

Synthetic Data Generation for Anomaly Detection

digital futures

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Problem Setup

- ► Want to apply machine learning to detect anomalies, e.g. leaks.
- ► Anomalies are rare so we must create **synthetic data**.
- ► Traditional method need one simulation per scenario—scales poorly!

Water Pipe Networks

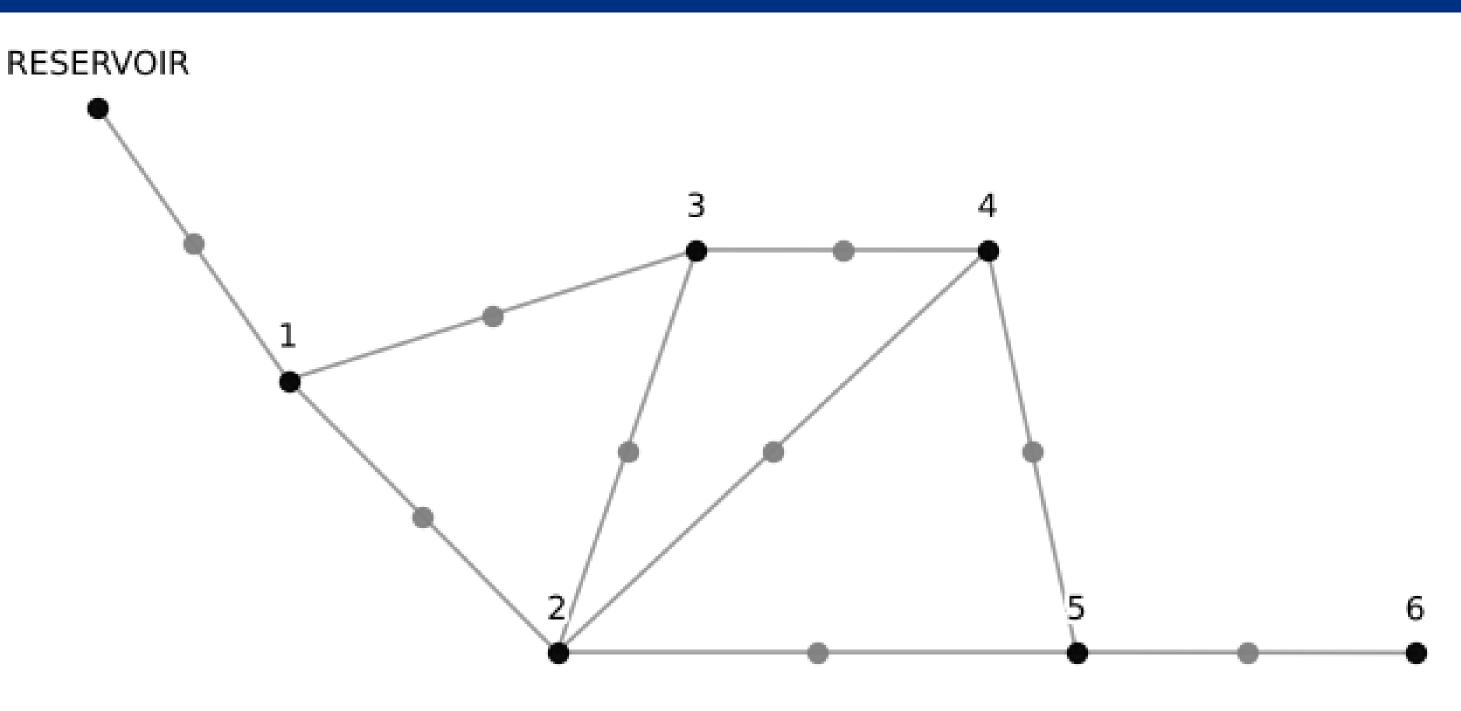


Figure: Pipe network example with junctions (\bullet) , leak nodes (\bullet) and pipes (--)

Governing System of Equations

$$\mathcal{A}_0 \mathbf{Q} = \mathbf{D} + d_{leak}(\mathbf{H})$$
 (1a)
 $\mathcal{A}_0^T \mathbf{H} = \mathcal{B} \mathbf{S} - h_L(\mathbf{Q})$ (1b)

Q: pipe flows

H: junction pressure heads

 A_0 : reduced incidence-matrix

D: junction flow demands

S: reservoirs pressure heads

 d_{leak} : leak mechanism h_I : friction head loss

 \mathcal{B} : maps reservoirs to connected nodes

Scenario Parameters

- Leak node(s)
- Demand D
- ► Leak location along pipe
- Leak area
- ► Leak discharge coefficient

Physics Informed Neural Network

- ► Neural network: parametrized "black box" function.
- Physics informed loss: residuals of (1).
- Scenario parameters sampled randomly—no discretization needed!

