

HydroNet: A Spatio-temporal Graph Neural Network for Modeling Hydraulic Dependencies in Urban Wastewater Systems

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Abstract

Wastewater infrastructures are vital in urban cities, but aging sanitary sewer systems face issues like cracked pipes and damaged manholes, leading to infiltration and inflow problems. Climate change contributes to more frequent heavy precipitation, potentially causing significant sewer overflows. These overflows can endanger public health by carrying disease-causing microorganisms, pathogens, chemicals, and pollutants. To improve the maintenance of wastewater systems, which often face challenges of sparse sensor coverage in the field, we develop a graph dataset and a spatio-temporal hydraulic model - HydroNet - tailored to urban wastewater systems. The trained HydroNet is able to predict temporal water depth, which can help identify potential infiltration, leading to an automated urban wastewater system with minimal time and labor costs.

CCS Concepts

• Computing methodologies → Machine learning approaches.

Keywords

AI4Science, Graph Neural Networks, Hydraulic Modeling

ACM Reference Format:

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1 Introduction

Wastewater infrastructures are a fundamental part of the modern city, but defects in the aging sanitary sewer system (e.g., cracked pipes and damaged manholes) allow large volumes of precipitation and groundwater to flow into the sewer system, known as the infiltration and inflow (I/I) problem. This can lead to sewer overflows and have serious consequences for public health and the environment. The management of infiltration and inflow requires a large amount of time and expensive costs of sensors, maintenance, operation, and engineering. There is a lack of efficient and cost-effective

methods for modeling hydraulic systems. The nature of an urban wastewater system, characterized by its temporal, spatial, and topological properties, can be represented as a graph with junctions represented as nodes and conduits as edges. Graph Neural Networks (GNN) are particularly well-suited for modeling graph relations with node embeddings preserving node features and edges carrying flow messages pass to each node. Mapping the urban wastewater system into a spatial-temporal deep model enables temporal water depth predictions, which can help with infiltration and inflow anomaly detection by comparing the predictive and sensor values.

We create a graph dataset with a real-world wastewater network. This dataset includes the water depth at each junction along with various node characteristics such as invert elevation, rim elevation, and freeboard, over a specified period. To test the quality of the dataset, we evaluate the dataset with a set of deep learning and non-deep learning-based models. To better customize a hydraulic model, we propose a HydroNet that captures spatio-temporal dependencies considering the static junction features.

2 An Urban Wastewater System Graph

An urban wastewater system can be naturally described as a graph; nodes will describe junctions, manholes, lift stations, outfalls, and storage facilities, and edges can be various conduits, including gravity-driven mains, force mains, and trunk mains. Given the context above, we formally design the wastewater system as $G = (V, E)$, which is an urban water system graph, $V = \{v_1, \dots, v_N\}$ is a

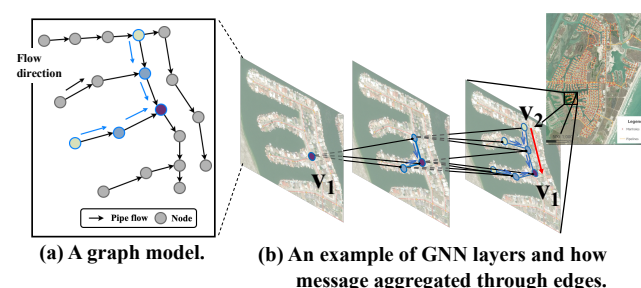


Figure 1: The conceptual design of Graph Neural Networks for water flow distribution. We propose a sewer system graph $G = (V, E)$, where node set V are the manholes, and edge set E are a set of directed edges representing messages passing in sewer mains. In this example, we show the two layers of the propagation process of vertex v_1 . Assuming an anomaly was found on v_2 , after training all the vertices, we are able to predict the cascading impacts of v_2 following the downstream passes.

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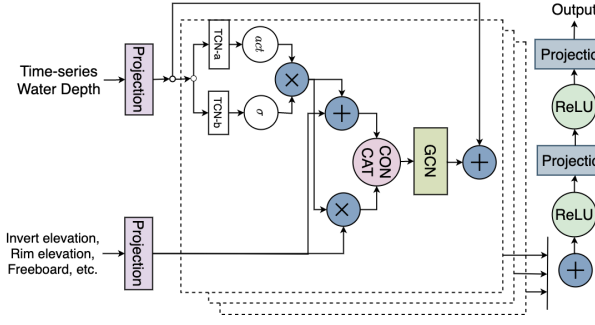


Figure 2: HydroNet Structure

set of vertices representing junctions, E is a set of edges representing conduits. The adjacency matrix derived from G is denoted as $\mathbf{A} \in \mathbb{R}^{N \times N}$ where N is the number of nodes (junctions). If $v_i, v_j \in V$ and $(v_i, v_j) \in E$, then $\mathbf{A}_{ij}$ is one otherwise zero. Figure 1(b) shows the conceptual design of an urban water system.

