Data Driven DMA Agnostic Leakage Detection in WDNs

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Research Interests

- Digitalization in Water Sector
- Data Driven Leakage Detection
- Predictive Maintenance of WDN Assets
- Machine Learning & Deep Learning

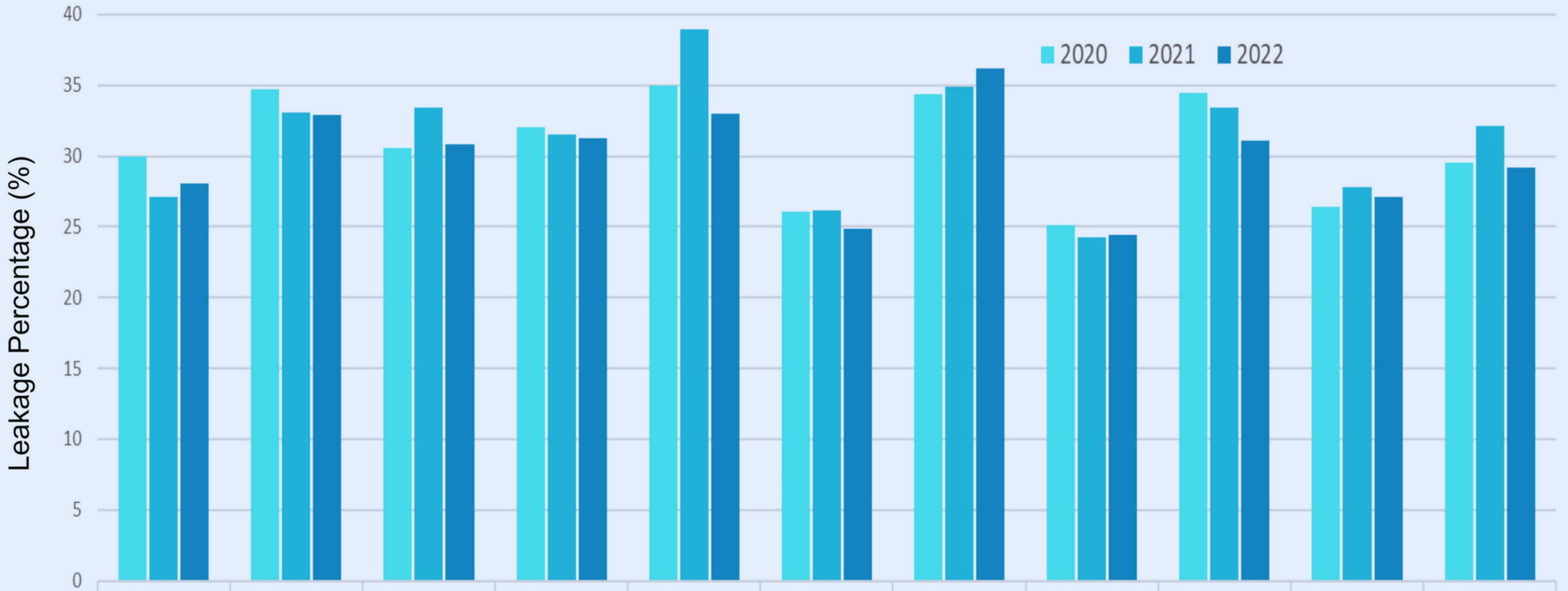
Background

- PhD Engineering (HydroInformatics)
- MPhil Applied mathematics

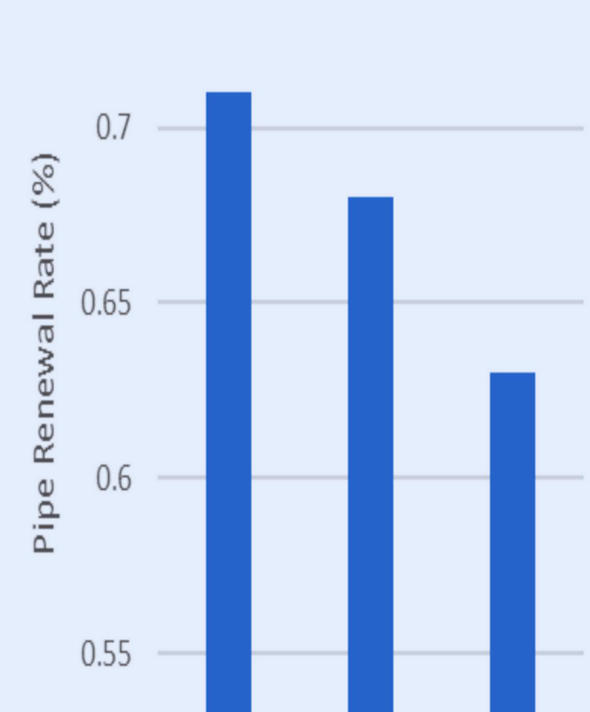
PhD Title: Data Driven Leakage Detection and Predictive Maintenance in Water Distribution Networks

Main Supervisor: Prof. Razak Seidu

Leakage Situation: County Breakdown



	Agder	Innlandet	Møre og Romsdal	Nordland - Nordlánnda	Oslo	Rogaland	Troms og Finnmark	Trøndelag - Tröödelage	Vestfold og Telemark	Vestland	Viken
2020	30	34.7	30.6	32	35	26.1	34.4	25.1	34.5	26.4	29.5
2021	27.1	33.1	33.4	31.5	39	26.2	34.9	24.3	33.4	27.8	32.1
2022	28.1	32.9	30.8	31.3	33	24.9	36.2	24.4	31.1	27.1	29.2



	2020	2021	2022
Rate	0.71	0.68	0.63

Statistics Norway (2022)

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Impact of Leakages -2022

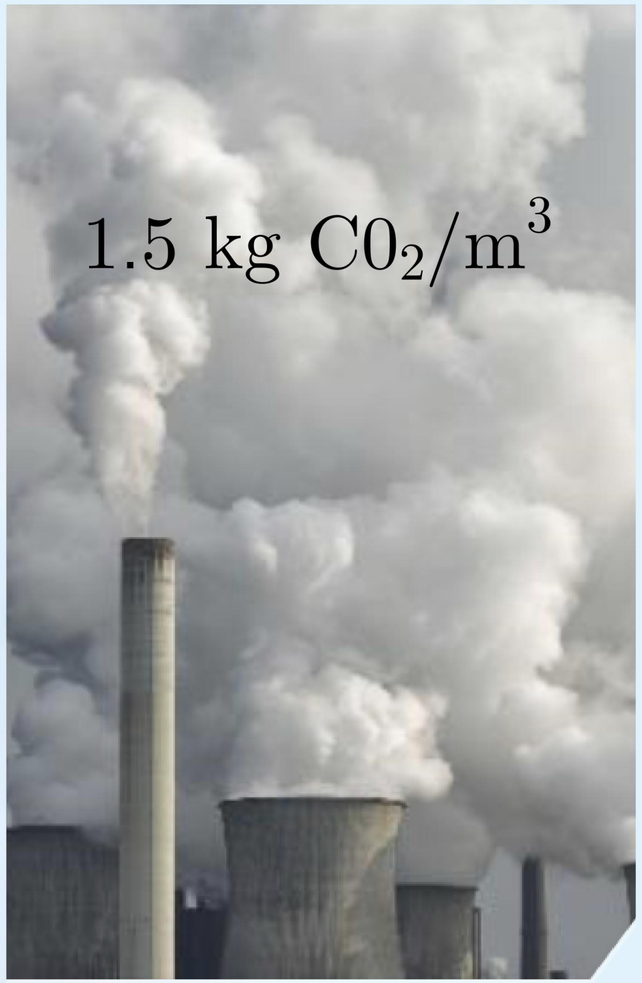
Volume Produced
$676,652,345\ \mathrm{m}^3$

