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# Comprehensive Evaluation of Real-time Control Strategies for Urban Drainage Systems Based on Deep Reinforcement Learning

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**Abstract:** Deep Reinforcement Learning (DRL) presents a promising solution for real-time control (RTC) in urban drainage systems (UDSs), potentially reducing sewer overflows and flooding. However, its comparative performance against traditional RTC methods remains underexplored. This study employs a multi-agent DRL framework to evaluate RTC effectiveness, focusing on control objectives, decision time, robustness, and adaptability. Results show that DRL can surpass traditional methods, improving weighted control objectives by 8.01% and 36.15% on average. DRL also demonstrates superior efficiency, robustness, and adaptability, particularly in short-duration, low-intensity events.

**Keywords**: Urban drainage systems; real-time control; deep reinforcement learning

## Introduction

Recently, Deep Reinforcement Learning (DRL) is utilized to implement real time control for Urban Drainage Systems (UDS). Numerous case studies have substantiated DRL's competitiveness as an RTC method. DRL has demonstrated significant advantages such as effective overflow and flooding reduction (Saliba et al., 2020), fast decision making (Liao et al., 2022). However, these advantages of DRL have rarely been evaluated in comparison to traditional methods. This study aims to establish a multi-dimensional evaluation framework that includes control objectives, decision time, robustness, and adaptability to assess DRL-based UDS control strategies.

## Material and Methods

The study formulated DRL reward functions aimed at three control objectives: environmental (minimizing overflows and flooding), economic (reducing energy consumption), and operational (lowering the frequency of control facility actions). The reward function is constructed as a weighted sum of these sub-objectives. DRL training was carried out using the SAC algorithm, with interactions with calibrated and validated UDS model based on EPA SWMM. For the trained DRL, the study proposed a multidimensional evaluation framework for control strategies, encompassing reward functions, individual control objectives, robustness, and adaptability. The study conducted simulations based on historical real rainfall events in the UDS system to assess these metrics, comparing the effectiveness of DRL with model predictive control and if-then-based static rule control strategies. The framework is shown in **Figure 1**.

## Results and Discussion

The case study examines the UDS of the CX-LDL district in Suzhou City, China, covering 313 hectares with an annual rainfall of 1094 mm. The separated sewer system includes two pump stations, LDL and CX, handling 7863 m³ of daily wastewater. A high-fidelity SWMM model, representing 335 manholes, 335 conduits, and 90 sub-catchments, served as the research environment. Model parameters, such as conduit Manning coefficients, were optimized using a genetic algorithm, achieving an average NSE of 0.8. Thirty-one historical rainfall events from 2019 to 2021 were used for strategy evaluation.

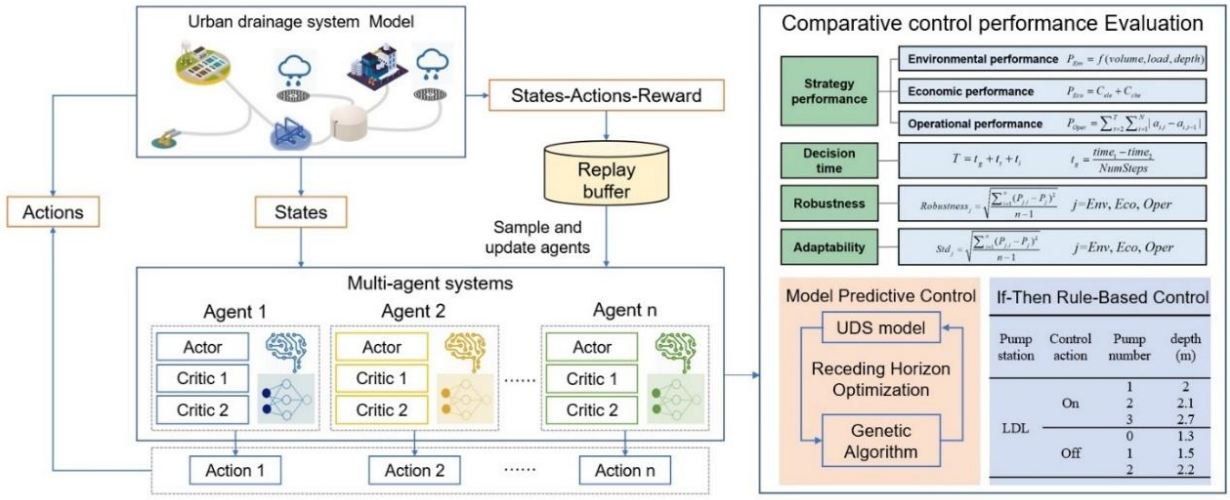


**Figure 1** Multi-agent DRL controller construction and comparative evaluation framework for DRL real-time control strategies.

