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MDPI

Unsupervised Timely Detection of DMA-Level Leaks in Water Networks using a Robust Regression Ensemble Method

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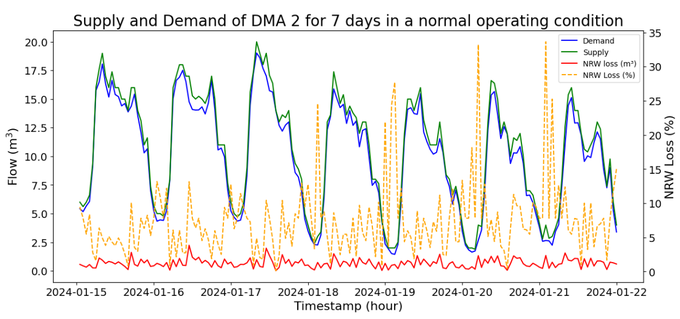
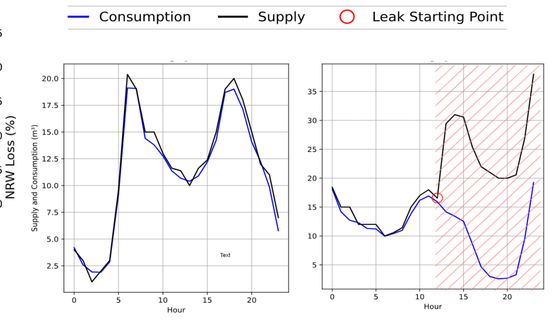
INTRODUCTION & AIM

Water Distribution Networks (WDN) face growing pressure from water scarcity, climate extremes, aging infrastructure, and workforce loss. **Non-Revenue Water (NRW)** from leaks increases operational costs and resource stress.
IoT sensing and data-driven analytics enable earlier **leak detection and localization**, but localization performance and added-value depends on **accurate and timely detection**.

- Supervised approaches are limited by **scarce and incomplete leak-event labels** and poor coverage of leak-size variability.
- Simulation-based data generation is constrained by **sparse sensors, incomplete GIS data, and changing hydraulic and demand conditions**.
- Unsupervised methods avoid labels but struggle to establish a **stable baseline** of normal behavior, leading to a **sensitivity vs. accuracy trade-off**.

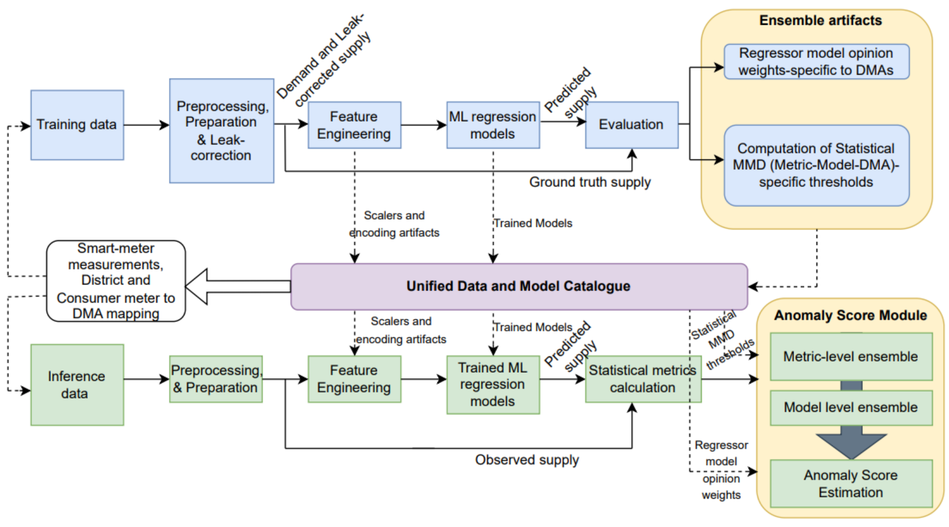




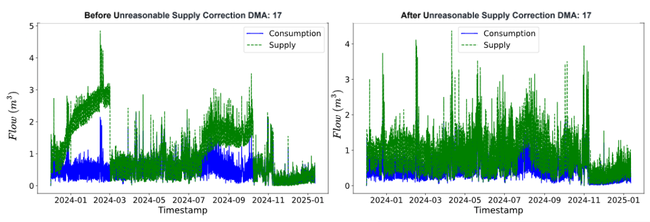
We exploit the **DMA-level demand-supply dynamics** and a novel **multi-regression model and metrics ensemble** technique to address:

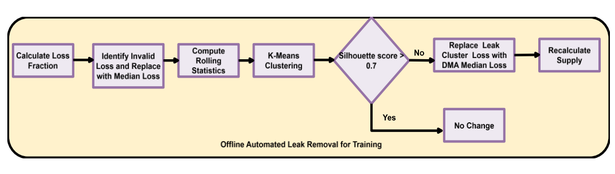
- Robust **timely detection** of new **emerging leaks** in DMA-level **in presence of background NRW loss,** using **smart meter** measurements and **unsupervised** approach,
- Achieve reliable performance with **reduced false alarm**,
- Understanding performance variations across **different leak-sizes**
- **Modular framework** for effortless onboarding of utilities

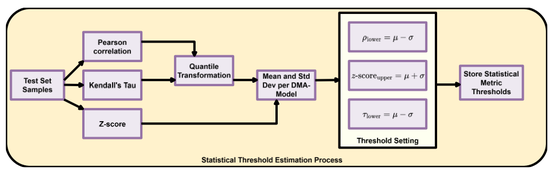
METHOD

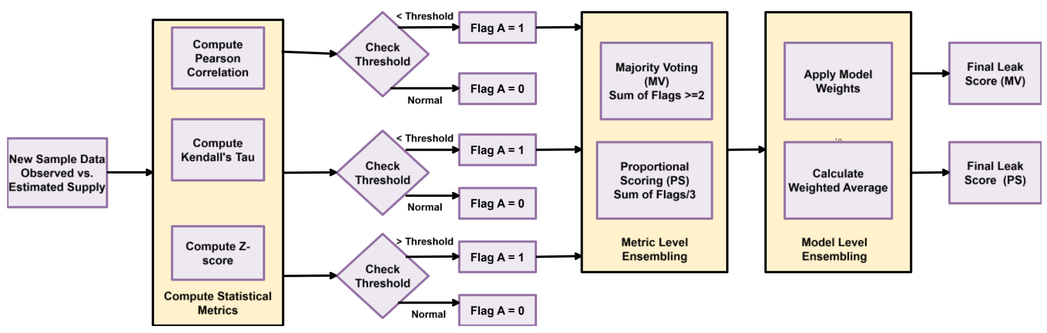


- **Preprocessing:** Meter data cleaning (negative flow, missing data), invalid supply data (e.g. supply < demand) correction and leak-removal for training of regression models.
- **Feature engineering:** Min-max sclaing and 24-hourly parsing of DMA- demand and supply data, one-hot-encoding of DMA-Ids
- **Regression models used:** Multi-layer Perceptron, XGBoost, Random Forest, Support Vector regression; Model accuracies (1-MAPE) as model opinion weights.
- **Statistical metrics used:** Pearson and Kendall's Tau correlation, Z-score