Leak Volume
$201,249,363\ \mathrm{m}^3$

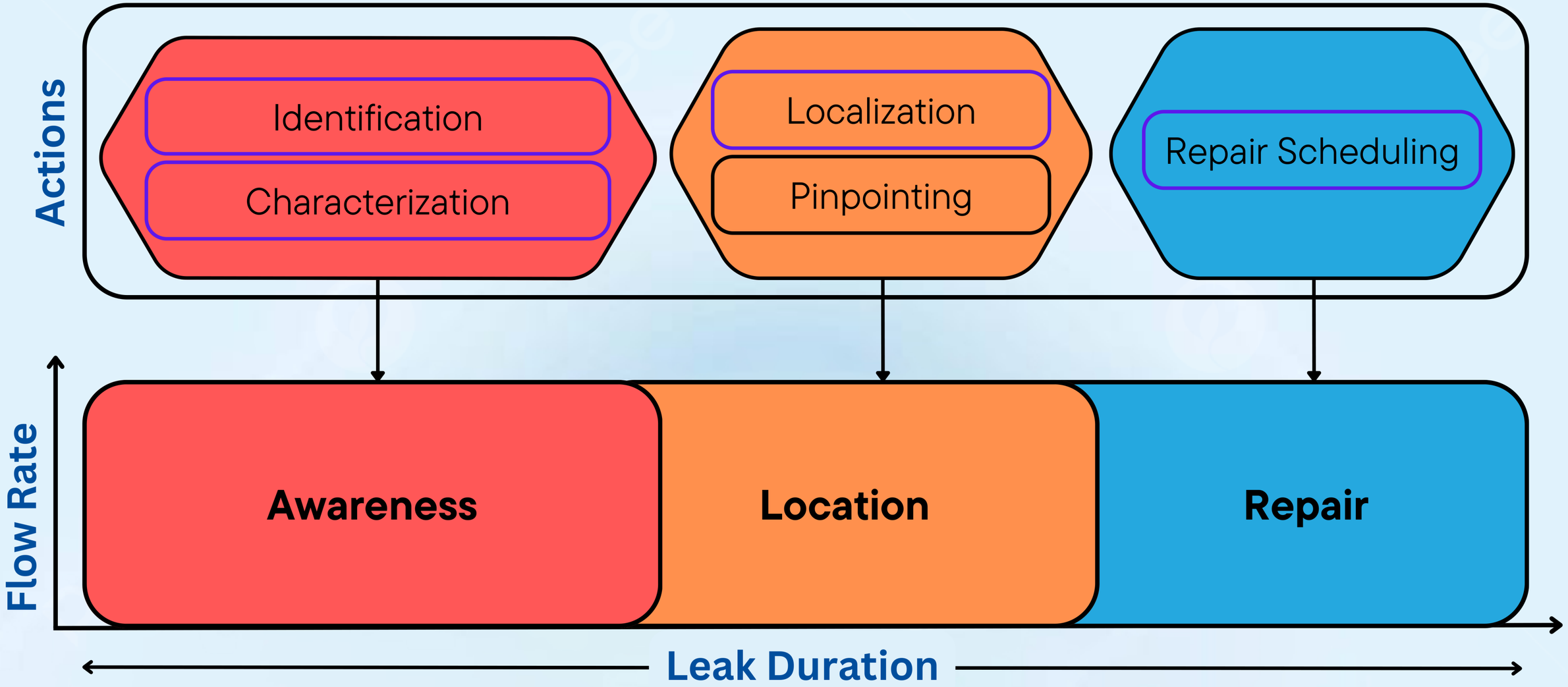
70% 30%

Cost per m^3: 14.00 kr

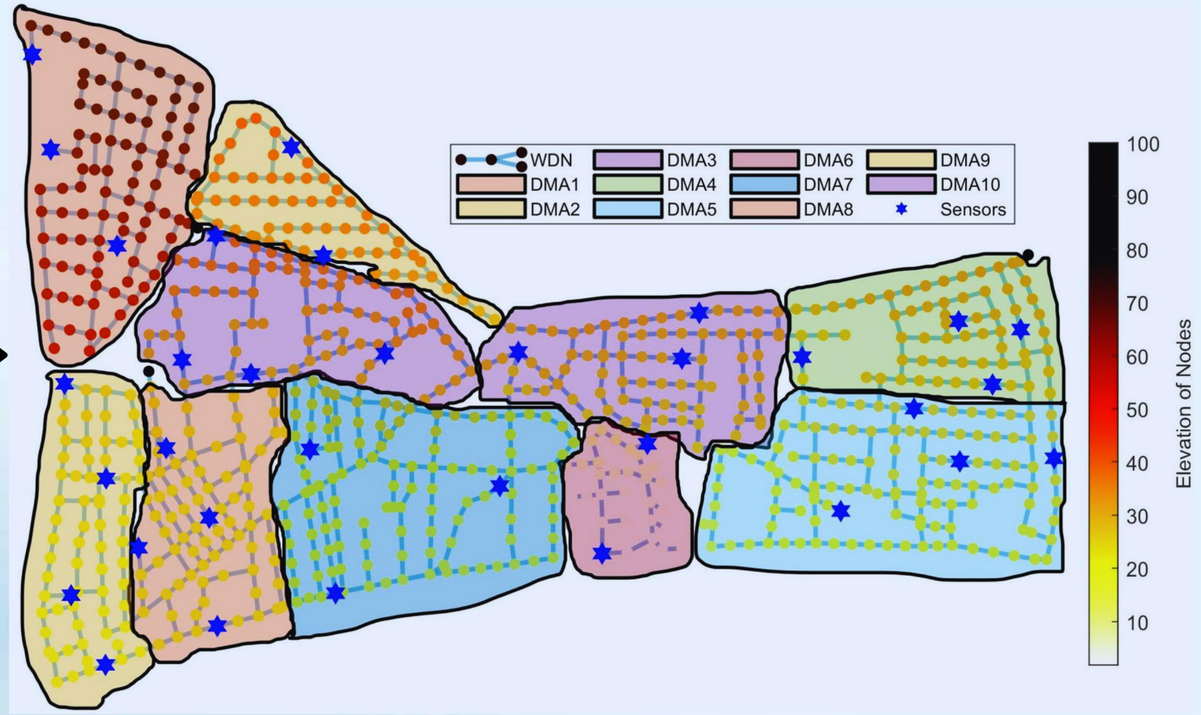
2.82 Billion NOK



Towards Active Leakage Detection



Pressure Sensor Placement and Virtual DMAs



- Utilizing existing Flow meters
- NetFlow enhances scalability
- Identification of Leakages

- Tractable Features per vDMA
- Enhances Leak Localization
- Leakage Identification & Localization

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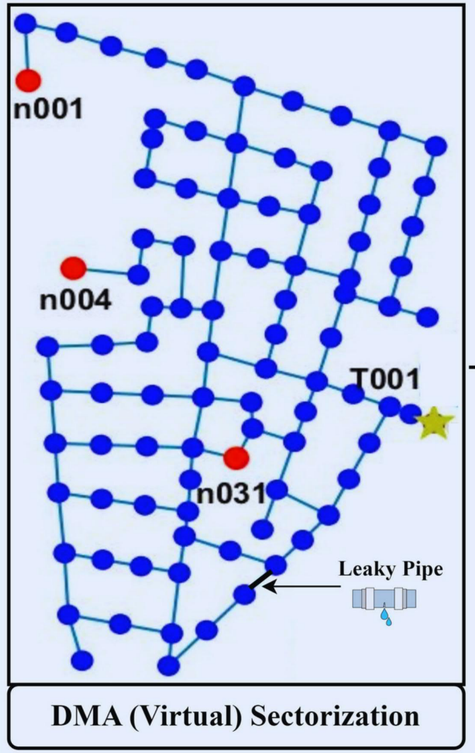
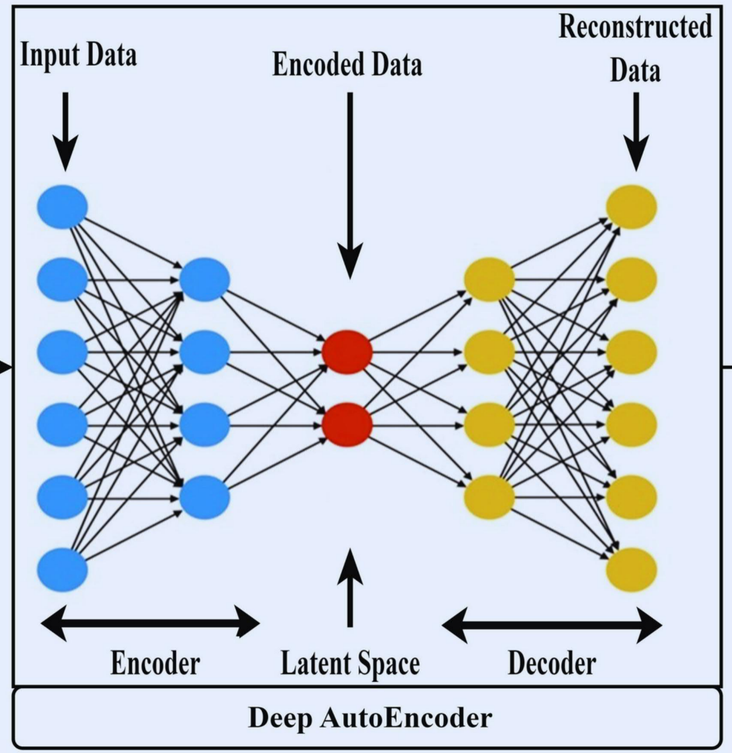
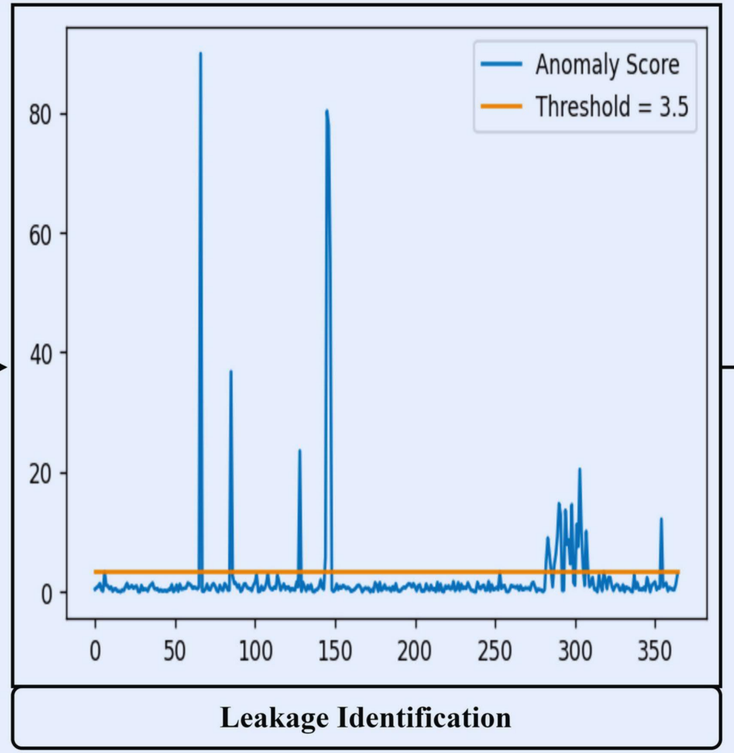
Identification and Localization Framework