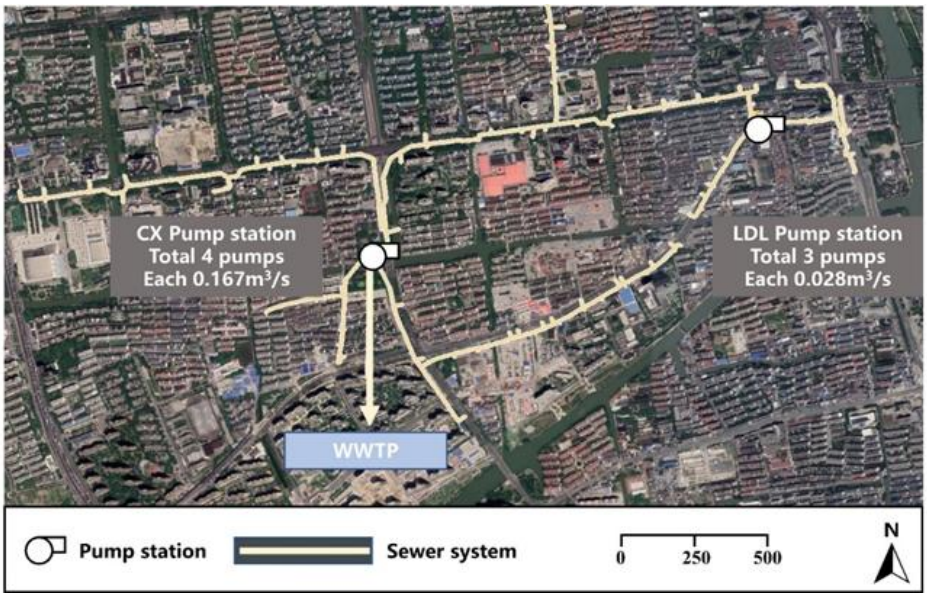


**Figure 2** Topological structure of the case UDS

To enable a comprehensive comparison, 31 historical actual rainfall events were conducted simulation tests to compute performance indicators in weighted objectives and sub-objectives. The obtained results are presented in **Figure 3**. DRL exceeded RBC and MPC on weighted objectives by 8.01% and 36.15% on average. The flooding risk is better served by DRL than the other strategies. DRL achieves improvements by decreasing the risk of flooding and overflow, reducing this by 15.1% and 43.5% when compared to RBC and MPC. However, at the same time, extra energy consumption (10.3% and 7.7%) and the number of pump switches (4.3 times and 2.2 times) increase with the DRL strategy. These results suggest there is a trade-off between the environmental performance indicator and the two other performance indicators. The average decision time among these 31 rainfall events for DRL is 1 second, accounting for merely 0.3% of the total time. For RBC and MPC, the proportions are 0.1% and 65.7%, respectively. This outcome shows that the efficiency of DRL is 199 times higher than MPC.

The performance of the DRL-based strategy varies across different rainfall events. Analysis of 400 designed events with varying depths, intensities, and durations showed DRL performs better with

shorter durations and lower maximum intensities. The flooding risks under different rainfalls are shown in **Figure 4**. For example, events under 10 hours had a significantly lower average risk function. Correlation coefficients between risk function and event duration for 20-, 40-, 60-, and 80-mm depths were 0.00, 0.44, 0.61, and 0.70, respectively. The coefficients between risk function and maximum intensity are 0.56, 0.60, 0.17, and 0.10, respectively, among events with different depths.

