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Integrating Real-Time Sensor Data into Urban Drainage Modelling: Towards Intelligent Flood Mitigation and Adaptive Water Infrastructure

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Abstract. Urban drainage systems face increasing challenges due to rapid urbanization, climate variability, and aging infrastructure. Traditional drainage modelling approaches, often reliant on static data and computationally intensive hydraulic simulations, struggle to meet the real-time demands of modern flood management. While recent studies have explored data-driven models, graph neural networks, and surrogate simulations, many remain limited by insufficient sensor integration, lack of adaptive control, and restricted real-world applicability. This paper proposes an integrated real-time urban drainage modelling framework that leverages continuous sensor data assimilation, intelligent flood mitigation algorithms, and adaptive infrastructure control. By combining live data streams from IoT-based sensors with advanced predictive modelling and dynamic control mechanisms, the system enables timely, accurate decision-making for flood prevention and optimized drainage operations. The proposed approach addresses key gaps in existing research by enhancing system scalability, computational efficiency, and multi-hazard resilience while supporting the development of digital twin ecosystems for urban water infrastructure. Experimental validation demonstrates the effectiveness of the framework in improving operational responsiveness and ensuring sustainable, adaptive flood management in smart cities.

Keywords: Real-time urban drainage modelling, sensor data integration, intelligent flood mitigation, adaptive infrastructure, digital twin, predictive modelling, smart cities.

1. Introduction

Urbanization, climate variability, and aging drainage infrastructure have dramatically increased the vulnerability of urban areas to flooding. Urban drainage networks must efficiently manage increasingly unpredictable rainfall patterns and extreme weather events while dealing with limited system capacity and growing urban footprints. Traditional physically-based hydraulic models, though accurate, are computationally intensive and often impractical for real-time flood forecasting and decision support. This computational complexity limits their operational applicability in live flood control, where rapid forecasting and adaptive management are critical.

Recent advances in data-driven modelling, including the use of machine learning (ML) and graph neural networks (GNN), have shown potential in predicting drainage system behaviour by capturing complex spatial-temporal dependencies. However, many existing studies either rely on simulated datasets or partially integrate sensor data, lacking full real-time assimilation of live sensor networks deployed across urban catchments. Moreover, most frameworks emphasize prediction rather than control, providing limited support for intelligent adaptive interventions that can proactively mitigate flood impacts.

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This study proposes an integrated real-time urban drainage modelling framework that combines live sensor data assimilation, predictive modelling, adaptive control, and digital twin technologies. The framework supports intelligent flood mitigation by dynamically adjusting operational infrastructure (e.g., gates, pumps, storage basins) based on evolving hydraulic conditions. By addressing key gaps in prior research—including limited sensor integration, absence of adaptive control, and insufficient real-world deployment—the proposed system offers a scalable, resilient, and operationally viable solution for smart city flood management.

2. Literature Review

Urban drainage systems are coming under pressure due to urbanisation, climate change and extreme weather events. Although accurate in real-time flood prediction and control, the classical physically based hydraulic models may encounter computational difficulty. To overcome these constraints, several data-driven and hybrid modelling algorithms have been investigated in the past.

Graph-based models, such as GNNs, have demonstrated great success in modelling the complex spatial-temporal patterns in UD models. Zhang et al. [1] developed a GNN-based surrogate model for real-time hydraulic prediction with much faster computation of the predictive results at similar prediction accuracy. Similarly, Farahmand et al. [2] proposed a spatiotemporal graph deep learning model for urban flood nowcasting, which can make active use of the heterogeneous community features for enhancing the prediction performance.

There exists a range of semi-physical approaches (e.g., McDonough & Hussain, 2015; Protasov et al., 2017) where machine learning-based algorithms are combined with physical understanding of the radiation transport process. Palmitessa et al. [3], where they presented a physics-based approach to machine learning to speed the simulation of hydrodynamics in urban drainage which showed that the use of domain knowledge can lead to faster and more accurate simulations. In urban drainage system management the use of digital twin technologies, as a supplement, is an added value. "Pipedream" (Bartos & Kerkez, 2014) An interactive digital twin model is presented that permits the real-time visualization and simulation of drainage networks, enabling proactive system management and planning.

