# Topology-guided Graph Neural Networks for Leak Localization in Water Distribution Networks

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***Abstract*—Leak localization in Water Distribution Networks (WDNs) is a challenging task, particularly in the presence of multiple simultaneous leaks and complex network topologies. Graph Neural Networks (GNNs) have recently emerged as an effective tool by leveraging the network structure to model the spatial propagation of anomalies. However, existing approaches typically rely on pairwise node interactions and do not capture higher-order dependencies induced by the looped structure of real WDNs. In this paper, we propose Top-GGNN, a Topology-guided Graph Neural Networks that incorporates higher-order structural information through a cell-complex representation. Specifically, the method introduces a topological refinement layer based on the first-order Laplacian, which captures both interactions between edges sharing common nodes and dependencies induced by cycles in the network, enabling the model to exploit higher-order structural relationships in addition to standard message passing. Experimental results on simulated WDNs show that the proposed approach improves leak localization performance over standard graph-based models, with more significant gains in multi-leak scenarios and networks with richer structures.**

***Index Terms*—Graph Neural Networks, Anomaly Localization, Internet of Things (IoT), Water Distribution Networks**

## I. Introduction

Water Distribution Networks (WDNs) are critical infrastructures whose reliable operation is essential for guaranteeing the continuous and safe delivery of water to end users [1]. However, a significant fraction of the water conveyed through these systems is lost because of leaks caused by pipe aging, pressure fluctuations, material degradation, or external damage [2]. Beyond the direct waste of a scarce resource, leaks also increase operational costs, reduce service quality, and may compromise the resilience of the network. For these reasons, the timely detection and accurate localization of leaks have become central problems in the monitoring and management of modern WDNs.

Traditional approaches to leak localization can be broadly divided into model-based and data-driven methods. Model-based techniques exploit hydraulic equations and calibrated simulators to identify deviations from expected operating conditions. These methods provide a physically grounded framework, but performance strongly depends on the availability of accurate network models and on the reliability of hydraulic parameters and demand estimates [3]. Data-driven methods, on the other hand, learn normal and abnormal patterns directly from sensor measurements, reducing the need for accurate calibration. Recent advances in machine learning and deep learning have demonstrated the potential of this paradigm, especially when large collections of simulated or measured pressure signals are available [4].

Among deep learning tools, Graph Neural Networks (GNNs) are particularly appealing for WDN monitoring because they naturally account for the relational structure of the WDN infrastructure [5]. Nevertheless, most existing graph-based approaches rely on a standard pairwise representation of the network, where interactions are modeled only through node-to-node connectivity [6]. This pairwise view may be insufficient to capture important structural properties of WDNs. Indeed, WDNs are often characterized by cyclic structures inducing higher-order dependencies that are not fully described by graph models. A simplified WDN is represented in Fig. 1

To address this limitation, we propose a Topology-guided GNN (Top-GNN) with structural information derived from Topological Signal Processing (TSP) [7]. The key idea is to move beyond a purely graph-based representation and to exploit a cell-complex model of the network, where in addition to nodes and edges, higher-order structures such as cycles are explicitly encoded. Starting from the node embeddings produced by the GNN, the proposed topological layer lifts these representations to the edge domain, propagates them through the higher-order operator, and maps them back to the node space to obtain topology-informed corrections.

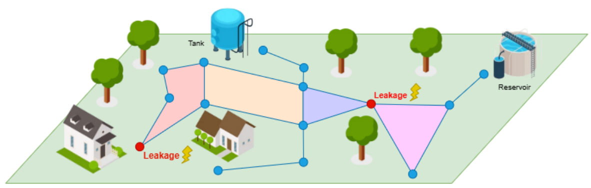


Fig. 1: Simplified WDN representation[Icons by Freepik] with leak nodes, edges and cell complexes

The proposed approach is evaluated on different WDN

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benchmarks generated through hydraulic simulation, under both single-leak and multi-leak conditions. The results show that the integration of higher-order topological information consistently improves localization performance over standard graph-based baselines, with the largest gains observed in the most challenging scenarios.

