DUAN Tingting, LI Pengfeng, KHU Soonthiam, et al. Layout configuration and joint scheduling optimization of green-grey-blue integrated system for urban stormwater management: Current status and future directions[J]. Water Resources and Hydropower Engineering, 2025, 56(7): 77-108. DOI: 10.13928/j.cnki.wrahe.2025.07.007
段亭亭，李鹏峰，邱顺添，等. 城市雨洪管理中绿灰蓝融合系统的布局优化和联合调度优化：现状及未来方向[J]. 水利水电技术(中英文)，2025，56(7)：77-108. DOI：10.13928/j.cnki.wrahe.2025.07.007

Layout configuration and joint scheduling optimization of green-grey-blue integrated system for urban stormwater management: Current status and future directions

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Abstract: [Objective] Under the combined impact of climate change and urbanization, urban rainstorm flood disasters occur frequently, seriously restricting urban safety and sustainable development. Relying on traditional grey infrastructure such as pipe networks for urban stormwater management is not enough to deal with urban rainstorm flood disasters under extreme rainfall events. The integration of green, grey and blue systems (GGB-integrated system) is gradually gaining recognition in the field of global flood prevention. It is necessary to further clarify the connotation, technical and engineering implementation strategies of the GGB-integrated system, to provide support for the resilient city construction. [Methods] Through literature retrieval and analysis, the relevant research and progress related to the layout optimization and joint scheduling optimization of the GGB-integrated system were systematically reviewed. In response to existing limitations and future engineering application requirements, key supporting technologies including the utilization of overground emergency storage spaces, safety protection of underground important infrastructure and multi-departmental collaboration, were proposed. A layout optimization framework and a joint scheduling framework for the GGB-integrated system were also developed. [Results] Current research on layout optimization predominantly focuses on the integration of green system and grey system, with relatively fewer studies incorporating blue system infrastructure into the optimization process. Moreover, these studies tend to be on a smaller scale with simpler scenarios, which do not fully capture the complexity of real-world systems. Additionally, optimization objective tend to prioritize environmental and economic goals, while social and ecological factors are less frequently considered. Current research on joint scheduling optimization is often limited to small-scale plots, with insufficient attention paid to the entire system. There is a deficiency in method for real-time, automated determination of optimal control strategies for combinations of multiple system facilities based on actual rainfall-runoff processes. Additionally, the application of emergency facilities during extreme conditions is not sufficiently addressed. Furthermore, both layout optimization and joint scheduling optimization lack consideration of the mute feed effect of flood and waterlogging in urban, watershed and regional scales. [Conclusion] Future research needs to improve the theoretical framework for layout optimization and joint scheduling optimization of GGB-integrated system. Through the comprehensive application of the Internet of things, artificial intelligence, coupling model development, multi-scale analysis, multi-scenario simulation, and the establishment of multi-departmental collaboration mechanisms, it can enhance the flood resilience of urban

Article history: Received 02 September 2024; Revised 11 December 2024; Accepted 12 December 2024; Available online 21 January 2025

收稿日期：2024-09-02；**修回日期**：2024-12-11；**录用日期**：2024-12-12；**网络出版日期**：2025-01-21

Financial Aid: National Key Research and Development (R&D) Program of China (2022YFC3800500); China Postdoctoral Science Foundation-Tianjin Joint Support Program (2023T006TJ); China Construction Technology Consulting Co., Ltd. (Z2024Q02); North China Municipal Engineering Design & Research Institute Co., Ltd. (2024-61-HJY)

基金项目：国家重点研发计划项目(2022YFC3800500)；中国博士后科学基金会与天津市联合资助(特别资助)(2023T006TJ)；中国建设科技集团股份有限公司创新基金-青年基金项目(Z2024Q02)；中国市政工程华北设计研究总院有限公司课题(2024-61-HJY)

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areas in response to rainfall events of varying intensities, particularly extreme rainfall events.