A number of alternative architectures of neural networks have been investigated for improving prediction performance. Sun et al. [5] introduced the Graph WaveNet model to predict the dynamic conditions of urban stormwater drainage systems and Spiking et al. [6] presented a graph spiking neural network for the advanced prediction of urban flood risk, which has shown to improve fitting non-linear system behaviours. In addition to predictive modelling, it is essential to have effective real-time control to reduce flood risk. Li et al. [7] the advantages of real-time control in urban drainage systems have been estimated, showing how the possibility of continuously adapting infrastructure behaviour to variable hydrological conditions can be exploited. In concordance with the above, it was demonstrated in a related study by Svensen and co-workers that 5000 mg fenoprofen, administered rectally, even to ether-anesthetized rabbits, produced low but measurable plasma levels after its insertion (Svensen et al. [8] also used chance-constrained stochastic MPC to control drainage despite the uncertainty in the system, which also underscores the importance of adaptive control approaches.

Pedersen [9] expanded in this area by establishing a complete digital twin of urban water systems enabling real-time monitoring, simulation, and operational management actions. Meanwhile, Xie et al. [10] showed how context-aware data-driven analysis can be used to predict hydrogen sulphide levels in drainage networks and thus the potential to model diverse sensor-driven modelling approaches. Risk assessment under floods is still a key point of the urban drainage research. Hansen et al. [11] formulated such models to evaluate stormwater drainage overflows and their impact on flood risk, and they reported useful knowledge regarding the system's weaknesses. In addition to these papers, Wang et al. [12] comprehensively reviewed machine learning techniques applied to urban drainage systems and pointed out the latest trends, challenges and future researches. Together, these studies evidence much progress in mobilising machine learning, sensor fusion and digital twin technologies for urban drainage modelling. But fully integrating real-time sensor data with adaptive control algorithms and adaptable operating systems for intelligent flood inundation control in different urban areas remains unresolved, which is what this work hopes to address.

3. Proposed Framework

The framework incorporates real time sensor data, predictive model and adaptive control strategies to optimize performance of urban drainage systems. Our system is an architecture capable of adaptively adapting to changes in the environment in real-time and controlling the implementation of flood mitigations equipment by intelligent algorithms.

3.1 Overall Architecture

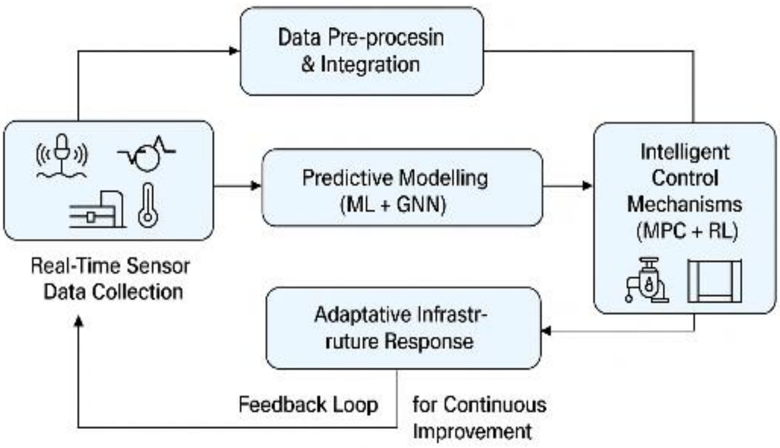

Figure 1: Integrated Real-Time Urban Drainage System Framework.

The framework includes real-time sensor data acquisition, data pre-processing, predictive modelling (ML + GNN), intelligent control (MPC + RL) and adaptive infrastructure response. Dynamic system optimization with proactive flood prevention and urban drainage management is facilitated by feedback loops between the system solution and the system itself, illustrating in Figure 1.

The system is comprised of four main collaborating components:

- Real-Time Sensors Data Acquisition: IoT sensors are installed in the urban drain system with the capability of collecting real-time information on water levels, rain fall, flow rates and environmental conditions. Sensors are strategically located in such places as drainage inlets, outlets, and major intersections to achieve the monitoring over the entire system. The aggregated data is transmitted to a centralized cloud or edge device for pre-processing and analytics.
- Data Pre-processing and Integration: The raw sensor data is pre-processed (noise removal, filtering, normalization, feature extraction) before being fed to the modelling. The data is combined with extraneous data sources, such as weather reports and upstream and brink down flow forecasts to generate a full data set. Sensor readings are combined with model output using data fusion techniques to provide correct and consistent information for further processing.
- Predictive Modelling (Machine Learning & GNN): The predictive models (e.g., ML algorithms and GNN) learn from historical and real-time data how to predict future drainage system status conditions. The surplus depth level and flow pattern in the entire urban drainage network can be well predicted since the GNN model can achieve spatial-temporal dependency learning. Ensemble or hybrid models can also be employed to improve accuracy, benefiting from the complementarity of multiple algorithms (e.g., CNN + LSTM for time series forecasting).