The paper is organized as follows. Section II reviews related work on leak localization methods and graph-based approaches for WDN. Section III introduces the proposed topology-aware framework. Section IV presents the experimental setup and discusses the obtained results. Finally, Section V concludes the paper and outlines future research directions.

## II. Related Works

Leak detection and localization methods used in literature can be classified into two main families of approaches: model-based and data-driven methods, according to their dependence on a hydraulic model of the network. Model-based methods rely on detailed hydraulic models to simulate normal operating conditions of WDNs and leaks are identified as deviations from normal behavior [8]. For example, authors in [9] use residual patterns derived from a hydraulic model for leak localization. Sensitivity-based methods localize leaks by analyzing the impact of hypothetical leaks on pressure or flow measurements [10], [11]. These methods suffer several limitations: they require a well-calibrated model and their performance may degrade due to uncertainty in parameters [12].

In contrast, data-driven methods learn patterns of normal and abnormal behavior directly from monitoring data, without explicitly requiring hydraulic models. Examples include Random Forest classifiers for leak identification from pressure data [13], prediction-based frameworks using residuals from learned models [14], and statistical process control methods for anomaly detection [12]. Recently, deep learning approaches have gained attention because of their ability to automatically extract informative spatio-temporal features from raw sensor signals. For example, a deep learning framework has been proposed in [15] for burst localization that maps pressure signals from multiple monitoring points to a location label. A particularly relevant direction within deep learning is the use of autoencoders. For instance, a convolutional autoencoder has been used to detect and localize leaks [16] also in presence of sparse measurements [4]. More recently, GNN have emerged as a promising direction for leak localization in WDN [5]. Their relevance derives from the fact that a WDN is naturally represented as a graph, with nodes corresponding to junctions or sensors and edges to pipes [5]. Although GNN applications to WDNs are still relatively limited, recent works have shown their potential for leak detection and localization. For example, in [17] authors use graph-based pressure reconstruction and prediction to detect leaks from residual signals, in [18] an algorithm-informed GNN has been proposed to improve generalization in leakage detection and localization. [5] In this direction, a new architecture has been proposed in [19] for localization. It is based on a Gated Graph Neural Network (GGNN), where message passing is combined with a recurrent gating mechanism to regulate how information is propagated and updated across the graph, helping capture the spatial dependencies in the network. Differently from the current state-of-the-art we focus on enriching the GNN architecture with information related to higher order interactions, going beyond the simple node-to-node connectivity [6].

## III. Topology-Aware Leak Localization

### A. Graph Representation of WDNs

Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ denote a graph representing the WDN, where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. In this intuitive representation, nodes correspond to hydraulic elements such as junctions, reservoirs, or tanks, while edges represent the pipes that convey water between them. Two nodes $i$ and $j$ are connected by an edge $(i, j) \in \mathcal{E}$ whenever a pipe physically links the corresponding junctions in the WDN. The connectivity structure of the graph can be encoded in matrix form. In particular, the adjacency matrix $\mathbf{A} \in \mathbb{R}^{N \times N}$ describes the presence and strength of interactions between nodes, where $N$ is the number of nodes. The element $a_{ij}$ is nonzero when a pipe connects nodes $i$ and $j$, and may optionally incorporate physical properties of the pipe such as length, diameter, or hydraulic resistance. In our case, we will consider a binary adjacency matrix. From the adjacency matrix it is possible to derive the degree matrix $\mathbf{D}$ and the graph Laplacian $\mathbf{L} = \mathbf{D} - \mathbf{A}$. Within this framework, the state of the WDN can be represented through graph signals. A graph signal associates a value (or a vector) to each node of the network and typically corresponds to measurable hydraulic quantities such as pressure, demand, or sensor observations. These quantities can be arranged in a node-feature matrix $\mathbf{X} \in \mathbb{R}^{N \times d}$, where each row represents the feature vector associated with a node.