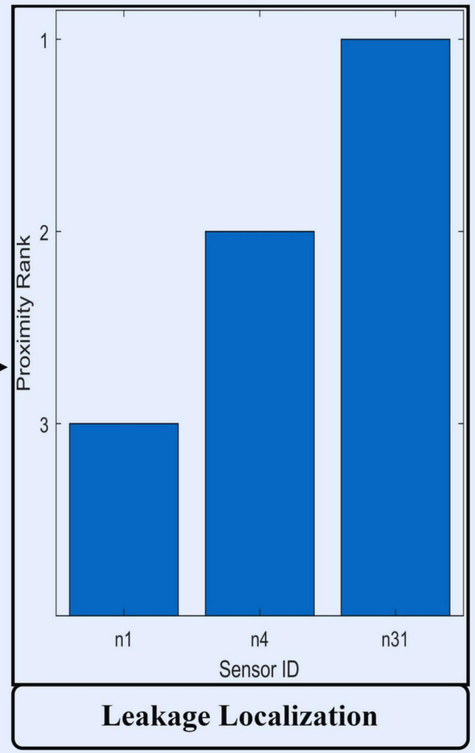
DMA (Virtual) Sectorization



Deep AutoEncoder



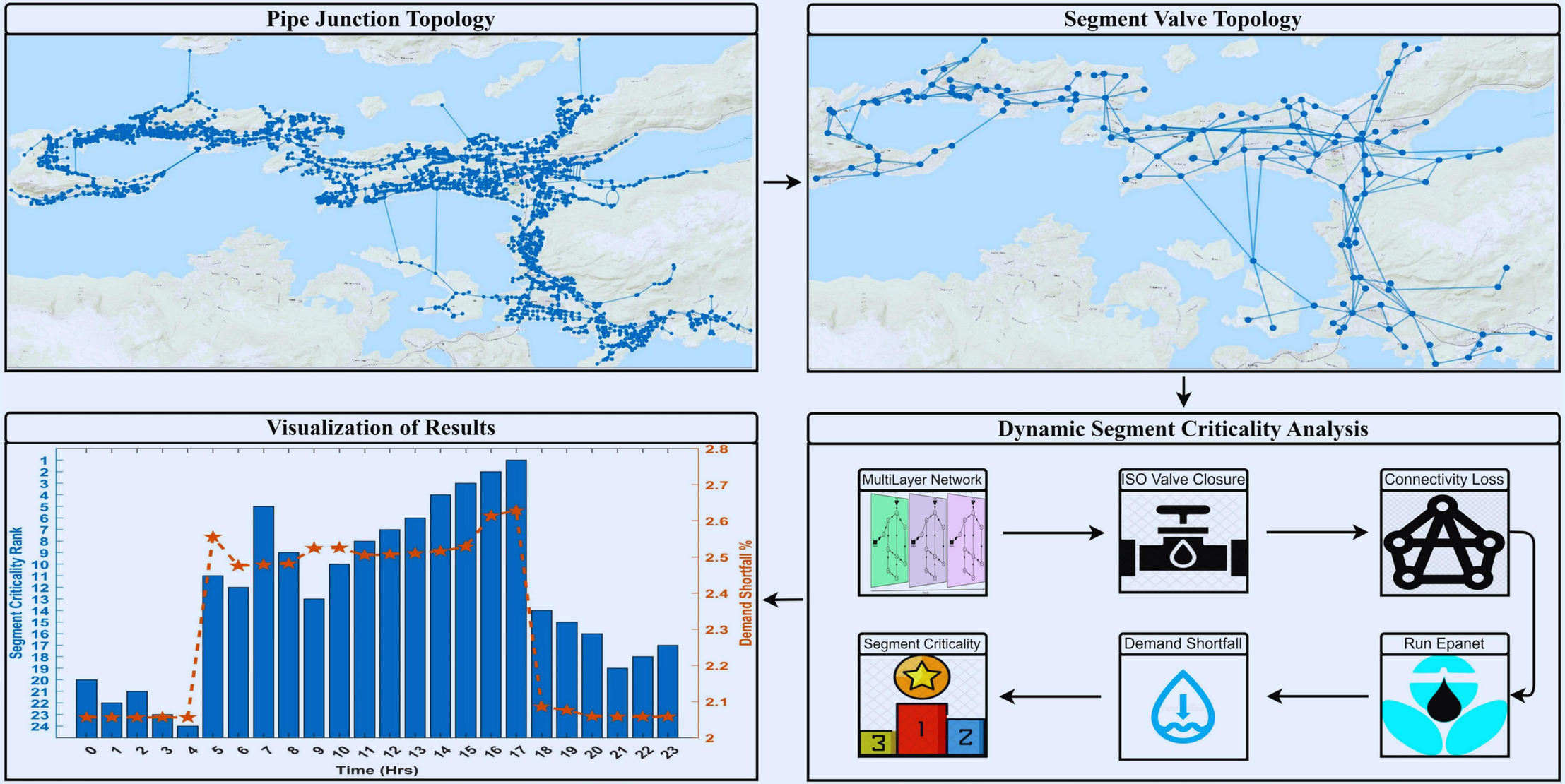
Leakage Identification



Leakage Localization

|| Purely Data Driven - No Hydraulic Models || Flow and Pressure Measurements Only ||

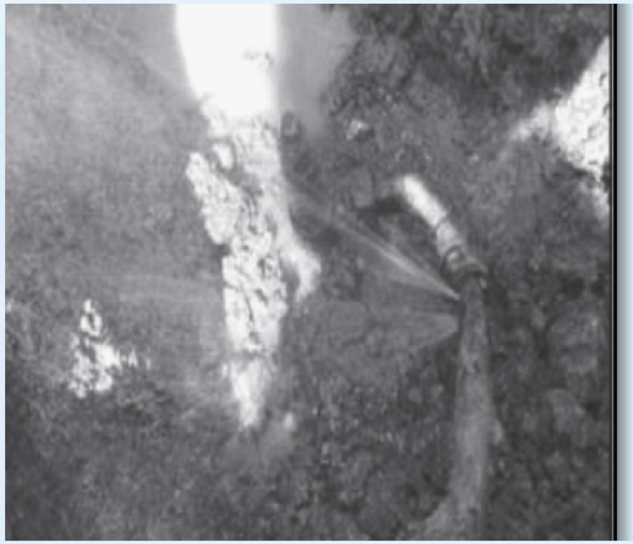
Leakage Repair Scheduling



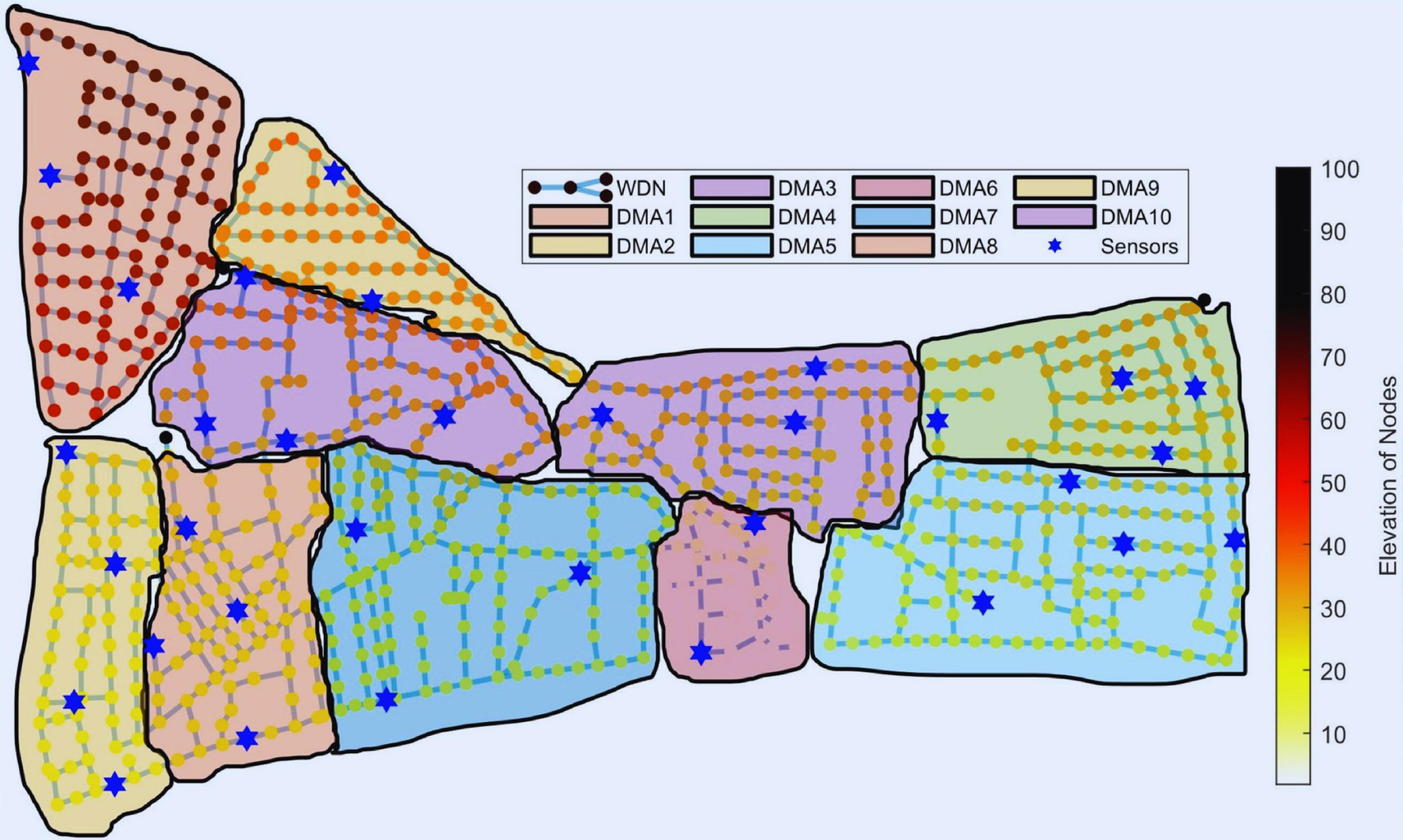
Types of Leakages

Abrupt Leakages: These are sudden leakages that occur in WDN usually resulting in large flow volumes within a very short period. Results in significant change in flow and pressure.

Incipient Leakages: These are leakages that grow over time. They normally start as background leakages but grow either linearly (metal pipes) or exponentially (plastic pipes) with time.