Training Data Generation The training data are generated using PCSWMM, an advanced version of the Storm Water Management Model 5 (SWMM5) developed by USEPA. The targeted system is a university campus sanitary sewer network, serving a 0.65 km² sewershed. It consists of 22 vitrified clay pipes (diameters 0.2–0.25 m) and 22 manholes (invert elevations -1.69 to 0.56 m). Sewershed data are derived from 15-cm aerial imagery and 1-m LiDAR digital elevation model. Inflow data is based on long-term observations from residential and commercial areas. The model solves the St. Venant flow equations to determine flow depths at 10-min intervals over a 72-hour period.

3 Methodology

At each time step t , the graph G has a dynamic feature matrix $\mathbf{X}^{(t)} \in \mathbb{R}^{N \times D}$ and static junction feature matrix $\mathbf{S} \in \mathbb{R}^{N \times D'}$. In our setting, the dynamic feature matrix represents the water depth at time step t with $D = 1$, and the static feature matrix represents 12 junction features ($D' = 12$) such as invert elevation, rim elevation, freeboard, etc. The junction features influence the time-series water depth at each junction.

In this paper, we evaluate our dataset on the time series prediction task. Given a water system graph G and past T steps' water flow as feature matrices $\mathbf{X}^{(t-T:t)}$, the prediction task is to learn a function f that predicts the next T' steps' water flow. The mapping can be defined as

$$\mathbf{X}^{(t+1:t+T')} = f(\mathbf{X}^{(t-T:t)}; \mathbf{S}, G) \quad (1)$$

Where $\mathbf{X}^{(t-T:t)} \in \mathbb{R}^{N \times D \times T}$ and $\mathbf{X}^{(t+1:t+T')} \in \mathbb{R}^{N \times D \times T'}$.

To address this prediction task, we propose the HydroNet model. As shown in Figure 2, HydroNet consists of stacked spatio-temporal layers taking both static and dynamic features. Unlike previous models, HydroNet is customized for hydraulic problems, incorporating both static junction features and dynamic time series data. HydroNet integrates temporal convolutions for time-dependent patterns and a Graph Convolutional Network (GCN) for spatial relationships. This architecture captures both the temporal nature of water flow and the spatial structure of the sewer network. The

training objective is to minimize the mean absolute error (MAE):

$$L(\hat{\mathbf{X}}^{(t+1:t+T')}; \Theta) = \frac{1}{T' * N} \sum_{i=1}^{T'} \sum_{j=1}^N |\hat{\mathbf{X}}_j^{(t+i)} - \mathbf{X}_j^{(t+i)}| \quad (2)$$

where $\hat{\mathbf{X}}_j^{(t+i)}$ and $\mathbf{X}_j^{(t+i)}$ are the predicted and actual water depths for junction j at time $t + i$, respectively.

4 Preliminary Results

We use historical data to predict future data. The *Lookback* length, set at 12, involves using data from the preceding 12 time steps to forecast the next 12 time steps. This establishes the temporal scope for the output of our predictive model.

We compare HydroNet with the following models: (1) CNN: Convolutional Neural Network. (2) RNN: Recurrent Neural Network. (3) GRU: Gated Recurrent Unit. (4) LSTM: Long Short-Term Memory. (5) Transformer. (6) STGCN: Spatio-temporal graph convolutional networks [2]. (7) ST-SSL: Spatio-Temporal Self-Supervised Learning [1]. The comparison is based on the following metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

The results (shown in Figure 3) emphasize HydroNet's superior predictive capabilities for sewer water levels. Consistently outperforming other models, HydroNet proves effective in complex time series forecasting.

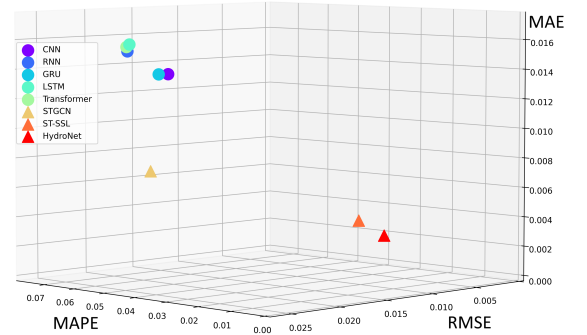


Figure 3: Performance comparison of different methods

5 Conclusion

Our experiments demonstrate that HydroNet, specifically developed for urban wastewater, surpasses traditional models in our dataset. HydroNet's success validates the use of complex models for precise predictions, which is essential for urban planning. This improved accuracy could significantly enhance wastewater system management and reduce overflow risks.

6 Acknowledgement

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