence and decision/control.

A. Sensing Layer

The sensing layer includes pressure transducers, flow meters, acoustic sensors, hydrophones, smart meters, water-quality sensors and valve-status sensors. Pressure and flow measurements are particularly useful for identifying deviations from expected conditions. Acoustic sensing provides information because leaks generate vibration and acoustic signatures that can be processed in the frequency domain.

B. Communication Layer

IoT communication technologies such as LoRaWAN, NB-IoT, Zigbee, Wi-Fi and networks can connect distributed measurement nodes. Power wide-area networking is attractive for water utilities because sensors may be installed at locations where continuous mains power is unavailable. Communication design must balance range, energy consumption, latency, bandwidth, reliability and security.

C. Data and Computing Layer

Cloud platforms provide storage and model training whereas edge computing can perform filtering, feature extraction, anomaly detection and local alarm generation close to the sensors. A hybrid edge-cloud architecture is therefore suitable for water networks where rapid response and centralized analytics are both required.

D. Intelligence Layer

The intelligence layer contains models, hydraulic simulations, machine-learning classifiers deep-learning networks graph neural networks, Bayesian models and hybrid physics-informed algorithms. Its functions include anomaly detection, leakage classification, localization, demand forecasting, state estimation and predictive maintenance.

E. Decision and Control Layer

The final layer converts outputs into operational actions, including field inspection, valve operation, pressure management, pipe rehabilitation, maintenance scheduling and customer notification.

III. EVOLUTION OF WATER LEAKAGE DETECTION

Traditional leakage detection methods include inspection, minimum night flow analysis, acoustic inspection, pressure monitoring, tracer methods and hydraulic model calibration. These approaches remain useful. May be labour intensive, sensitive to environmental noise or unable to localize leaks rapidly in large networks.

Data-driven approaches have expanded the capabilities of systems. The recent literature demonstrates the progression from classical machine learning toward learning graph-based learning, probabilistic inference and hybrid hydraulic-data-driven methods. This evolution is motivated by the topology of water distribution networks and the nonlinear relationship between demand, pressure, flow and leakage.

IV. RECENT MACHINE-LEARNING APPROACHES

A. Classical Machine Learning

Support Vector Machines, Random Forests, k-Nearest Neighbours, decision trees and multilayer perceptions have been applied to classify normal and leaking operating conditions. A 2025 study by Gaurav and Rathi evaluated KNN, Random Forest and SVM using EPANET Network 3 and a real campus network. Random Forest achieved 88.13 % and 95.84 % accuracy on the two networks, respectively with AUC values of 0.87 and 0.98.

B. Convolutional Neural Networks

CNN architectures can learn temporal patterns directly from sensor measurements. Jun, Jung and Lansey proposed a 3-D CNN for leakage detection and localization using spatially distributed pressure information from advanced metering infrastructure. Tested on an Austin water distribution network using hydraulically simulated realistic leaks the model outperformed an optimization-based approach. The authors nevertheless identify hydraulic-model error and retraining requirements after network changes as limitations.

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C. Graph Neural Networks

Water distribution networks naturally form graphs in which junctions, reservoirs, tanks and meters can be represented as nodes and pipes as edges. GNNs therefore provide a mechanism for incorporating topology. A 2024 IEEE MetroInd4.0 and IoT study evaluated graph-based leakage localization under LPWAN data restrictions. Combining GNNs with regression at intermediate nodes achieved up to 80 % accuracy while reducing the number of sensor nodes by 37 % demonstrating the potential of topology-aware learning under limited sensing.

D. Wavelet and Signal-Processing-Based Learning

Pressure signals contain both slow hydraulic variations and transient information. A 2024 study proposed a two-phase approach in which daily pressure data are decomposed using wavelets before machine-learning-based classification and sensor-based localization. The reported leak-classification accuracy reached 99 % illustrating the value of extracting signal features before learning.