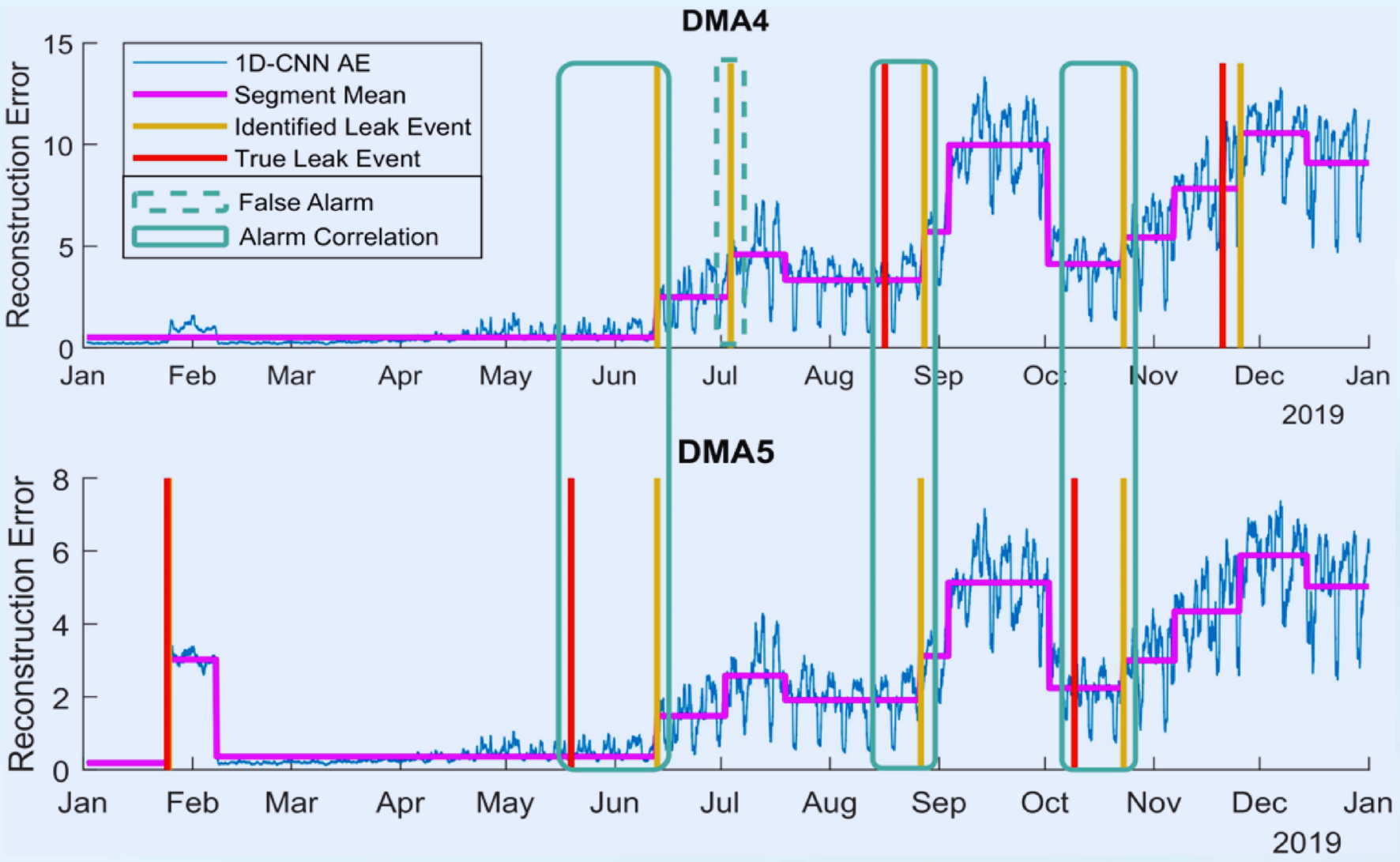


Benchmark Validation: BattLeDIM



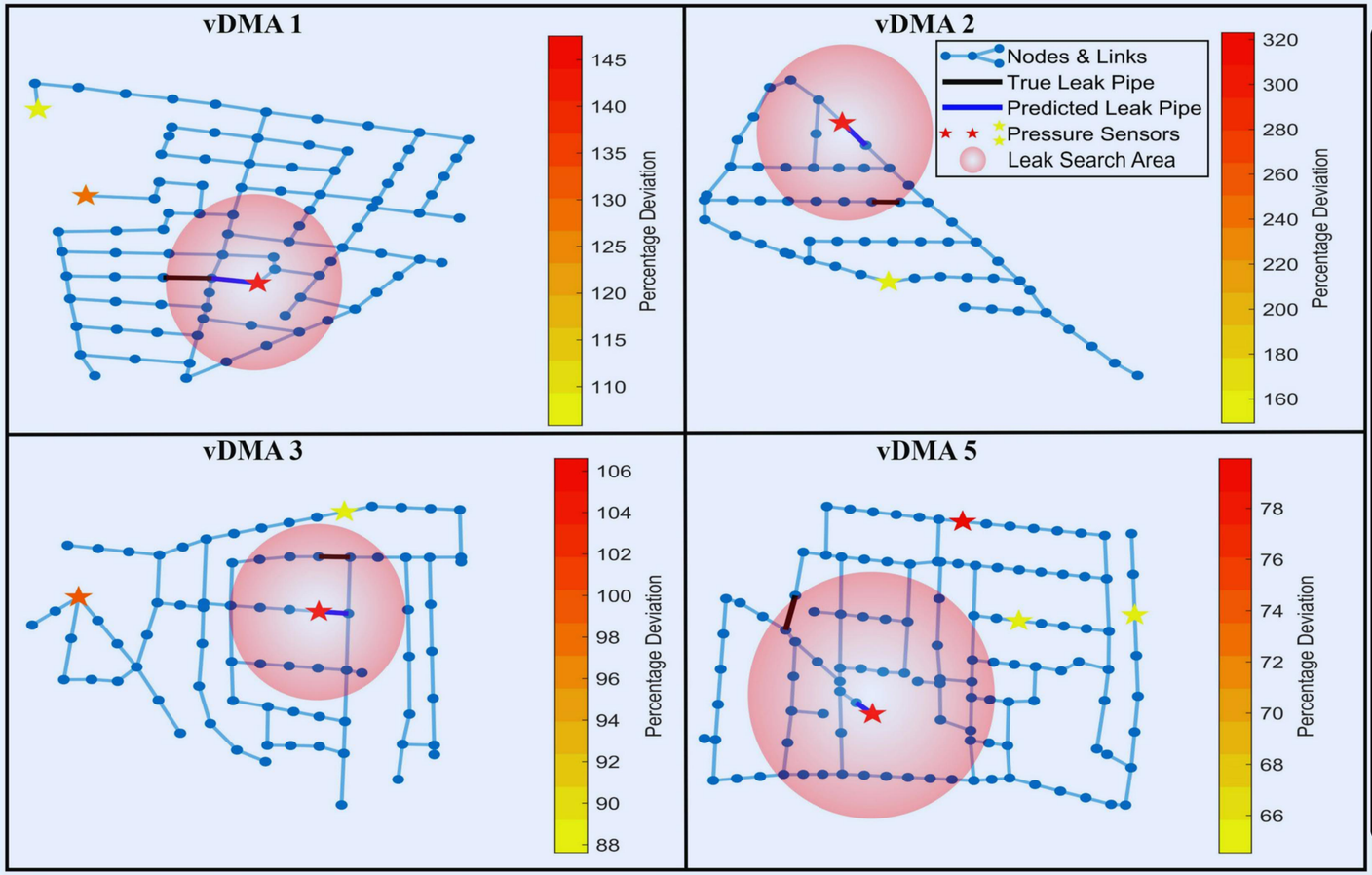
- **Three (3) distinct zones**
  - 10 virtual DMAs
- **19 Independent Leaks**
  - 9 Abrupt Leakages
  - 10 incipient leakages
- **1 year SCADA data**
  - Flow & Pressure
  - 5 minutes interval
- **Stochastic Demand**

Leak Identification Results



- **Purely Data Driven**
- **Robust against Drifts**
  - Multivariate Data
- **Alarm Correlation**
  - Neighbouring vDMAs
  - Leak Growth Rate
- **Prompt Identification**
  - Abrupt Leakages
- **Lagged Identification**
  - Incipient leakages

Leak Localization Results



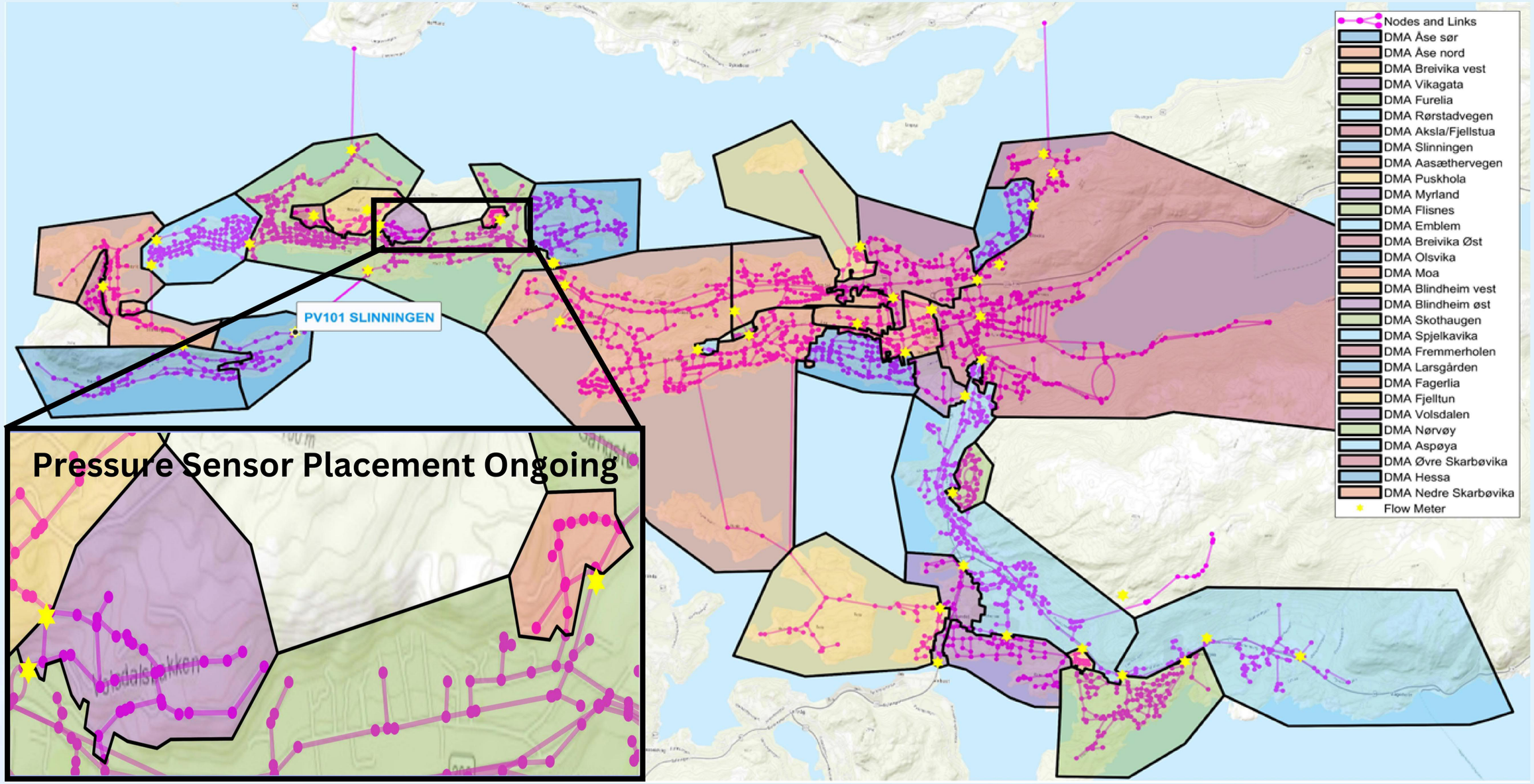
- **Pressure Sensor ID Prioritization**
  - Highest deviations implies leak in vicinity
  - Lowest deviations implies leak further away
- **Predicted Leak Pipe**
  - Pipe ID closest to the Sensor ID
  - **Failure history of Pipes in vicinity of Sensor**
- **Leak Search Area Reduction**
  - Less than 1 km depending on sparsity of pressure sensors in the vDMA

Results Summary

Study	Methodology	Identified Leaks	Localized Leaks	False Positives	Economic Score
Daniel et al. (2022)	hybrid	19	17	0	€ 307,852
Tornyeviadzi et al. (2023)	**data-driven**	**16**	**13**	**5**	**€ 246,555**
Romero et al. (2022)	hybrid	12	10	1	€ 210,772
Wang et al. (2022)	model-based	16	8	5	€ 167,981
Ma et al. (2022)	hybrid	8	6	2	€ 96,666
Huang et al. (2022)	hybrid	10	7	2	Unreported

Tornyeviadzi, H. M., & Seidu, R. (2023). Leakage detection in water distribution networks via 1D CNN deep autoencoder for multivariate SCADA data. *Engineering Applications of Artificial Intelligence*, 122, 106062.