### B. Graph Neural Networks and Gated Graph Neural Networks

Most GNN architectures rely on an iterative information propagation mechanism, commonly referred to as message passing. At each layer, the representation of a node is updated by aggregating information from its neighbors and combining it with its current state. From a signal processing perspective, this operation can be interpreted as a diffusion process over the graph. A GNN layer can be described as a parametric function $\mathbf{H} = f(\mathbf{X}, \mathbf{A})$, where $\mathbf{X}$ denotes the matrix of node features and $\mathbf{A}$ encodes the connectivity of the graph. By stacking several layers of this type, the model progressively aggregates information from nodes that are multiple hops away, integrating the connectivity of the graph.

Several families of GNN architectures have been proposed in the literature. Here we focus on the recurrent GNNs (RGNNs) that have shown high potential in WDNs [5],

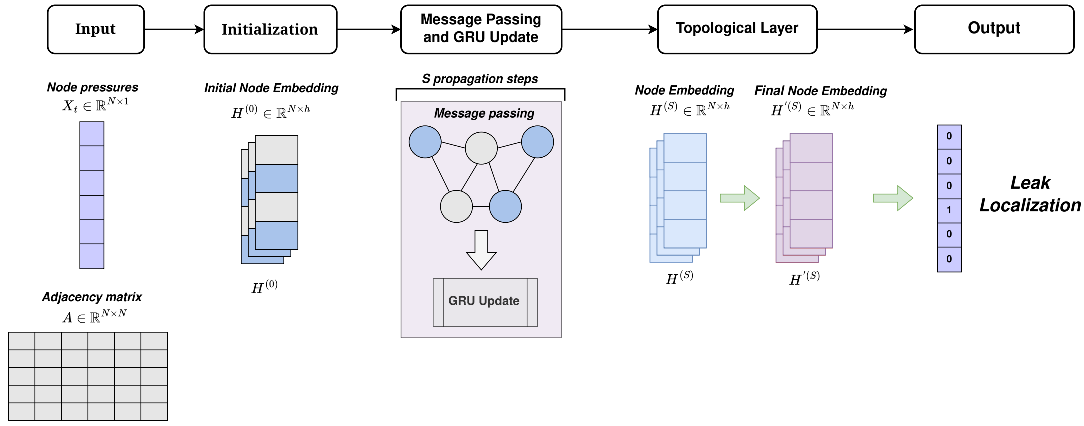


Fig. 2: Pipeline for leak localization in WDNs. Node pressures $X_t \in \mathbb{R}^{N\times 1}$ and the adjacency matrix $\mathbf{A} \in \mathbb{R}^{N\times N}$ are used to initialize node embeddings $H^{(0)} \in \mathbb{R}^{N\times h}$. After $S$ message-passing steps with GRU updates, the model produces the final node representation $H^{(S)}$, which is passed to the topological layer.

and they works by updating node representations through an iterative process. RGNNs update node embeddings through a sequence of iterations in which each node exchanges information with its neighbors. Gated Graph Neural Network (GGNN) extend recurrent graph models by introducing gating mechanisms inspired by Gated Recurrent Units (GRUs). These elements control how information is updated at each node, enabling the model to balance newly received messages with previously stored information. This allows GGNN to capture longer-range dependencies across the graph while maintaining stable training behavior. At each propagation step, every node collects information from its neighboring nodes $\mathcal{N}(v)$ through the graph connectivity structure. This aggregated message summarizes the local context around the node and represents the incoming information from adjacent nodes. The node then updates its internal representation by combining this aggregated message with its previous state. The update is regulated by a set of gates that determine how much of the new information should be incorporated and how much of the previous state should be retained. In particular, one gate controls the relevance of past information, while another determines the extent to which the new message contributes to the updated representation. This process allows the network to selectively propagate useful information while filtering out non relevant signals. The visual representation of the GGNN is in Fig.2.