E. Acoustic Machine Learning

Acoustic localization is particularly useful when pressure changes are too small to provide an indication. Recent research combining FFT-based signal decomposition with machine learning has demonstrated the ability to reduce the leakage region substantially. Such methods can provide spatial precision although sensor coupling, background noise, pipe material and installation conditions affect performance.

F. Mixture-of-Experts Models

Recent research has also explored architectures in which multiple specialist models are combined through a gating mechanism. A 2025 Mixture-of-Experts study using LeakDB-based Hanoi and Net2 datasets reported leakage detection accuracy above 90 %. The approach illustrates a movement toward combining models rather than relying on a single classifier.

V. HYDRAULIC MODELING AND PHYSICS-INFORMED AI

Hydraulic modelling remains important because water networks obey conservation of mass, momentum relationships, pressure-flow characteristics and network connectivity constraints. Purely data-driven models can learn correlations that may not generalize when operating conditions change. Conversely hydraulic approaches require accurate network information, calibration and computational effort.

A promising direction is the integration of models and machine learning. Computational Fluid Dynamics combined with learning has recently been investigated for leak detection and localization. Hybrid approaches can use simulation to generate training scenarios while AI provides inference during operation. Physics-informed learning can further incorporate constraints into the training objective reducing physically implausible predictions.

VI. DIGITAL TWINS FOR WATER GRIDS

A Digital Twin is a continuously updated virtual representation of a physical water distribution network. In a Smart Water Grid, the Digital Twin can integrate network topology, GIS information, hydraulic models, sensor streams, maintenance records and AI predictions. It can support what-if analysis, leak scenario simulation, pressure optimization, asset-health assessment and predictive maintenance.

The major advantage of Digital Twins is that they connect data analytics with the infrastructure. Of generating an isolated machine-learning prediction a Digital Twin can show where the predicted event occurs estimate its hydraulic impact simulate alternative interventions and provide actionable insight for operators.

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VII. COMPARATIVE REVIEW OF RECENT STUDIES

Study/Year	Technology	Data	Main Contribution	Reported Result	Major Limitation
Taloma et al., 2025	ML/DL survey	Smart-meter & WDS literature	Taxonomy of smart-water ML applications	Identifies leakage localization as core infrastructure task	Need for real-world benchmarking
Jun et al., 2024	3-D CNN	AMI pressure + hydraulic simulation	Spatio-temporal leak detection/localization	Outperformed optimization baseline	Model uncertainty; retraining
Rolle et al., 2024 IEEE	GNN + regression	Simulated WDN / LPWAN constraints	Topology-aware localization with fewer sensors	Up to 80% accuracy; ~37% fewer sensors	Simulation-based validation
Wavelet + ML, 2024	Wavelets + ML	Pressure signals	Two-phase detection/localization	99% classification accuracy	Generalization to other networks
Acoustic ML, 2024	FFT + Decision Tree	Real leak acoustic data	Locate and pinpoint leakage	Potential scope reduced to 0.3 m	Noise and deployment effects
Gaurav & Rathi, 2025	RF/KNN/SVM	EPANET + real campus WDN	ML leakage identification	RF: 88.13–95.84% accuracy	Further real-world validation needed
Mixture of Experts, 2025	MoE + hydraulic model	LeakDB Hanoi/Net2	Ensemble leak detection/localization	>90% detection accuracy	Benchmark dependence

VII. CRITICAL RESEARCH GAPS

A. Dependence on Simulated Data
A portion of recent research generates leak scenarios using hydraulic simulators. Simulation is valuable for controlled experiments. Simulated data may not reproduce sensor noise, demand uncertainty, valve states, pipe deterioration, environmental effects and undocumented network modifications.

B. Sensor Placement and Cost
Installing sensors throughout a network is expensive. Research therefore needs optimization methods that identify a sensor set while preserving localization accuracy. The 2024 IEEE graph-based study demonstrates the potential of topology- estimation for reducing sensing requirements.