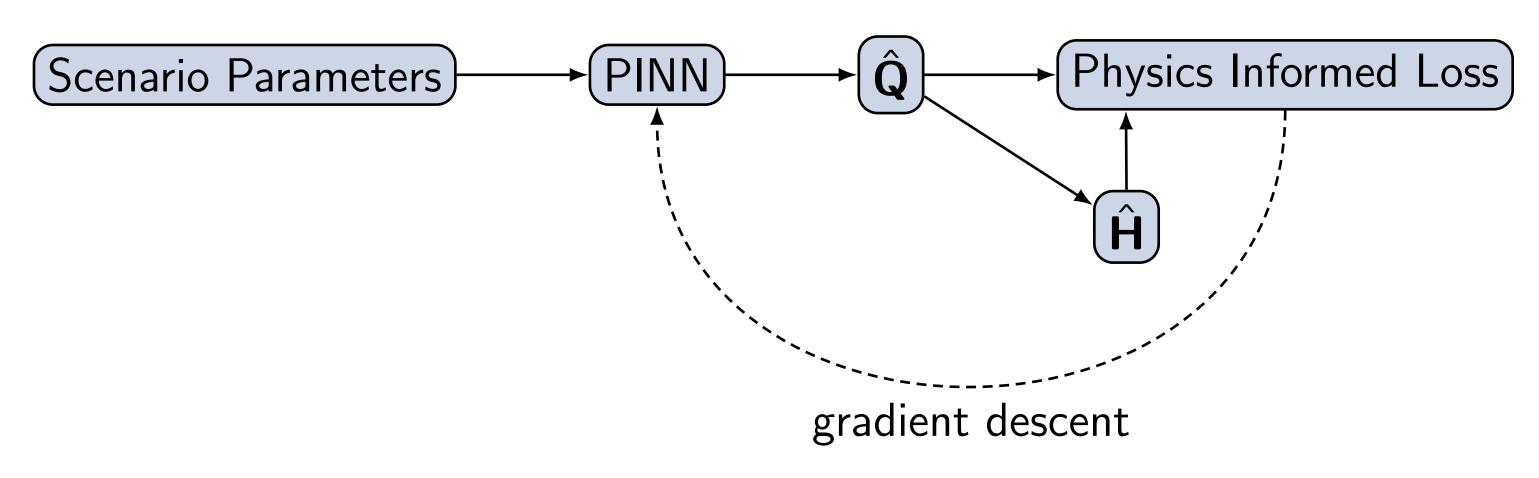


Figure: PINN training

Useful Trick

Avoid predicting $\hat{\mathbf{H}}$ by setting $\hat{\mathbf{H}} = (\mathcal{A}_0^T)^+ \left(\mathcal{B}\mathbf{S} - h_L(\hat{\mathbf{Q}})\right)$.

• Must still enforce (1b) via loss.

Amortized Data Generation

- ► Neural network handles many scenarios simultaneously.
- ► Gives amortized data generation—scales well!

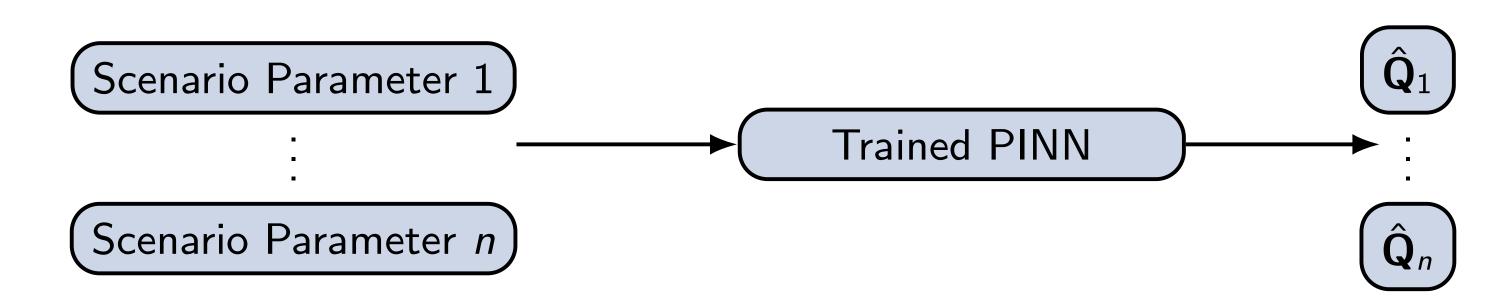


Figure: Amortized data generation via PINN

Experimental Results

- lacksquare Predict flows based on leak node index and lacksquare lacksquare $[0,1]^{\# \ demand \ junctions}$.
- Neural network trained until 90% of predictions have NRMSD ≤ 10 %.

$$NRMSD = \frac{\sqrt{mean(\hat{\mathbf{Q}} - \mathbf{Q})^2}}{max\mathbf{Q} - min\mathbf{Q}}$$

Experiment 1

#Points / axis	Simulator time (s)	PINN time (s)	Mean NRMSD
5	5.90	13.00	6.8%
10	40.91	8.36	7.3%
15	136.10	10.74	7.6%

Table: Simulation times for different demand grid resolutions (#demand junctions = 3).