### C. Top-GNN: Topology-guided GNN

In this subsection we introduce a topology-guided extension of this architecture that incorporates high order structural information. Indeed, standard graph-based models describe only pairwise interactions between nodes through edges. It may not fully capture more complex structural dependencies that arise in complex networks [3], [6]. In this direction, TSP extends classical graph signal processing by considering higher-order topological domains, such as cell complexes, where relationships are not limited to pairs of nodes but can involve sets of interconnected elements. In this framework, the network is described through elements of increasing dimension: nodes (0-cells), edges (1-cells), and higher-order structures such as loops or polygons (2-cells). To analyze these interactions, TSP introduces operators that generalize the graph Laplacian to higher-order domains. In particular, the first-order Laplacian plays a central role and is defined as

$$\mathbf{L}_1 = \mathbf{B}_1^T \mathbf{B}_1 + \mathbf{B}_2 \mathbf{B}_2^T, \tag{1}$$

where the first term reflects relationships between edges that share a common node trough the incidence matrix $\mathbf{B}_1 \in \mathbb{R}^{N\times N_e}$, while the second term encodes interactions between edges that belong to the same higher-order structure through the incidence matrix $\mathbf{B}_2 \in \mathbb{R}^{N_e\times N_c}$. In this notation, $N_e$ is the number of edges and $N_c$ is the number of nodes. This first-order Laplacian represents the key component of the Topological layer, as it allows the construction of topology-guided node corrections for the embeddings produced by the GGNN block. The Topological layer takes in input the node embeddings $\mathbf{H}^{(S)} \in \mathbb{R}^{N\times h}$ from the GGNN block and the boundary matrices $\mathbf{B}_1$ and $\mathbf{B}_2$. Using these matrices, the first-order Laplacian $\mathbf{L}_1$ is constructed. To compute the node correction, we observe that the embeddings are defined on nodes, while the operator $\mathbf{L}_1$ acts on edges. Therefore, the node embeddings are first lifted to the edge domain:

$$\mathbf{E} = \mathbf{B}_1^\top \mathbf{H}^{(S)} \tag{2}$$

The first-order Laplacian is then applied to propagate topological information across the edge space:

$$\mathbf{E}_{\text{top}} = \mathbf{L}_1 \mathbf{E} \tag{3}$$

The resulting signal is then projected back to the node space, producing a correction term $\Delta H$ that incorporates higher-order structural information:

