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PHYSICS-INFORMED HYBRID LEARNING FOR PREDICTIVE LEAK DIAGNOSTICS IN HIGH-RISE WATER SYSTEMS

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ABSTRACT

High-rise building water distribution systems (WDS) present significant leak diagnostic challenges due to complex transient flow behaviours (e.g., unpredictable flow and demand (randomness and density - number of branches/consumption nodes), transient waves interactions) and scarce real-world leak data. To address limitations of conventional methods and enable continuous monitoring without supply interruption, this study proposes a physics-informed hybrid learning framework for leak detection, localization, and quantification. Our core innovation integrates convolutional neural networks (CNNs) with physics constraints derived from transient flow governing equations, fusing hydraulic mechanisms with multi-sensor data. This physics-constrained deep learning architecture leverages numerical simulations for data augmentation and is being validated using experimental data from a living lab at HKUST. The framework aims to advance transient flow-based diagnostics by significantly reducing data dependency and improving accuracy for small leaks in multi-floor systems, supporting proactive maintenance, water conservation, and sustainable urban water management through quantified environmental benefits.

Keywords: Transient pressure analysis, Physics-informed AI, Leak detection, High-rise buildings

1. Introduction

1.1. Problem Statement High-rise buildings feature vertically segmented water distribution systems (WDS) with variable pressure zones (e.g., low/mid/high) and dynamic demand, leading to intricate transient flows (e.g., water hammer from valve closures, pump startup transients). These complex systems suffer substantial resource loss, with undetected leaks causing approximately 40 annual leaks at institutions like HKUST (Hong Kong University of Science and Technology, 2022) and compromising structural integrity through mold growth and material degradation (e.g., mold from hidden leaks) (World Health Organization, 2011). Existing leak detection methods face critical limitations: (1) Requirement for disruptive system shutdown during inspection, preventing continuous monitoring; (2) Hard to reliably detect low-magnitude pressure fluctuations caused by small leaks amid operational noise during normal water usage; and (3) High false alarms triggered by routine consumptionnormal usage patterns. Furthermore, pure physics-based models (e.g., method of characteristics for transient analysis) struggle with real-world complexities like environment noise, unknown demand and uncertainties, while data-driven models (e.g., CNNs) require large labeled datasets—scarce in buildings due to the impracticality of controlled leak tests in occupied buildings.

*1.2. Research Gap*While transient signal-based leak detection in municipal WDS is well-established, its adaptation to high-rise buildings remains underdeveloped. This gap stems from fundamental topological differences: high-rise WDS feature shorter pipe segments and denser network configurations—contrasting sharply with the long, predominantly horizontal pipelines in municipal systems. Our work bridges this gap by developing specialized methodologies validated through progressive complexity for enabling effective transient analysis in high-rise environments.*1.3. Objective*Develop a physics-informed hybrid learning framework to: (1) Detect leaks using transient pressure/flow signals; (2) Localize leaks to specific floors/flats; (3) Quantify leak size (l/s); (4) Generalize to unseen high-rise buildings with minimal data.

2. Methodology

2.1. Transient Flow Physics and Leak Signatures

Leak-induced transient features were identified via fundamental hydraulic analysis:

- **Pressure waves**: A leak creates an impedance discontinuity generating partial wave reflections. The reflection coefficient R follows:

$$R = \frac{Z_{\text{pipe}}}{Z_{\text{pipe}} + 2Z_{\text{leak}}}. \tag{1}$$

- **Wave propagation**: Under the assumption of small pipe wall deformations and linear elasticity, the pressure wave speed in a fluid-filled pipe is governed by:

$$a = \sqrt{\frac{K}{\rho\left(1 + \frac{KD}{Ee}\varphi\right)}}. \tag{2}$$

  Where $Z_{\text{pipe}} = \rho a/A$ =pipeline characteristic impedance, $Z_{\text{leak}} = H_{\text{leak}}/Q_{\text{leak}}$ = leak impedance, ρ = fluid density, a = pressure wave speed, A = pipe cross-sectional area, H_{leak} = pressure head at leak location, Q_{leak} = volumetric leak flow rate, K = fluid bulk modulus, E = Young's modules of pipe material, D = pipe diameter, e = pipe wall thickness, φ = dimensionless pipe anchoring factor (accounting for axial/radial constraints). Wave speed a decreases with pipe aging (e.g., due to material degradation (reducing the effective stifness Ee) and constraint variations (changing φ)).