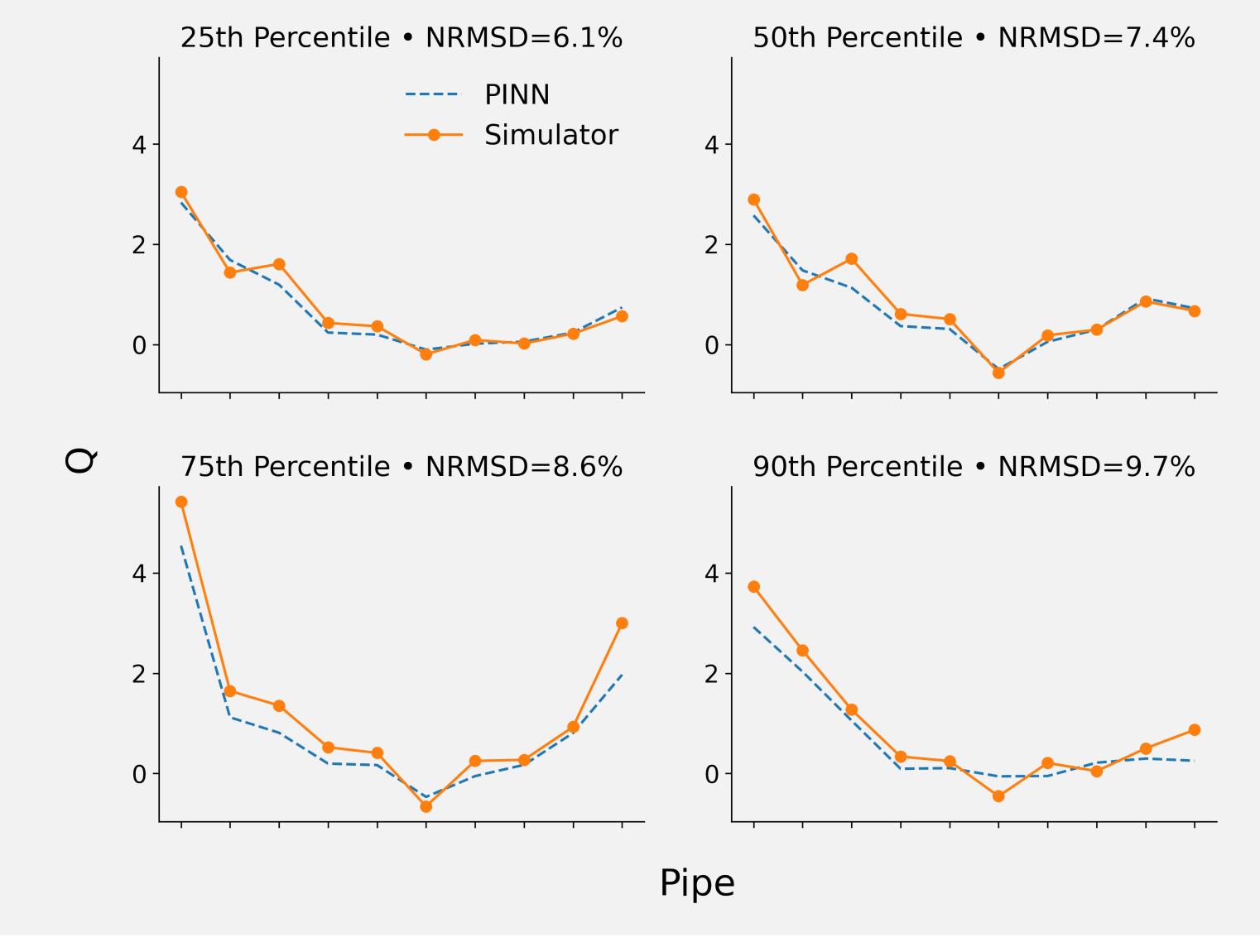
Experiment 2

#Demand junctions	Simulator time (s)	PINN time (s)	Mean NRMSD
3	5.60	12.97	6.8%
4	25.25	12.16	5.8%
5	119.19	8.90	6.4%

Table: Simulation times for different numbers of demand junctions (#points / axis = 5).

Visualized Accuracy

Figure: Predictions in different percentiles of NRMSD (#points / axis = 15, #demand junctions = 3)



Future Work

- ► Increase complexity: more scenario parameters and larger pipe networks.
- ► Add network components, e.g. valves, tanks and pumps.
- Expand to similar systems, e.g. gas and electricity.