$$\Delta\mathbf{H} = \mathbf{B}_1 \mathbf{E}_{\text{top}}. \tag{4}$$

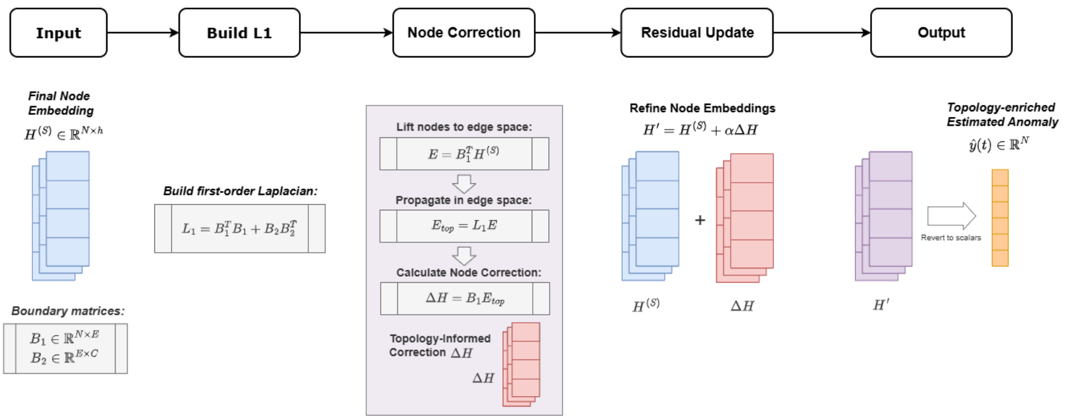


Fig. 3: Topology-aware refinement module. Starting from the GGNN output $\mathbf{H}^{(S)} \in \mathbb{R}^{N\times h}$, the first-order Laplacian $\mathbf{L}_1$ is built from the boundary matrices $\mathbf{B}_1$ and $\mathbf{B}_2$. Node embeddings are lifted to the edge space, propagated through $\mathbf{L}_1$, and mapped back to obtain a topology-informed correction $\Delta\mathbf{H}$. The refined representation $\mathbf{H}' = \mathbf{H}^{(S)} + \Delta\mathbf{H}$ is then used for leak localization.

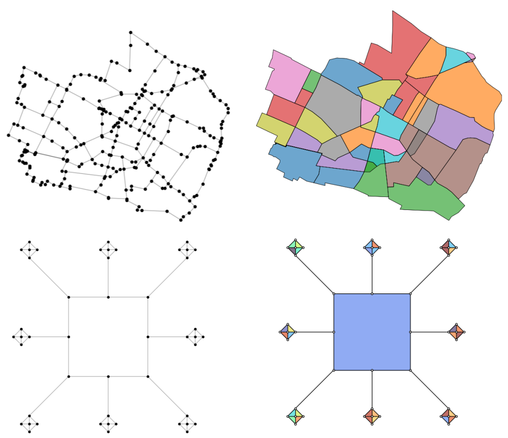

Fig. 4: Two WDNs used during the experiments. The bottom one is a small synthetic WDN, while the top one is Modena WDN. On the left we have the network with nodes and edges while on the right panles we identify the cell complexes.

This correction is then integrated with the original GGNN embeddings through a residual update of the form $\mathbf{H}'^{(S)} = \mathbf{H}^{(S)} + \alpha\Delta H^{(S)}$, where $\alpha$ is a learnable parameter controlling the contribution of the topological component. As final step, the refined node embeddings are linearly transformed into scalar anomaly scores, providing the final topology-aware predictions. The visual representation of the Topopology aware refinement module is in Fig. 3.

## IV. Experimental Results

In this section, we evaluate the proposed Top-GGNN model against a baseline GGNN architecture lacking higher-order topological information, and a standard 2-layer Graph Convolutional Network (GCN) with dropout. Comparisons are conducted on two WDNs of differing size and structural complexity: the GRID network and the Modena network (Fig. 4). This selection allows us to assess whether topology-aware message passing yields increasing benefit as network complexity and localization difficulty grow. Hydraulic scenarios for training and testing are generated via the WNTR simulation environment [20]. Each configuration is evaluated over 1000 simulated episodes of 72 hours, with a 30-minute hydraulic timestep. Leaks are injected at randomly selected junctions with randomized onset times within the first half of each episode, following WNTR's discharge coefficient model, enabling assessment under both single- and multi-leak conditions across variable temporal profiles.

At each timestep, the model receives as input the nodal pressure vector $X_t \in \mathbb{R}^{N\times 1}$, where $N$ is the number of junction nodes in the network. In the current experimental setup, pressure is assumed to be observable at all junctions, corresponding to a full observability scenario. The adjacency matrix $\mathbf{A} \in \mathbb{R}^{N\times N}$ is binary and encodes only the connectivity structure of the network. The model is trained for 500 epochs using the Adam optimizer. For the three-leak scenario, results for the Top-GGNN model are averaged over three independent random seeds (each comprising 500 test episodes); remaining configurations report single-seed results over 1000 episodes.