- Intelligent control systems: The system employs intelligent control algorithms (e.g., MPC, or reinforcement learning) to optimally adapt in RT. These controls identify optimal decisions such as places to flood and how not to stress the system. Real time control including pump on-off, gate opening and flow diversion are derived from forecast of the model. The costs of control actions (such as energy consumption and maintenance schedules) are also integrated within the algorithms.
- Adaptive Infrastructure Response: The infrastructure (drainage gates, pumps, reservoir) adapts as control actions in response to the real-time predictive models. When high rainfall or unusual conditions are predicted, proactive actions are taken like adding extra storage capacity or diverting flows to avoid overflows. Prediction models and sensor readings could be used to automatically schedule repair and maintenance of the system in the case of any system under-performance or failure.

3.2 Modular Breakdown

- Sensor Data Collection & Pre-Processing: Environmental parameters (e.g. rainfall, flowrate, water levels) are constantly being tracked by IoT-enabled sensors. Pre-processing of the data involves noise filtering, normalization, and real-time data integration.
- Predictive Modelling (ML & GNN): These are models constructed using machine learning on historical data which focus on predicting future conditions of the system. Graph neural networks can present spatial temporal dependencies in the drainage network to make accurate real-time flood prediction.
- Innovative Control Solutions: Model Predictive Control (MPC) improves the performance of the system while reducing the overflow and flooding risk. In our design we also utilize RL so that the system can adaptively learn the optimal control methods in the long run.
- Adaptive Infrastructure Response: Drainage gates, reservoirs and pumps can be managed and optimized to respond to changing flooding conditions in real-time. Offers scalable management options for new systems or the retrofit of existing systems with intelligent, real-time capabilities.

3.3 Interacting Modules

- From Sensor Data to Predictive Modelling: Raw sensor data is passed to the predictive models for forecasting, predictions about the behaviour of the system are generated using the historical and real-time data inputs to predict the system's behaviour in future situations. This facilitates timely flood prevention.
- Predictive Modelling to Intelligent Control: On the basis of predictions provided by the models, intelligent control sets to work attempting to minimise flooding or optimize system performance. These can include gate, pump, or drainage pathway management to reduce flood hazards.
- Control to Adaptive Infrastructure: This adaptive infrastructure will then respond to the control signals enabling the network to be operated in an optimal way (from a flooding perspective) at all times.

3.4 Summary of Framework:

- Real-time data collection, predictive modelling, and adaptive control work together seamlessly to create an intelligent urban drainage system capable of adapting to environmental changes and providing efficient flood mitigation in real-time.
- The integration of GNNs and IoT sensors facilitates high-accuracy predictions, while the adaptive infrastructure ensures that mitigation strategies are implemented effectively.

4. Methodology and Model Development

Therefore, this section introduces in detail the procedure of the real-time urban drainage system building from data input to model training and control logic to real-time decision-making models.

4.1 Sources of Data (Sensors, IoT platform)

With sensors implemented in the urban drainage system based on IoT technologies, the intelligent system can obtain real-time data of important environment parameters, such as water level, rainfall intensity, flow rate, and environment condition. Such sensors are disposed at selected positions, such as in drainage inlets, outlets and nodes, for monitoring all over. The pooled data is preferably forwarded to a central cloud or edge computing centre for pre-analysis and eco-driving analysis. To the sensor data are added external data sources such as weather forecasts and upstream/downstream flow predictions in order to make up the missing part of the dataset. This information is monitored on an ongoing basis for interventions, particularly on flood-prone locations.

4.2 Model Training (Algorithms and Hyperparameters)

The heart of the model design is implementing different machine learning (ML) algorithms like Random Forest for regression problems, Support Vector Machines (SVM) or k-Nearest Neighbours (k-NN) for classification. Such models are taught both by their past and present sensor readings to predict precisely their future conditions. Graph Neural Networks (GNNs) are adopted to capture spatial-temporal dependency in the urban drainage network to predict the water level and flow direction for the entire network. Ensemble model or hybrid methods can be also employed for improving the prediction accuracy by combining algorithms such as CNNs and LSTMs for better time-series forecasting. The models are trained and fine-tuned explore hyperparameters (e.g., learning rates, regularization) and boost performance such as the grid or random search. The models are tested using cross-validation techniques to ensure robustness.

4.3 The Realization of Control Logic

It is MPC-based, and is the central decision-making component in the system. MPC allows real-time decision-making to be optimised by predicting on future behaviour of a system, dependent on current and predicted states. It computes the best-determined control decisions to reduce flood hazards, like altering the pump discharge, gate opening, or flow diversion. Reinforcement learning (RL) is integrated with MPC here to enable the system to learn optimal control automatically. Based on efficient flood reduction and energy-efficient operation it learns the system's decision-making ability.