Key governing equations embedded as physics constraints:

- Continuity equation for transient flow:

$$\frac{\partial H}{\partial t} + \frac{a^2}{gA}\frac{\partial Q}{\partial x} = 0. \tag{3}$$

- Momentum equation:

$$\frac{\partial Q}{\partial t} + gA\frac{\partial H}{\partial x} + f\frac{Q|Q|}{2DA} = 0. \tag{4}$$

Where H = hydraulic head (pressure-related measure), t = time, Q = volumetric flow rate, x = spatial coordinate along the pipeline, g = gravity, A = pipe cross-sectional area, f = friction factor, D = pipe diameter.

2.2. Hybrid Learning Framework

The model architecture (Table 1) includes three modules:

Table 1. Model architecture

Module	Components	Physics Integration
Physics-Embedded Feature Extractor	CNN layers with wavelet initialization	Kernels initialized using transient wavelet coefficients derived from Eq. 1-4
Data Fusion Module	Multi-sensor attention mechanism	Prioritizes 100-300 Hz features from turbulent leak flow
Predictive Head	Multi-task output layers	Physics-constrained loss function

1. **Physics-Embedded Feature Extractor**: A CNN layer where convolution kernels are initialized using transient wavelet coefficients (capturing pressure wave patterns from Eq. 1-4), reducing reliance on labeled data.
2. **Data Fusion Module**: Fuses transient pressure (sampled at 1 kHz) and vibration signals from sensors installed at floor junctions, with attention weights prioritizing features aligned with leak signatures.
3. **Predictive Head**: Outputs leak probability, location (floor/flat), and size, with loss function penalizing violations of Eq. 1-4. The composite loss function incorporates both data-driven and physics-based terms:

$$L_{\text{total}} = L_{\text{data}} + L_{\text{physics}}. \tag{5}$$

Where $L_{\text{data}} = \text{loss}_{\text{Standard cross-entropy}} + \text{loss}_{\text{MSE}}$. This term combines standard classification and regression losses and ensures the model fits the training data well, capturing patterns in the observed data. $L_{\text{physics}} = \lambda_1 \| Q_{\text{leak}} - k\sqrt{\Delta H} \| + \lambda_2 \| R_{\text{pred}} - R_{\text{phys}} \|$ enforces compliance with hydraulic principles through two constraints. Q_{leak} is predicted leak size. k is a proportionality constant related to hydraulic properties. ΔH is measured pressure drop. R_{pred} is a model-predicted wave reflection coefficient and R_{phys} is physically derived wave reflection coefficient (based on hydraulic theory). λ_1 and λ_2 is weighting factors. This physics-informed neural network (PINN) approach ensures predictions comply with fundamental hydraulic principles.

2.3. Data Generation and Validation

- **Numerical dataset**: Simulated Tower 4 (floors 5-8) with 220,000 leak scenarios; Parameters: Leak floor (5-8), leak flat (A-C), size (0.01-0.1 L/s).

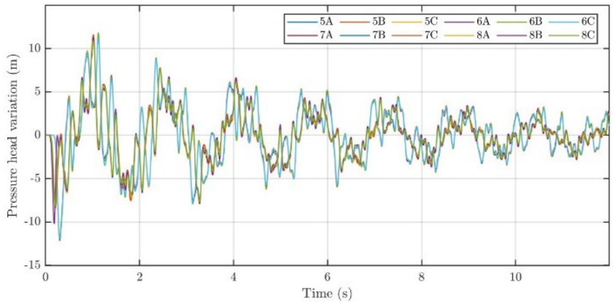

Fig. 1 Simulated pressure data variation at all measurement points: per flat model, leak of 0.5 l/s at flat 8C (35 meters from the flat measurement point), transient generated by valve opening and closing in the measurement location of flat 8A within 100 milliseconds.

- **Experimental dataset**: HKUST Tower 4 monitoring system (2025); Distributed pressure sensors (1 kHz) and accelerometers; Controlled leak tests at floor 6.
- **Training strategy**: Physics-constrained pretraining on synthetic data; Transfer learning with 30% experimental data; Validation on 70% real-world measurements.

3. Expected Contributions

a. Continuous monitoring capability: First framework enabling leak detection without system shutdown

b. Physics-embedded AI: Novel CNN architecture with hydraulic equation constraints

c. Resource efficiency: Significant reduction in training data requirements anticipated via physics-guided learning

d. Scalable solution: Transfer learning approach for rapid deployment in new buildings

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