Table I reports the localization performance of GGNN and Top-GGNN across the three networks under scenarios with one, two, and three simultaneous leaks. The reported metrics are Top-$K$ accuracy, Top-5 accuracy, Top-10 accuracy, and Precision@K, with $K$ set equal to the number of simultaneous leaks. Overall, the results show that the advantage of the topology-informed model becomes more evident as the localization task becomes more difficult, particularly in multi-leak scenarios and in networks with richer cyclic structure. The GRID network represents the smallest benchmark considered in this study, consisting of 49 nodes and 84 pipes organized in

TABLE I: Leak localization performance across the considered WDNs for one, two, and three simultaneous leaks. Top-$K$ and Precision@$K$ are evaluated with $K$ equal to the number of injected leaks. For intensive tests, results are reported as mean $\pm$ std over independent seeds.

| Network | Leaks | Model | Top-K | Top-5 | Top-10 | MRR | Prec@K |
|---|---|---|---|---|---|---|---|
| | | GGNN | 100.0% | 100.0% | 100.0% | 1.000 | 1.000 |
| GRID | 1 | GCN | 100.0% | 100.0% | 100.0% | 1.000 | 1.000 |
| | | Top-GGNN | 100.0% | 100.0% | 100.0% | 1.000 | 1.000 |
| | | GGNN | 79.1% | 100.0% | 100.0% | 0.993 | 0.895 |
| GRID | 2 | GCN | 82.2% | 96.0% | 100.0% | 0.999 | 0.911 |
| | | Top-GGNN | **99.1%** | 100.0% | 100.0% | **1.000** | **0.996** |
| | | GGNN | 88.6% | 98.3% | 98.6% | 0.933 | 0.887 |
| Modena | 1 | GCN | 81.0% | **98.6%** | **99.8%** | 0.886 | 0.81 |
| | | Top-GGNN | **94.6%** | 96.3% | 97.0% | **0.954** | **0.947** |
| | | GGNN | 72.6% | 92.3% | 95.0% | 0.982 | 0.862 |
| Modena | 2 | GCN | 61.4% | **93.4%** | **97.0%** | 0.951 | 0.783 |
| | | Top-GGNN | **87.0%** | 92.0% | 92.6% | **0.997** | **0.935** |
| **— Intensive tests —** | | | | | | | |
| | | GGNN | 60.0$\pm$2.3% | 85.1$\pm$0.7% | 94.6$\pm$0.3% | 0.99$\pm$.005 | 0.85$\pm$.003 |
| GRID | 3 | GCN | 71.2$\pm$0.9% | 82.1$\pm$0.5% | 97.5$\pm$0.4% | 0.99$\pm$.002 | 0.90$\pm$.002 |
| | | Top-GGNN | **93.7**$\pm$0.5% | **99.9**$\pm$0.1% | **99.9**$\pm$0.1% | 0.99$\pm$.005 | **0.97**$\pm$.002 |
| | | GGNN | 53.77$\pm$2.0% | 77.4$\pm$0.9% | 87.8$\pm$0.5% | 0.97$\pm$.007 | 0.82$\pm$.005 |
| Modena | 3 | GCN | 36.9$\pm$2.3% | 70.3$\pm$5.3% | **93.1**$\pm$1.4% | 0.97$\pm$.001 | 0.74$\pm$.002 |
| | | Top-GGNN | **75.4**$\pm$2.4% | **82.2**$\pm$2.1% | 85.1$\pm$2.7% | **0.995**$\pm$.004 | **0.904**$\pm$.009 |

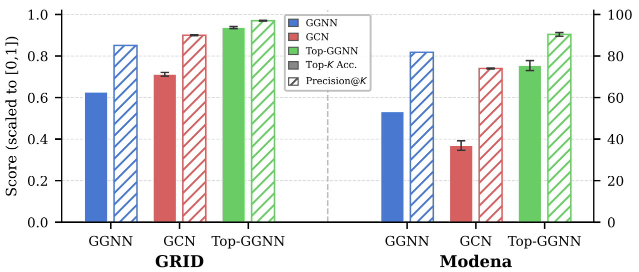


Fig. 5: Leak localization performance under three simultaneous leaks on the GRID and Modena WDN. Solid bars denote Top-K accuracy; hatched bars denote Precision@K. Bar color identifies the model: GGNN (blue), GCN (red), and Topo-GGNN (green). Error bars represent ± one standard deviation over independent random seeds.