Real-life Validation: Ålesund WDN



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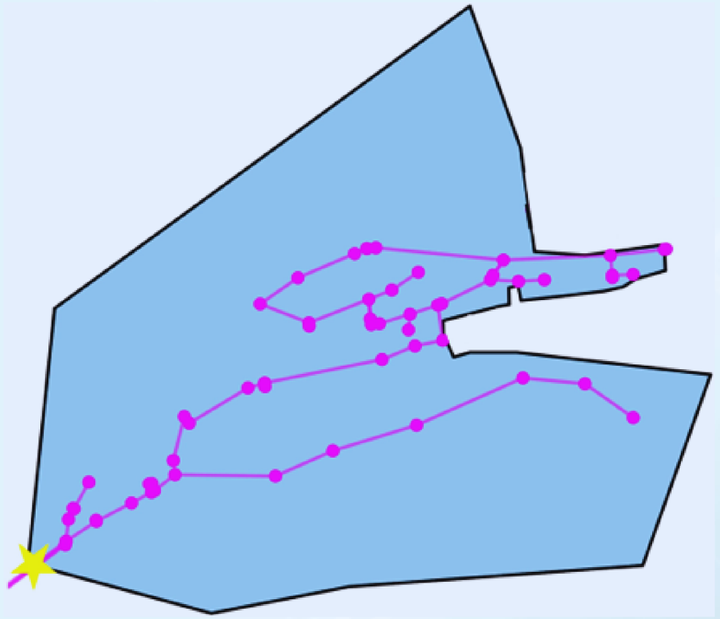
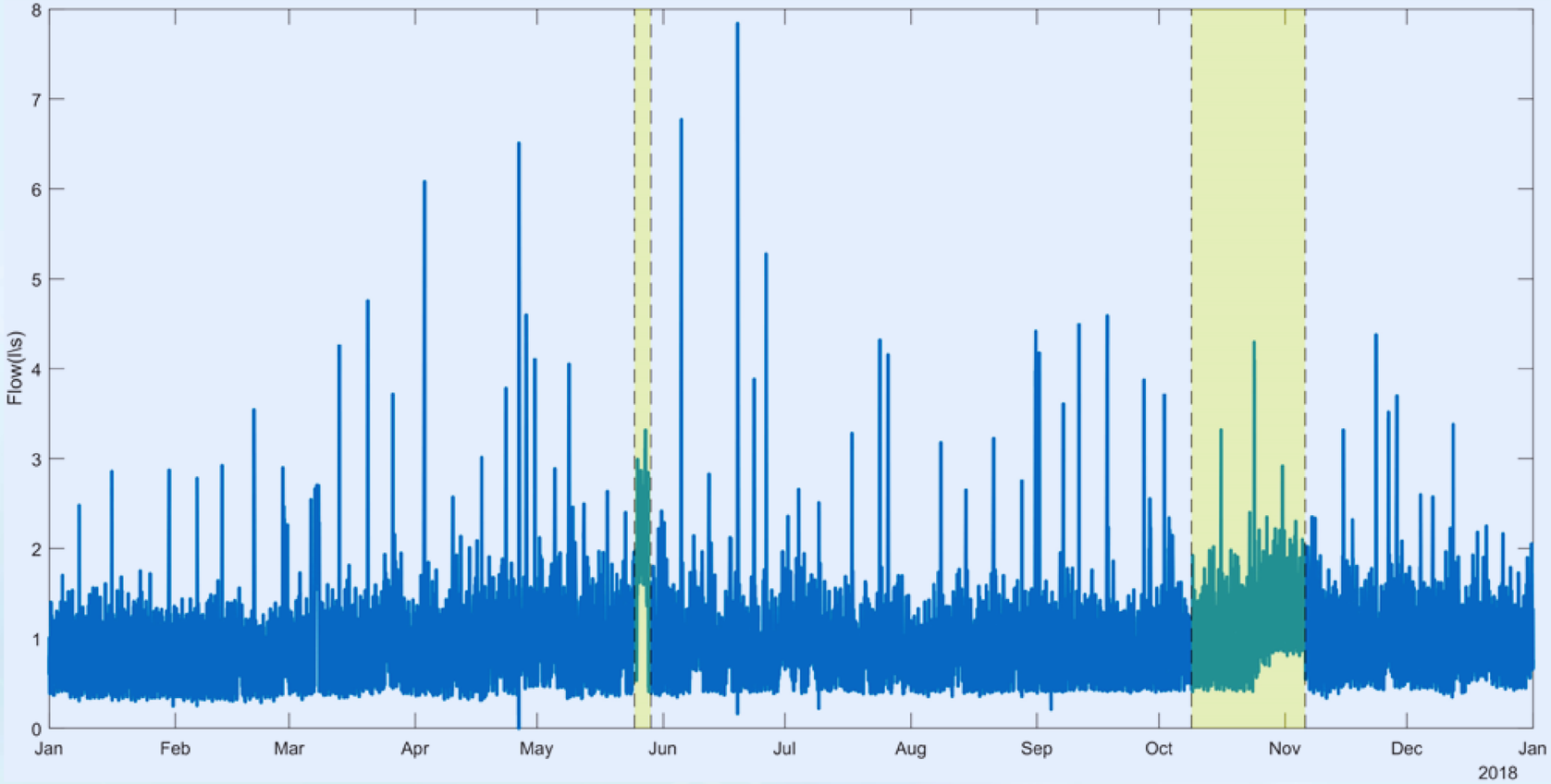
Night Flow Analysis in DMA 8





- Small Residential DMA
- 1 year Flow Data
- Stochastic Demand
- Number of Leaks: 2

Start: 26-05-2018
End: 29-05-2018

Start: 10-10-2018
End: 05-11-2018

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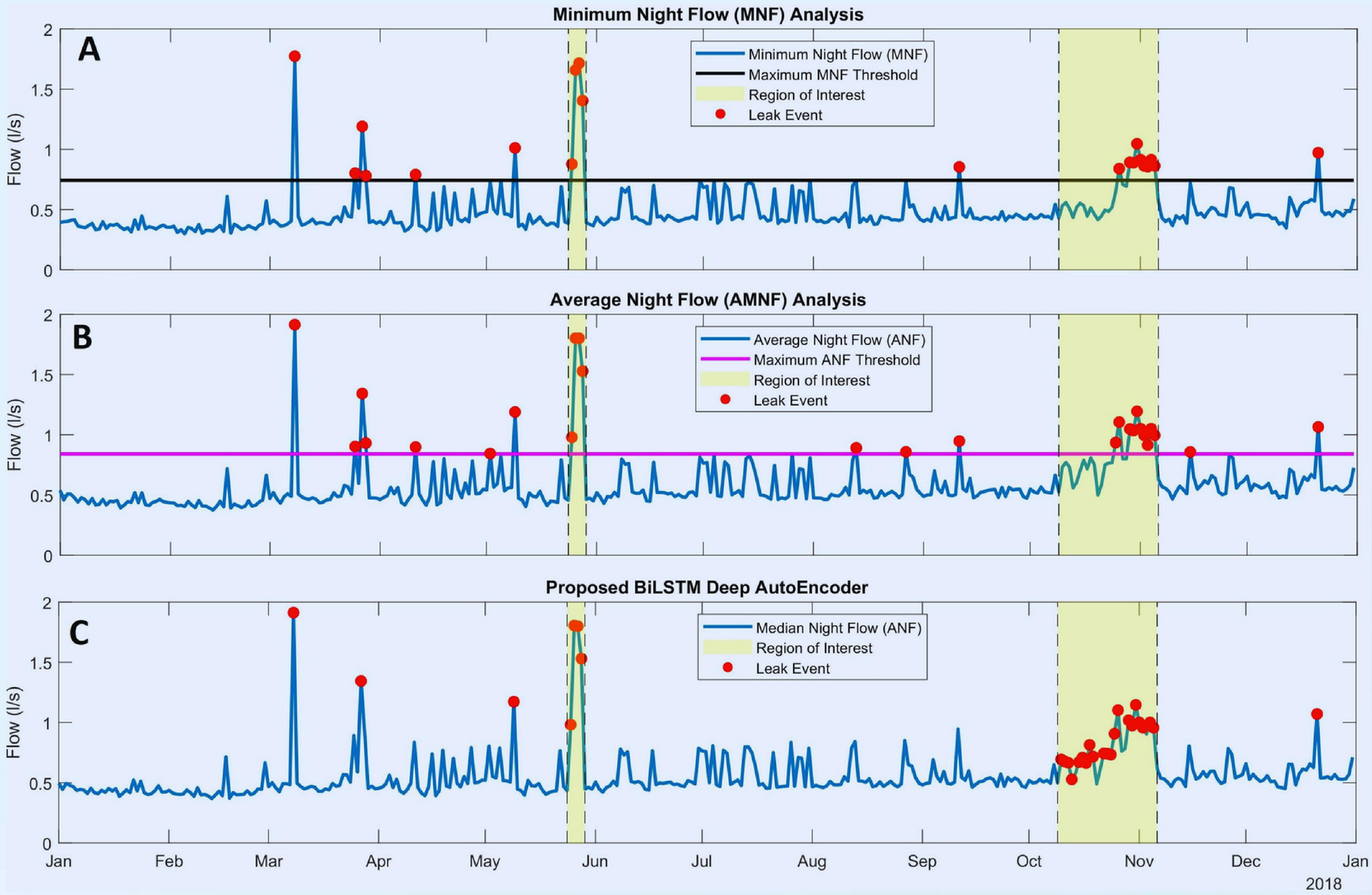
Leakage Identification