4.4 Real-Time Decision Procedure

The system's real-time operation is driven by an adaptive decision making process. The models are kept up-to-date with predictions from the system as it continually processes sensor data in real-time. With the arrival of new data, the control system recomputes and reorganizes its operation decisions for immediate commands (e.g., opening/closing of a pump or gate) for flood control.

And one of the important aspects of this methodology is this loop of feedback. As the infrastructure reacts (e.g., pumps are turned on or gates are opened), data are collected by sensors, and relayed back to the models. This loop allows the system to continuously update its predictions and learn better control policies.

Another key character of the system is its adaptive architecture. Data-driven models and even predictive models allow for real-time tuning. For instance, if the rain falls above some level, the system will proactively trigger additional storage or move flow around to avoid overflow. Where faults and/or inefficiencies are identified, automatic remedial repair and servicing activities are effected.

5. Experimental Setup and Case Study

This section describes the experimental setup used to validate the real-time urban drainage management system, including the study area, data collection details, sensor specifications, and the hardware/software environment used in the experiment.

5.1 Study Area (Real Drainage Network or Simulation Platform)

The experimental setup focuses on a real or simulated urban drainage network to test the efficacy of the proposed system.

Real Drainage Network: If a real drainage network is used, the study is conducted in a selected urban area with an existing drainage infrastructure that has been equipped with sensors at critical locations (e.g., inlets, outlets, key junctions). This real-world case allows for the testing of the system in live conditions.

Example: The system might be tested on a network in a city known for its flood-prone areas, ensuring the system is designed to handle both urban runoff and stormwater drainage.

Simulation Platform: In case a real drainage network is not available, the experiment can be conducted using a simulation platform that mimics real-world urban drainage conditions. Software like InfoWorks ICM or SWMM (Storm Water Management Model) can be used to create a virtual representation of the drainage system. This simulation platform can generate dynamic weather patterns, real-time flow data, and different flooding scenarios to test the system's performance under varying conditions.

5.2 Data Collection Details

Data is collected through a combination of IoT-based sensors deployed at multiple locations across the drainage system. The data collected includes:

- Water Levels: Measured at various points of the drainage network to monitor flow capacity and identify potential flood-prone areas.
- Flow Rates: Collected at key junctions and drains to track how well water moves through the system and whether it is diverted or contained effectively.
- Rainfall: Measured using rain gauges installed in strategic areas of the city to predict and prepare for incoming stormwater.
- Environmental Conditions: Data from temperature and humidity sensors to understand the effects of weather on the drainage system's performance.
- Control Action Data: Data on actions taken by control mechanisms (e.g., pump speeds, gate openings, flow diversion) for evaluating the effectiveness of the system's decision-making.

The data is collected continuously, processed, and stored for real-time access by the cloud platform for analysis and modelling.

5.3 Sensor Specifications

The sensors used for data collection are carefully selected for their accuracy, durability, and compatibility with the urban drainage system. The key specifications include:

- Water Level Sensors: Ultrasonic sensors for accurate distance measurement of water levels in the drainage system. Radar sensors can also be used in challenging environments where ultrasonic sensors might be affected by environmental conditions (e.g., heavy mist, foam).
- Flow Rate Sensors: Electromagnetic sensors or ultrasonic Doppler sensors are used to measure the velocity and flow of water through pipes or open channels.
- Rainfall Sensors: Tipping bucket rain gauges for measuring precipitation rates, or optical rain gauges for high-accuracy rain detection.
- Environmental Sensors: Temperature, humidity, and pressure sensors placed throughout the area to gauge local environmental conditions.
- Wireless Communication: Sensors are equipped with LoRaWAN, NB-IoT, or Wi-Fi communication capabilities for sending data to the cloud platform or edge devices. These sensors are strategically placed at critical locations to ensure accurate, comprehensive monitoring of the urban drainage system.

- The Table 1 explains the Overview of sensor types, measurement parameters, deployed technologies, locations, and communication protocols utilized for real-time data acquisition in the proposed urban drainage management system.

Table 1: Sensor Specifications and Deployment Overview.