C. Concept Drift
A trained model may lose accuracy when demand patterns, network topology, pressure regimes or pipe conditions change. Continuous or incremental learning is therefore important, for lived Smart Water Grid deployments.

D. Uncertainty Quantification
Utilities need not only a predicted leak location but also confidence information. Probabilistic approaches can provide uncertainty estimates, helping operators prioritize inspections.

E. Explain ability
Deep learning models may give predictions but do not clearly explain why a specific pipe was identified. Explainable AI can build operator trust.

F. Cybersecurity
Water infrastructure is more and more linked to communication networks and supervisory control systems. Fake sensor data, communication loss, unauthorized control and adversarial manipulation can hurt leak detection and operational decisions. Security must be seen as a core part of Smart Water Grid design.

IX. PROPOSED RESEARCH FRAMEWORK

Based on the reviewed literature, a practical Smart Water Grid research architecture can combine distributed pressure and flow sensors with acoustic sensing at selected critical locations. Sensor data can be transmitted through a low-power IoT network to an edge gateway. The gateway performs preprocessing and anomaly screening. A cloud or local server maintains a hydraulic Digital Twin and executes topology-aware AI models.

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The proposed analytical pipeline is: (1) sensor acquisition, (2) noise filtering and synchronization, (3) hydraulic feature extraction, (4) anomaly detection, (5) leakage classification, (6) graph-based localization, (7) confidence estimation, (8) Digital Twin simulation, and (9) maintenance decision support.

For a network represented by G=(V,E), node features can contain pressure, demand estimates, and sensor status, while edge features can contain pipe length, diameter, roughness, and flow. A graph model can then learn a mapping from observed measurements to a probability distribution over candidate leaking pipes. A hybrid loss function can combine classification error with hydraulic consistency constraints.

X. SUSTAINABILITY IMPLICATIONS

Leakage localization directly supports Sustainable Development Goal 6 by reducing unnecessary water losses and improving the efficiency of urban water services. Reduced leakage also decreases the energy consumed for abstraction, treatment, and pumping. Predictive maintenance can extend asset life and reduce emergency excavation and replacement. Smart water metering can additionally support demand awareness and equitable resource management.

A sustainable Smart Water Grid should therefore be evaluated not only by localization accuracy but also by water saved, energy saved, false-alarm rate, sensor lifetime, communication energy, maintenance cost, response time, and lifecycle cost.

XI. FUTURE RESEARCH DIRECTIONS

Future research should concentrate on the following directions:

- Physics-informed Graph Neural Networks that explicitly incorporate hydraulic conservation laws. Federated learning for collaborative model training without centralizing sensitive customer-level data.
- Edge AI for low-latency leakage alarms in bandwidth-constrained networks.
- Digital Twin platforms that combine GIS, hydraulic simulation, sensor data, and AI predictions.
- Adaptive sensor placement based on uncertainty and network criticality.
- Self-supervised and unsupervised learning to reduce dependence on labeled leak events.
- Uncertainty-aware localization that produces confidence intervals or ranked candidate pipes.
- Explainable AI interfaces that provide evidence for every leakage alarm.
- Cyber-resilient architectures capable of distinguishing physical anomalies from malicious data manipulation.
- Large-scale field trials using continuously collected utility data across multiple cities.

XII. CONCLUSION

This literature review shows that Smart Water Grid technology is moving from conventional monitoring toward integrated cyber-physical infrastructure supported by IoT, advanced metering, machine learning, graph learning, hydraulic simulation, and Digital Twins. Recent work demonstrates that deep-learning and topology-aware methods can improve leakage detection and localization, while hybrid methods offer a promising route toward physically consistent and operationally useful predictions. Nevertheless, the gap between simulated research and field deployment remains substantial. Future systems must address sensor cost, model uncertainty, network changes, cybersecurity, explainability, and interoperability. A sustainable urban Smart Water Grid should therefore combine multi-modal sensing, efficient communication, hydraulic knowledge, topology-aware AI, uncertainty estimation, and Digital Twin-based decision support.

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