Model	1D-CNN Deep AE
Precision	0.8621
F Score	0.8562
PR AUC Score	0.6232
Time Lag	1 day(s)

Start: 26-05-2018
End: 29-05-2018

Start: 11-10-2018
End: 05-11-2018

Comparative Performance



Model	MNF	ANF	Deep AE
Recall	0.4194	0.4516	**0.8065**
Precision	0.6191	0.5385	**0.8621**
F beta Score	0.5910	0.5283	**0.8562**
PR AUC Score	0.4142	0.4884	**0.6232**
Identification Time Lag	16 days	15 days	**1 day**
Leak Savings	~ 16,000 NOK	~ 17,000 NOK	**~ 30,000 NOK**

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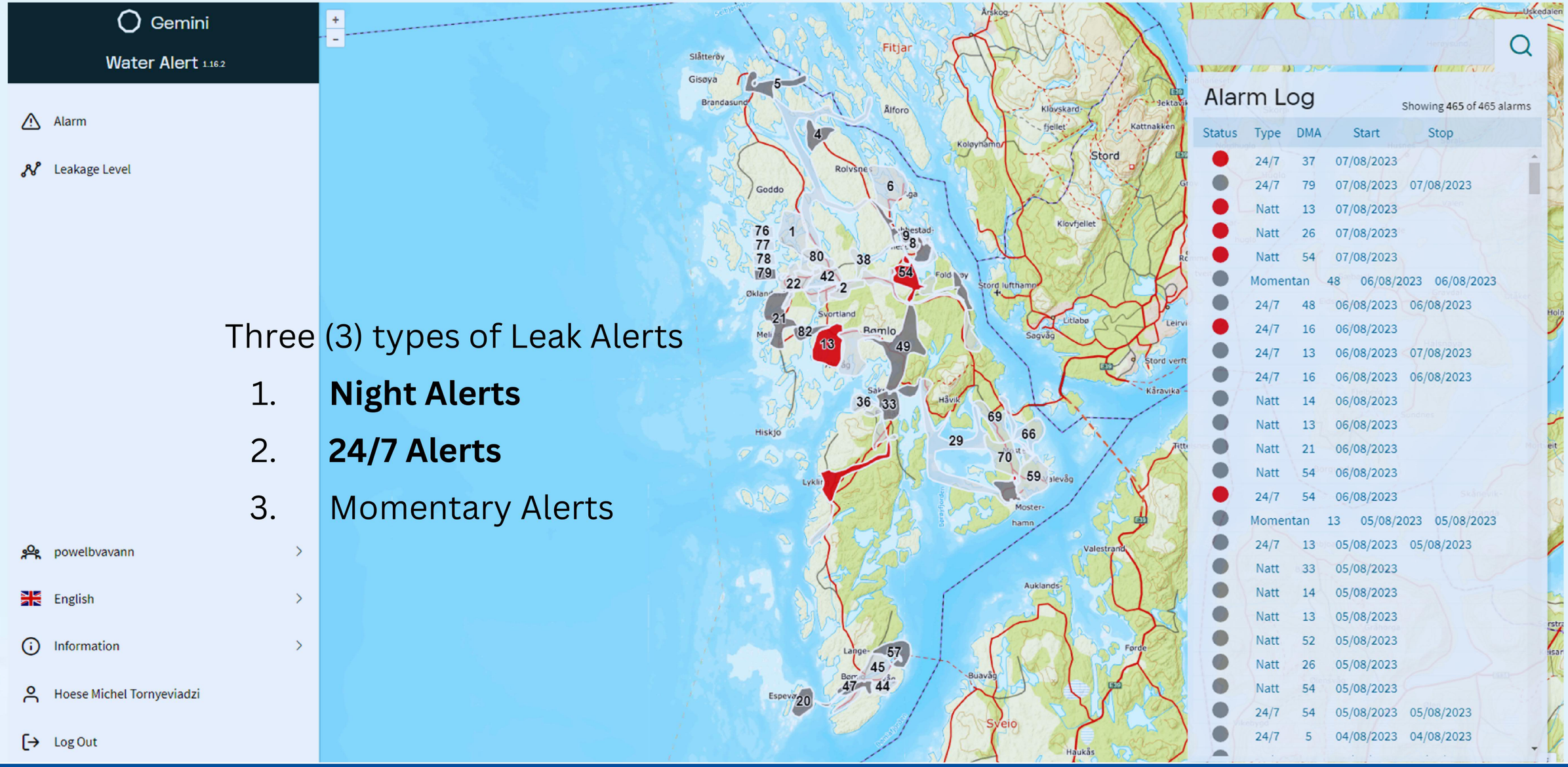
General Performance & Leak Savings

DMA Name	DMA Type	Recall	Precision	F beta Score	PR AUC Score	Identification Lag Time	Leak Savings
DMA 8	Residential	0.8065	0.8621	0.8562	0.6232	1 day	**~ 30,000 NOK**
DMA 26	Commercial + Tank	0.9226	0.9687	0.9639	0.9048	2 days	**~ 25,000 NOK**
DMA 5	Industrial	0.8469	1.0	0.9822	0.8147	4 days	**~ 52,000 NOK**

Tornyeviadzi, H. M., Mohammed, H., & Seidu, R. (2023). Robust night flow analysis in water distribution networks: A BiLSTM deep autoencoder approach. Advanced Engineering Informatics, 58, 102135.

Independent Validation: Bømlo WDN



Three (3) types of Leak Alerts

1. **Night Alerts**
2. **24/7 Alerts**
3. Momentary Alerts

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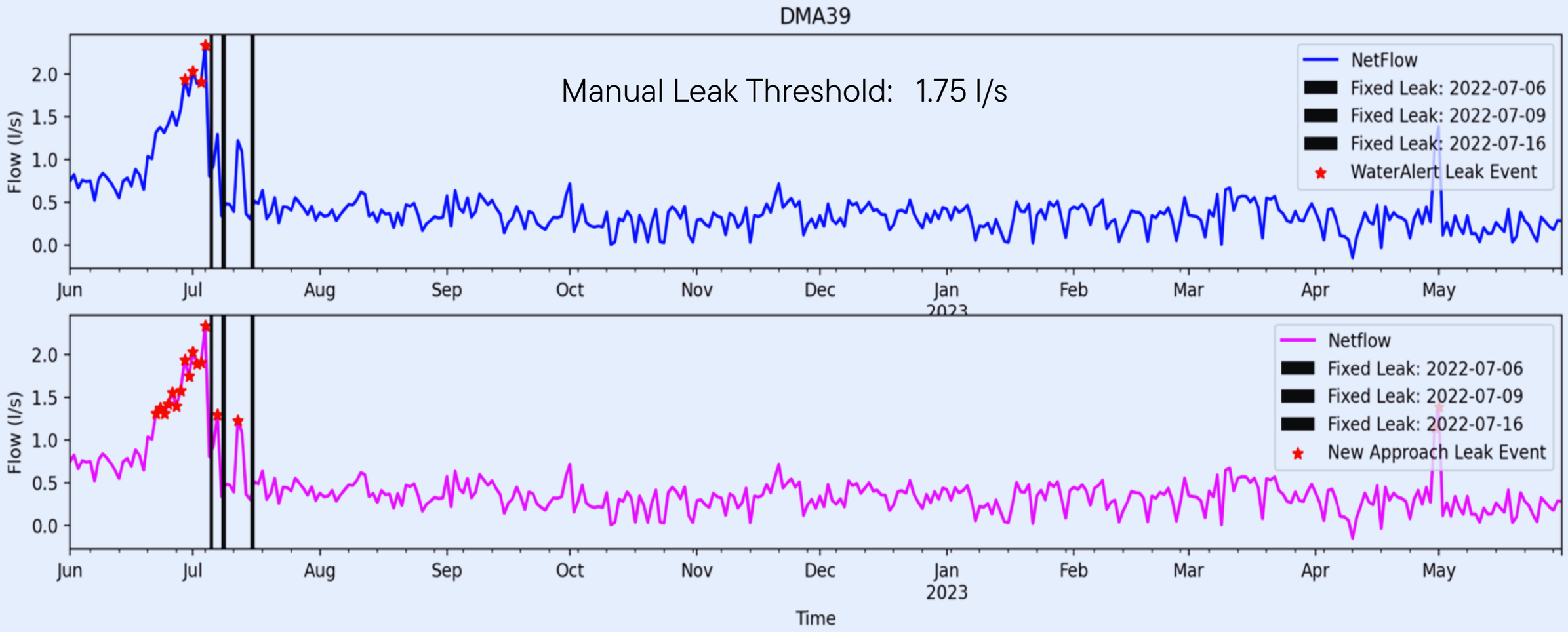
Night Flow Alerts: Incipient