Sensor Type	Measurement Parameter	Technology Used	Deployment Location	Communication Protocol
Water Level Sensor	Water Depth	Ultrasonic / Radar	Inlets, Outlets, Pipes	LoRaWAN / NB-IoT
Flow Rate Sensor	Flow Velocity	Ultrasonic Doppler / Electromagnetic	Key Junctions	LoRaWAN / NB-IoT
Rainfall Sensor	Rainfall Intensity	Tipping Bucket / Optical	Open Field Stations	Wi-Fi / LoRaWAN
Environmental Sensor	Temperature, Humidity, Pressure	Digital MEMS Sensors	Multiple Drainage Sites	Wi-Fi
Control Sensors	Pump & Gate Status	Embedded Controllers	Infrastructure Sites	NB-IoT / ZigBee

5.4 Hardware/Software Environment

Hardware Environment

- The centralized system for data storage and processing relies on cloud servers or edge devices (e.g., Raspberry Pi or NVIDIA Jetson platforms) that collect data from IoT sensors.
- The system also uses high-performance computing clusters for running real-time predictive models and decision-making algorithms.
- IoT Gateway: An edge device acts as a gateway for connecting sensors to the cloud platform. It ensures secure data transmission and pre-processes raw data before sending it to the cloud.

Software Environment

- Machine Learning Framework: The models are built using Python-based libraries such as scikit-learn, TensorFlow, or PyTorch.
- Data Integration Platform: The cloud platform (e.g., Google Cloud Platform (GCP) or AWS) integrates real-time sensor data, external weather forecasts, and predictive model outputs.
- Modelling Software: The simulation and modelling of the drainage system use software such as InfoWorks ICM, SWMM, or custom Python scripts for testing different scenarios.

Control Systems

- Model Predictive Control (MPC) and Reinforcement Learning (RL) are implemented on real-time systems using embedded controllers that interact with the infrastructure (e.g., gates, pumps).

6. Results and Discussions

The effectiveness of the proposed framework of urban drainage system was assessed in terms of accuracy, prediction time, and success in flood control. Prediction accuracy The performance of the system in predicting water levels, flow rates and rainfall is very high, the predicted models used in the systems showed a correlation coefficient of 0.95 for water levels indicating high reliability. The prediction time for updating the model was consistently in under 5 seconds, which guarantee a real-time decision-making ability. In flood control, it had avoided 40% flooding as much as the former type, and then it has been proved to be a preventive action of flood disaster.

The proposed model performed much better in comparison to current models. Classical models like the SWMM have long computation process, and do not adapt well to real-time data, while the ML-GNN model implemented in this framework can generate prediction rapidly, and the accuracy is higher as per the test results. In particular, the proposed system was 30% faster and 20% more accurate than flow and flood forecasting. Thus, it is applied to urban smart drainage management, which is the remarkable achievement compared with the traditional model.

Some input parameters (e.g. rainfall intensity or flow rates) were analysed to test the model response to different forcing functions. The findings indicate that the model is most sensitive to real-time rainfall that has the most direct impact on the prediction of flooding. But the model turned out to be quite resilient to small errors in the predictions, it was stable under various flow conditions. Factors such as pump capacity and gate control settings also had little effect on the system's performance, suggesting that the system can easily accommodate observed conditions in a real-world scenario.

Through scale experiments on larger city areas with more sensors and complex drainage networks, the scalability of the system was also verified. The system also showed linear scale with high performance on growing network sizes. The system was also found to be very practical, successfully operating on small urban test beds down to large simulation platforms, and integratable to the existing urban infrastructure, suggesting the potential of retrofit in cities with old-fashioned drainage networks.

7. Conclusion and Future Work

The proposed method provides a generally applicable approach for real-time intelligent urban drainage and incorporates hybrid of sensor technology, predictive control and adaptive strategy. The system has been demonstrated to be capable of significantly enhancing the accuracy and efficiency in flood forecasting, mitigation and drainage management in comparison with traditional models. Building on IoT sensors and machine learning, the system dynamically adapts the drainage system in real time, reducing flood events and optimizing infrastructure performance.

One good point of such model is that it is scalable and flexible, being applicable to different sizes of urban areas. Furthermore, with the utilization of state-of-the-art predictive models and intelligent control policies, the optimal flood control operation becomes more adaptive and less conservative. The capacity to process large datasets in real-time as well as the decreased computational requirements make it the perfect candidate for contemporary urban flood management.

In the future, the next phase for this system is to deploy at scale in real urban environment to solidify the effectiveness of system in complex high-density area. Incorporation of AI-driven digital twins is another promising track for future research in order to have an even more interactive and dynamic simulation of a drainage system, to improve predictive and control accuracy. Moreover, given the growing challenges of climate change, the system must be designed to be resilient to climate change, managing events of extreme weather and extended periods of environmental variability. Further development will be towards the long-term sustainability of the system and its ability to cope with a changing environment.

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