a predominantly looped topology. In the single-leak scenario, both models achieve perfect performance, indicating that leak localization is straightforward in this setting. Differences emerge, however, when multiple leaks are present. In the two-leak scenario, Top-GGNN reaches a Top-2 accuracy of 99.1%, compared to 79.1% for the baseline GGNN. In the three-leak scenario, the gap becomes larger: Top-GGNN achieves a mean Top-3 accuracy of 93.7% ($\pm$0.5%) over three seeds, against 62.6% for GGNN. These results indicate that, even in a relatively small network, higher-order topology becomes beneficial as leak multiplicity increases.

The Modena network represents a more realistic benchmark derived from the water distribution system of the city of Modena and contains 272 nodes and 317 pipes. Compared to the synthetic networks, this system exhibits heterogeneous demand patterns and longer cycles (often exceeding ten pipes), making the localization task more representative of real-world conditions. The mean Top-3 accuracy over three seeds is 75.4% ($\pm$2.4%), compared to 53.1% for GGNN. The higher variance relative to the other networks reflects the greater heterogeneity of this benchmark. The more moderate gains can be attributed to two structural factors: first, Modena contains only 46 cycles, providing less higher-order information to the topological layer; second, its cycles are considerably longer, which may dilute the propagated signal.

To further investigate the contribution of the topological component, we perform an additional structural analyses on the Modena network under the three-leaks setting. We progressively remove cells from the cellcomplex representation, starting from those with the lowest average relevance score (estimated by comparing each cycle's contribution under leak vs. no-leak conditions). Fig. 6 reports the variation of Top-3 accuracy and Precision@$K$ as a function of the percentage of retained cells. Performance degrades progressively rather than abruptly, indicating that the model exploits distributed topological information and does not rely on a single dom-

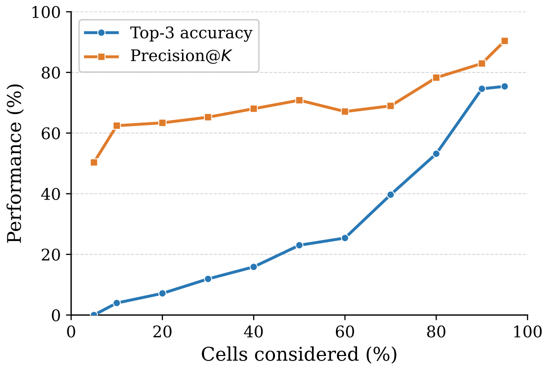


Fig. 6: Leak localization performance as a function of the percentage of retained cells in the cell complex representation.

inant subset of cycles. Importantly, even when only 10-20% of cells are retained, localization performance remains substantially above the baseline GGNN under the same leak setting (Top-3 = 15.2%, Prec@$K$ = 0.618), confirming that the gains are genuinely attributable to higher-order structural information rather than to increased model capacity alone.

The overall results show that the advantage of the topology-informed model increases with task difficulty and is most pronounced in networks where richer higher-order structure is available to guide message passing.

## V. Conclusions and Future Work

Our paper investigated leak localization in WDN using a topology-informed graph neural architecture that explicitly incorporates higher-order structural information through a cell complex representation. The proposed Top-GGNN model was evaluated against a baselines on two benchmarks, namely GRID and Modena, under both single-leak and multi-leak scenarios. The results consistently show that incorporating higher-order topology improves localization performance, with the largest gains observed in the most challenging settings.

Several directions emerge for extending the present work. Relaxing the assumption of full observability by considering realistic sensor placement constraints, missing measurements, sensor noise, and time-varying hydraulic conditions would enhance the practical relevance of the framework. Future research may explore more computationally efficient higher-order representations, the integration of richer hydraulic and operational features, and the development of online deployment strategies,to enable scalable and robust leak localization in large-scale WDNs.

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