|| 7 days (1 week) earlier alerts || Leak Savings: ~ 180,000 NOK ||

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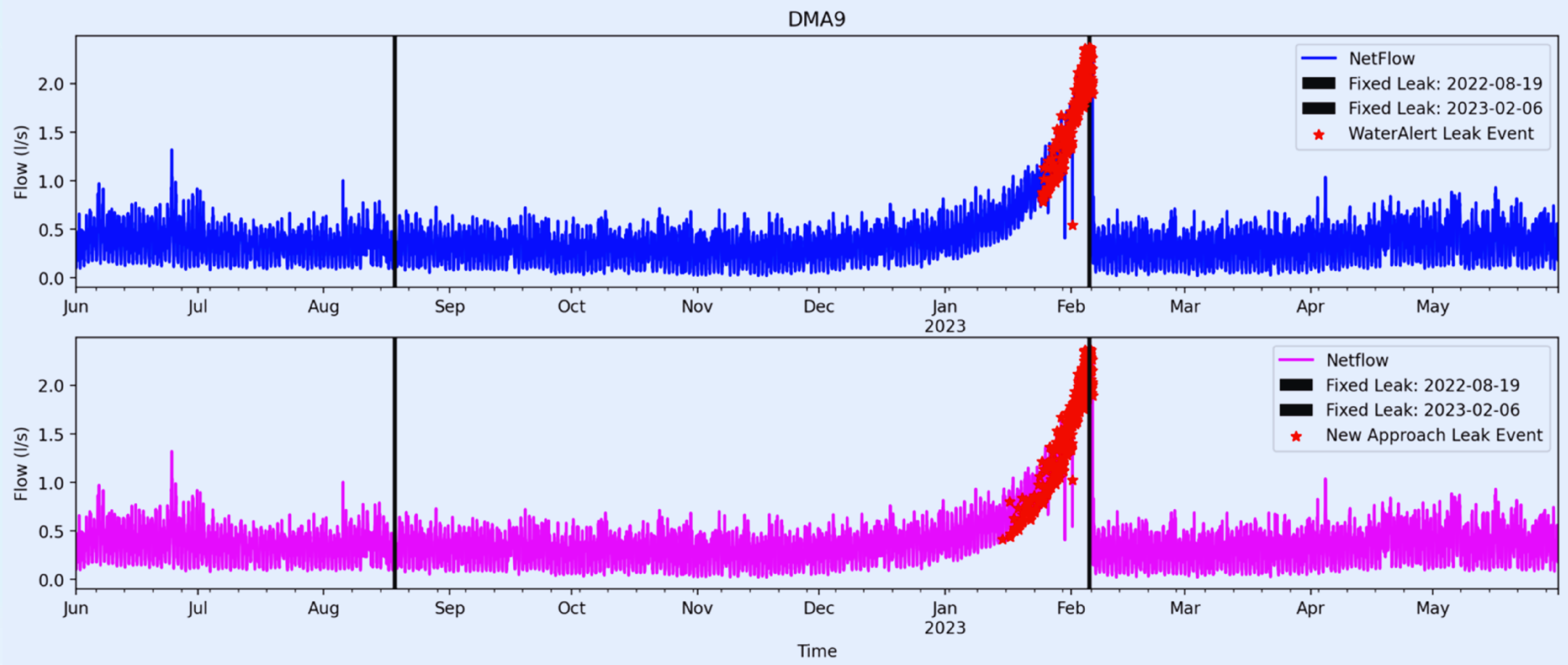
24/7 Alerts: Incipient



|| 1 week plus earlier alerts || Leak Savings: ~ 75,000 NOK ||

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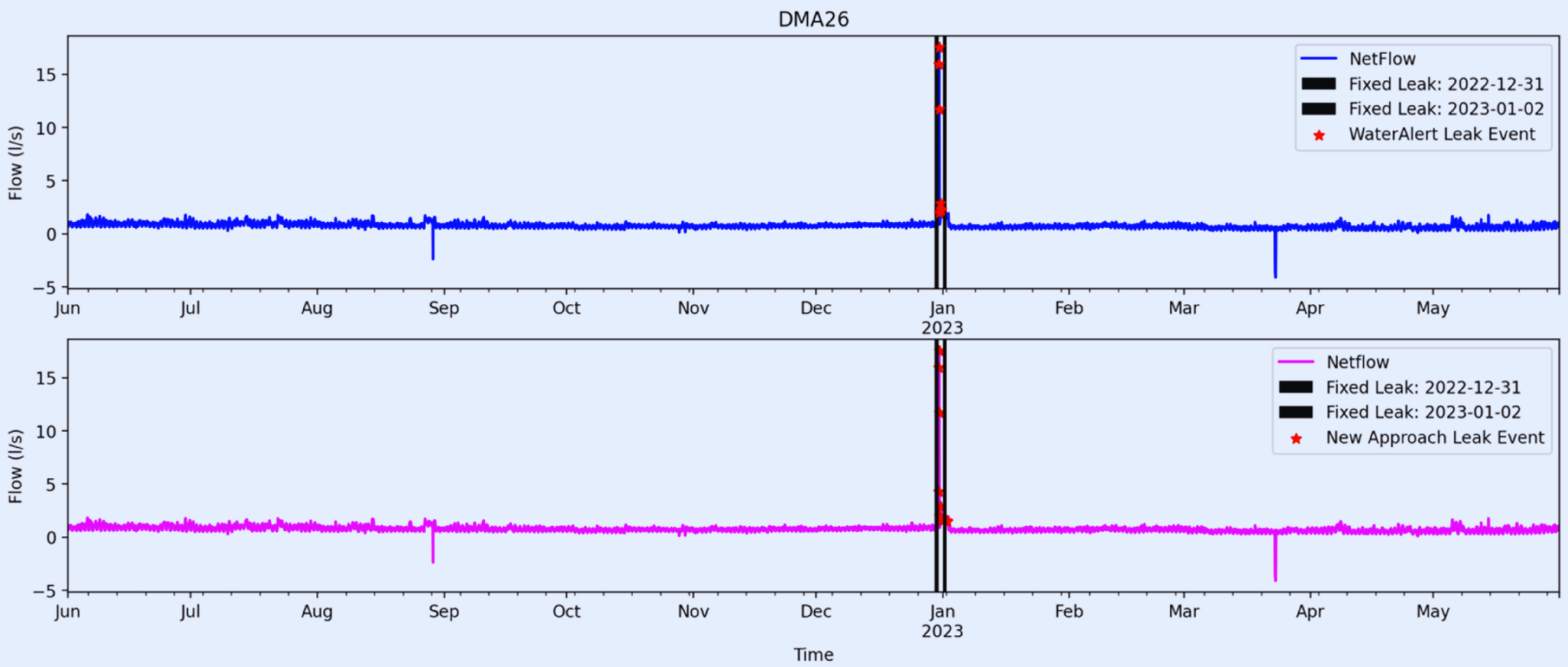
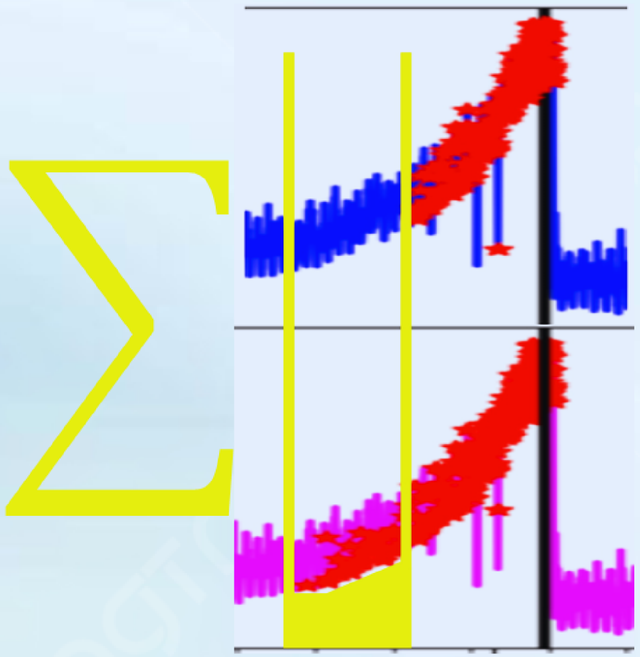
24/7 Alerts: Abrupt



|| Prompt Identification || Similar Performance ||

Conservative Leak Savings for Bømlo

- 45 breaks over a year period (June 22 – May 23)
- 36 independent (unique) pipe breaks
  - 20 Incipient Leakages
  - 16 Abrupt Leakages
- Early Awareness Savings = $\sum_{i=1}^{20} TD_i \times V_i \times W_{cost}$
  - TD = Identification Time Difference
  - V_i = Volume of Water Lost
  - Average Cost of Water per m^3



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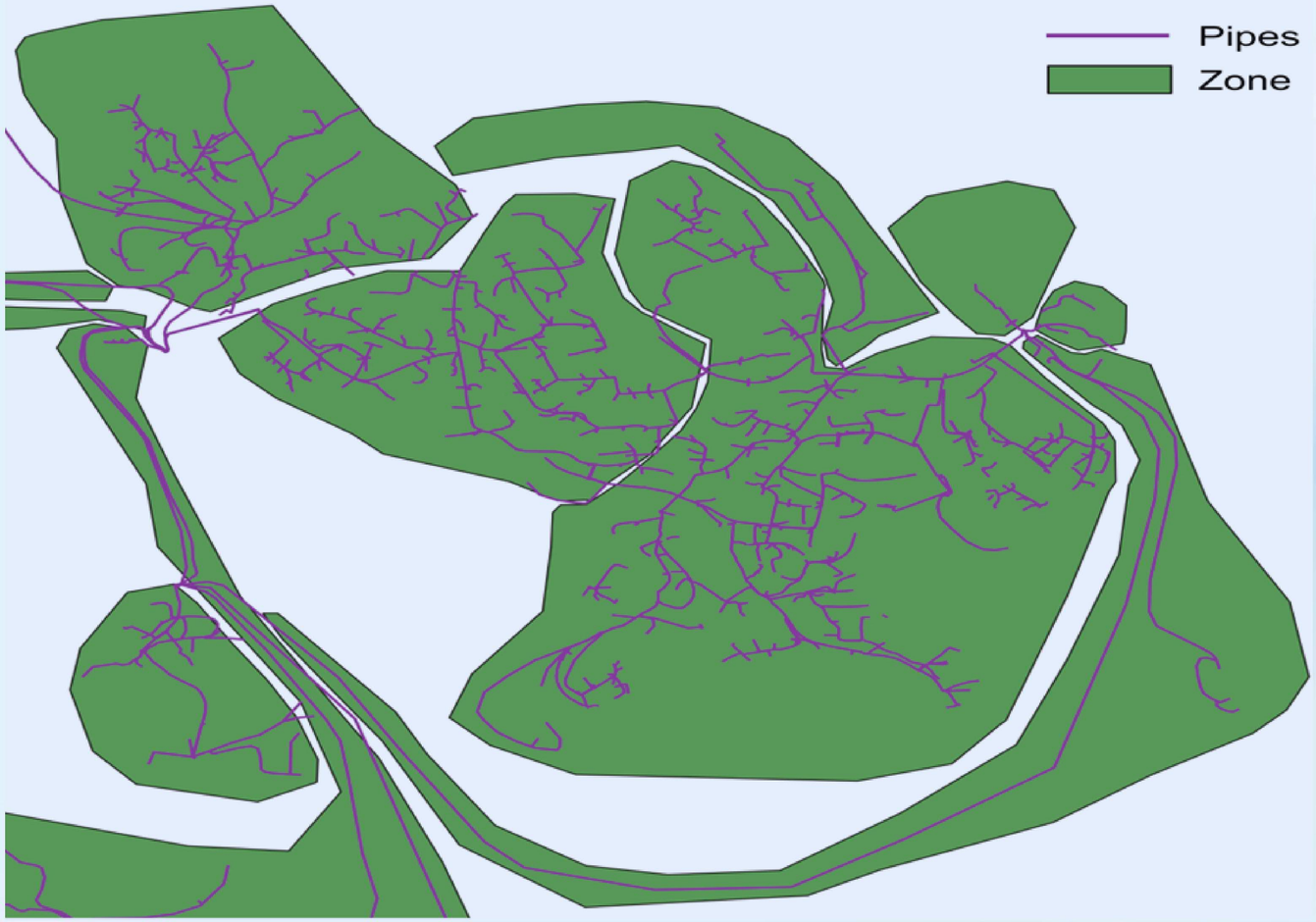
2 MILLION NOK