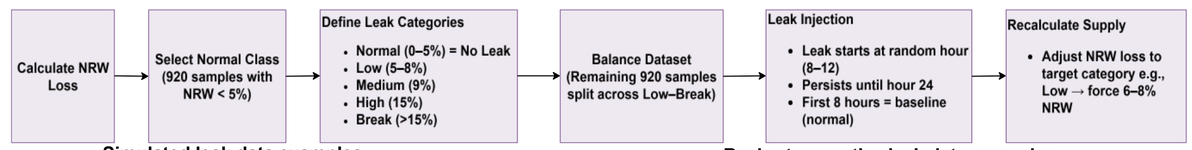




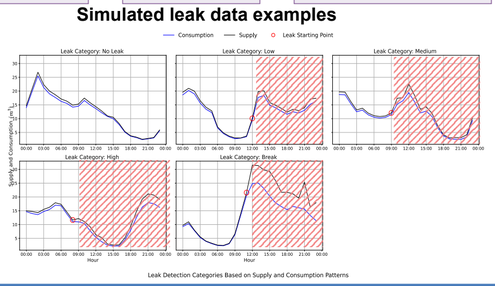
Leak Detection Process

EXPERIMENTS AND DATA

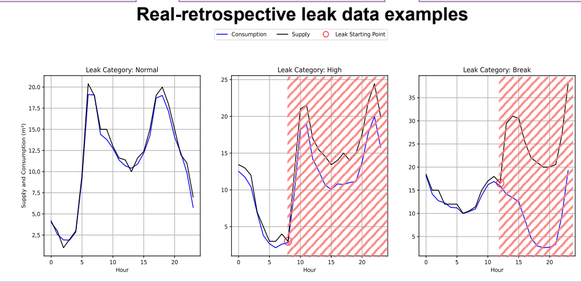
- **Experiment I:** Unified Regression Modelling approach (DMA-number being one-hot-encoded)
- **Experiment II:** DMA-specific regression modelling
- **Experiment III:** Leak detection (LD) with Majority-Voting-based anomaly scores
- **Experiment IV:** LD with Proportional-Score-based anomaly scores
- **Smart meter data** of **21 DMAs** of Bronderslev WDN from Denmark, **real leak-annotations**
- **Simulated leak-dataset** for validation of proposed method across various leak-sizes and onsets:



Simulated leak data examples

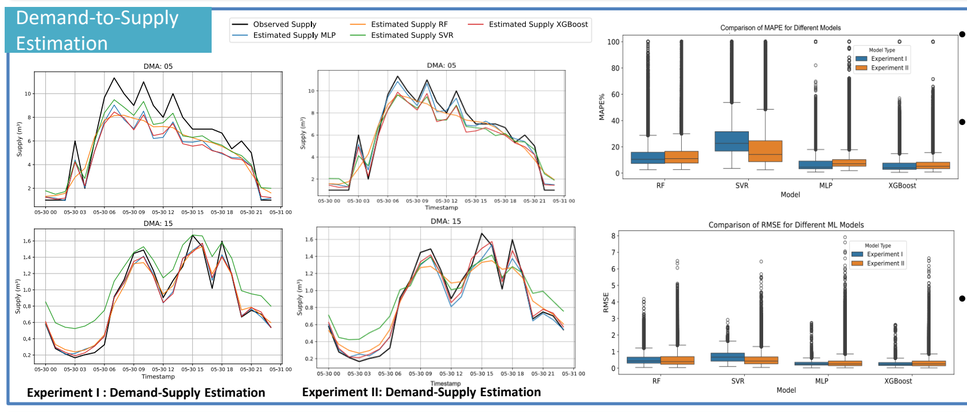


Real-retrospective leak data examples



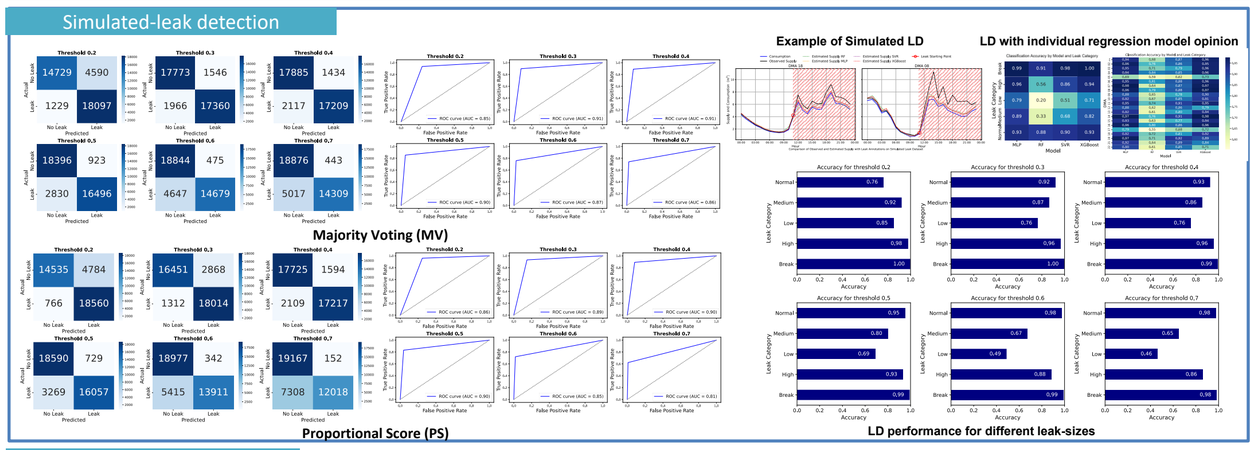
RESULTS & DISCUSSION

Demand-to-Supply Estimation

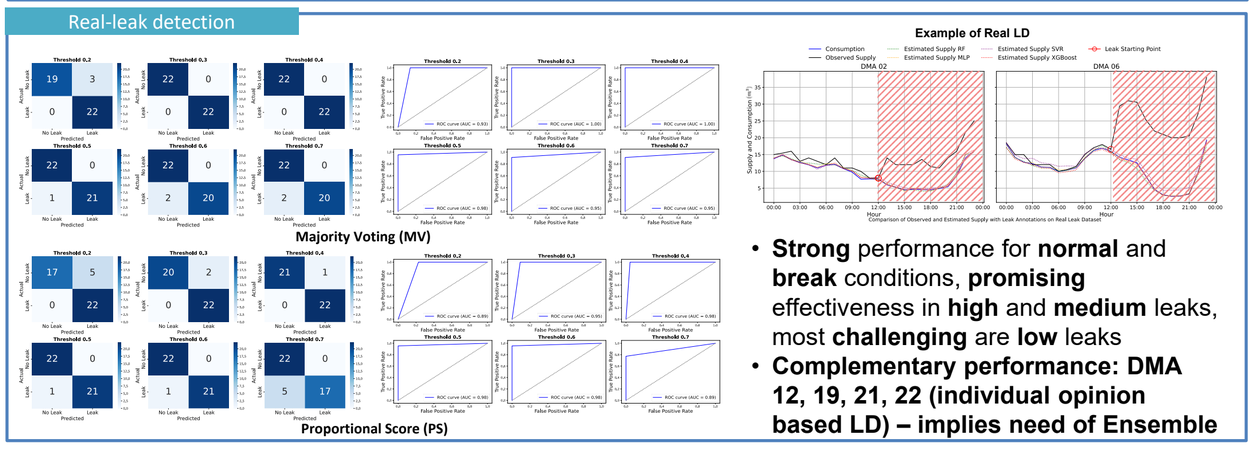


- **Experiment I** shows robustness across DMAs
- Offers **sclability** compared to Experiment II **(4 models vs 4N models,** with N No. of DMAs)
- Hence for **the LD pipeline**, **regression approach of Experiment I** is used

Simulated-leak detection



Real-leak detection



- **Strong** performance for **normal** and **break** conditions, **promising** effectiveness in **high** and **medium** leaks, most **challenging** are **low** leaks
- **Complementary performance: DMA 12, 19, 21, 22 (individual opinion based LD) – implies need of Ensemble**

CONCLUSION

- Scalable, Modular, Reusable and Robust framework for DMA-level leak detection
- Metric-level and Model-opinion ensemble per DMA to detect leak
- Learning DMA-specific boundary conditions of statistical metrics based on status-quo situation
- Detecting leak with reliable accuracy within 8-12 hours of leak onset

Outlook

- Investigate if one model maintaining the same scalability can attain equivalent performance
- Continual learning to capture evolving DMA-hydraulics and demand-supply dynamics
- Enhancement of demand-to-supply regression performance with more robust model collection
- Utilizing simulated leak dataset for evaluating performance of supervised classification of leaks