**Conclusion**

This study evaluates the RTC performance of UDS using a multi-agent DRL approach, compared to RBC and MPC. Utilizing the soft actor-critic algorithm, the DRL strategy optimizes multiple objectives. Key outcomes include a comprehensive RTC evaluation framework and a case study showing DRL outperforming RBC and MPC by 8.01% and 36.15% in objective function performance. Despite increased energy use and pump switches, DRL significantly reduced flooding risk and maintained an average decision time of 1 second per control step, demonstrating robustness to rainfall prediction uncertainties. While based on specific RBC and MPC settings, this research advances understanding of DRL's potential in RTC for UDS, suggesting further studies to validate these findings across diverse urban drainage scenarios.

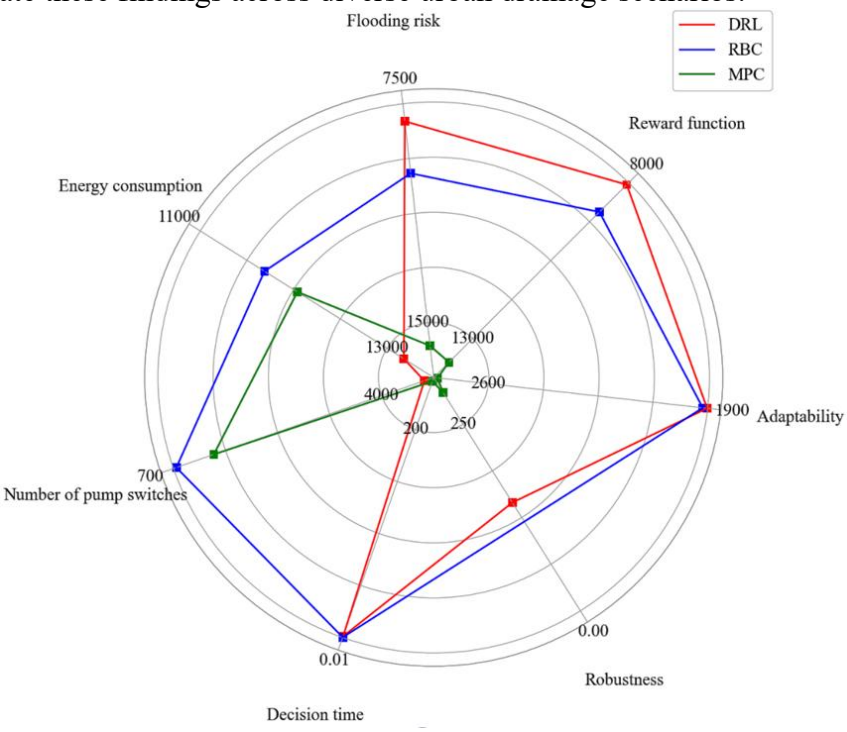


**Figure 3.** The evaluation results of the strategies in all performance indicators.

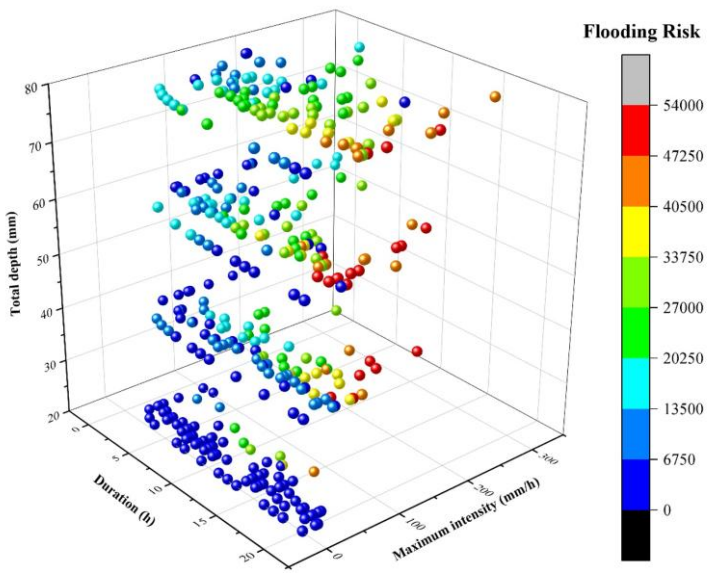


**Figure 4** Relationships between flooding risk and rainfall characteristics under 400 designed events using DRL strategy. Events with 20, 40, 60, and 80 mm in total depth account for one-quarter each. The color of symbols quantifies the value of risk function.

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