Scalability to Different DMAs



DMA (zone) Types:

1. Residential zones
2. Commercial zones
3. Industrial zones

Differences in:

1. Topology
2. Hydraulics
3. Demand Patterns

Currently ML models are built per DMA. Consider

1. **200 water utilities** (tenants)
    a. Each with **50 DMAs**
2. Resulting in **10,000 ML models in Production**
    a. Skyrocketing resource utilization

NOT SUSTAINABLE!!!

DMA Agnostic Solution

A single ML model that works different DMA types (residential, commercial & industrial) and Multiple Water Utilities.

APPROACH:

1. One generic model
2. For each DMA, a non-leak period is identified
3. The model is adapted to this data, **No Training Required**

Demo Link: http://localhost:8501

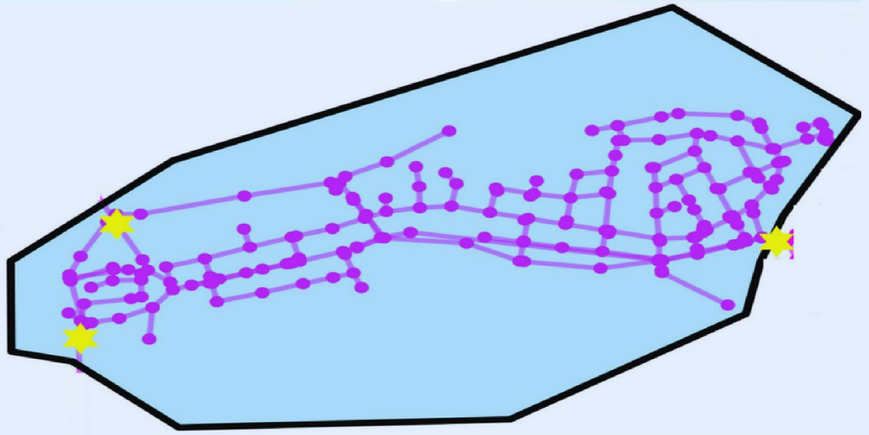
Case: Bømlo

No. DMAs: 75

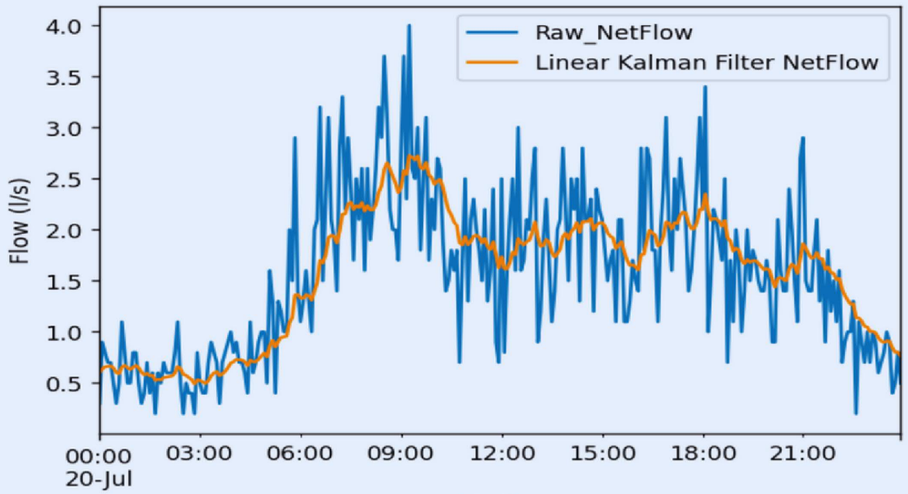
ML: 75 ML models in Production

Solution: DMA Agnostic ML

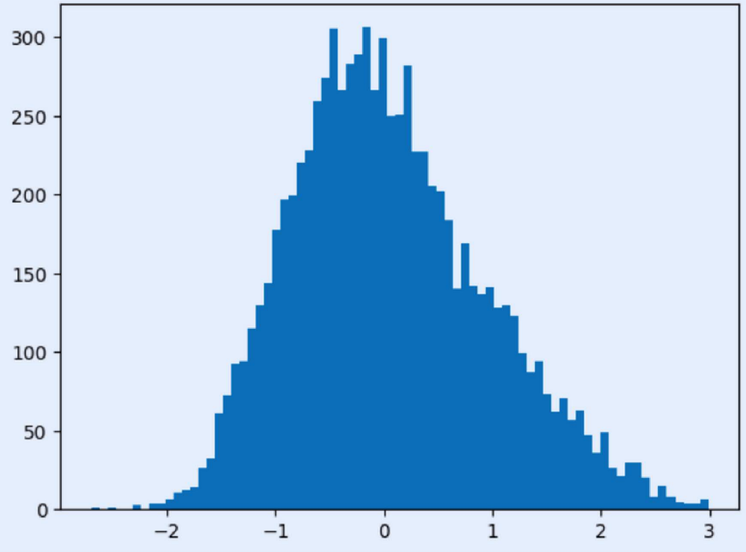
Model Count: 1 Model Model



$$\text{DMA NetFlow} = \sum_{i}^{n} \text{Inflow}_i - \sum_{j}^{m} \text{Outflow}_j$$



Novel Time Invariant Sequencing

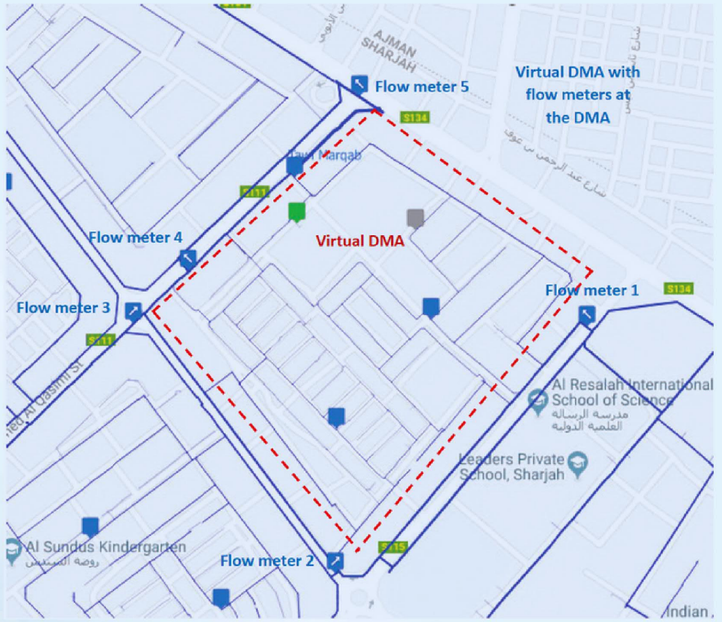


Key Accomplishments

- **A comprehensive framework for simultaneous Leakage Diagnosis in WDNs**
  - Flow Sensors: Leakage Identification
  - Flow & Pressure sensors: Leakage Identification & Localization
- **Robust ML Models for Night Flow Analysis and 24/7 Leak Alerts**
  - Incipient Leaks: minimum 1 week reduction in awareness time
  - Abrupt Leaks: Similar performance with enhance robustness
- **Solved Scalability Problem using DMA Agnostic ML Models**
  - From 75 models to at most 2 ML models in Production
  - Only 1 month data needed to onboard new DMAs
- **Implemented DMA Agnostic ML models in DataBricks Test Environment**

Implementation Requirements

- **Water Distribution Network Sectorization**
  - Physical District Metering Areas
  - Virtual District Metering Areas
- **Water Distribution Network Instrumentation**
  - Flow Sensors
  - Pressure Sensors
- **Solution Platform**
  - Deployment of Machine Learning Algorithms



PhD Publications

Machine Learning with Applications xxx (xxxx) 100501

Contents lists available at ScienceDirect

Machine Learning with Applications

journal homepage: www.elsevier.com

Semi-supervised anomaly detection methods for leakage identification in water distribution networks: A comparative study

Hoese Michel Tornyeviadzi *, Hadi Mohammed, Razak Seidu

Smart Water Lab, Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology, Ålesund, Norway

Engineering Applications of Artificial Intelligence 122 (2023) 106062

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Leakage detection in water distribution networks via 1D CNN deep autoencoder for multivariate SCADA data

Hoese Michel Tornyeviadzi *, Razak Seidu

Smart Water Lab, Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology, Ålesund, Norway

Advanced Engineering Informatics 58 (2023) 102135

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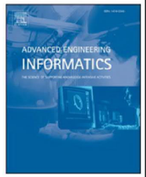

Full length article

Robust night flow analysis in water distribution networks: A BiLSTM deep autoencoder approach

Hoese Michel Tornyeviadzi, Hadi Mohammed, Razak Seidu *

Smart Water Lab, Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology, Ålesund, Norway

Alexandria Engineering Journal **61** (2022) 9261–9272

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Alexandria Engineering Journal

journal homepage: www.elsevier.com

Dynamic segment criticality analysis: A precursor to scheduling of maintenance routines in water distribution networks

Hoese Michel Tornyeviadzi *, Hadi Mohammed, Razak Seidu

Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology, Ålesund, Norway

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Thank You