Keywords: excessive rainfall runoff; green-grey-blue integrated system; emergency response; intelligent control; optimization framework; multi-departmental collaboration; climate change; flood

DOI: 10.13928/j.cnki.wrahe.2025.07.007　　开放科学(资源服务)标志码(OSID):

中图分类号: X43　　文献标志码: A　　文章编号: 1000-0860(2025)07-0077-32

听语音 聊科研 与作者互动

城市雨洪管理中绿灰蓝融合系统的布局优化和联合调度优化: 现状及未来方向

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摘　要: 【目的】气候变化和城市化叠加影响下, 城市洪涝灾害频发, 严重制约城市安全可持续发展。依靠雨水管网等传统灰色排水设施进行雨洪管理思路不足以应对极端暴雨下的城市洪涝灾害。绿灰蓝融合系统在全球洪涝灾害防控领域逐渐得到认可, 需进一步明确绿灰蓝融合系统的内涵、技术与工程实施策略等基础内容, 为下一步开展韧性城市建设提供支撑。【方法】通过文献检索和分析, 系统梳理绿灰蓝融合系统在布局优化和联合调度优化两个重点方向的相关研究工作和进展, 对绿灰蓝融合系统概念的提出与发展、技术体系构建与应用、优化策略等重点问题进行阐述。针对现有局限和未来工程应用需求, 提出了地表应急调蓄空间利用、地下重要基础设施安全防护、多部门协作等关键支撑技术, 同时构建了绿灰蓝融合系统的布局优化框架和联合调度优化框架。【结果】当前布局优化研究更多集中于绿灰系统融合, 将蓝色系统基础设施纳入优化的研究相对较少, 且研究尺度较小、场景简单, 难以反映实际系统的复杂性; 优化目标更多考虑环境和经济目标, 较少纳入社会和生态因素。当前联合调度优化研究多局限于小范围的地块尺度, 对整个系统的关注不足, 缺乏根据实际降雨-径流过程实时、自动确定多系统设施组合优化调控的方法, 且未充分考虑极端情况下的应急设施。此外, 布局优化和联合调度优化中均缺乏考虑城镇尺度与流域、区域尺度之间洪涝互馈效应。【结论】未来的研究需进一步完善绿灰蓝融合系统的布局优化和联合调度优化的理论框架。通过综合运用物联网、人工智能、耦合模型开发、多尺度分析、多情景模拟等技术方法并建立跨部门协作机制, 促进城市面对不同强度降雨特别是极端暴雨时洪涝韧性水平的提升。

关键词: 超量降雨径流; 绿灰蓝融合系统; 应急响应; 智慧调控; 优化框架; 多部门协作; 气候变化; 洪水

1　Introduction

Globally, the trend of global warming is conspicuous, as evidenced by the data in 2022, which showed an average global temperature 1.13 ℃ above pre-industrial levels, making it the sixth highest since temperature records began in 1850. Amidst global warming, rising temperature results in escalated evaporation and an accelerated water cycle, subsequently leading to a tendency for more frequent intense rainfall events. According to the Sixth Assessment Report by the Intergovernmental Panel on Climate Change (IPCC AR6) (https://www.ipcc.ch/report/sixth-assessment-report-cycle/), a 1 ℃ rise in global temperature corresponds to a 7% increase in the intensity of extreme daily precipitation events. Worldwide research on the response of extreme precipitation to global warming shows that although the trends of extreme precipitation exhibit temporal and spatial variability influenced by temperature, there is an overall increasing trend in both the frequency and intensity of extreme events in the future[1-4]. Excessive runoff caused by extreme precipitation events can overwhelm urban stormwater management systems, thereby exerting adverse effects on human society and posing substantial threats to the life, property security, and sustainable development in highly populated and economically concentrated urban areas[5-6]. According to the statistics of the top ten international natural disaster events from 2020 to 2023, urban floods triggered by extreme weather conditions is the main disaster, with a total of 17 incidents, accounting for nearly 57% (Global Disaster Data Platform, https://www.gddat.cn). The most typical examples include the "7·20 (2021)" extraordinarily heavy rainfall flooding event in Zhengzhou, Henan (China)[7], the 2021 summer flood in Central Europe[8-9], the 2022 Pakistan flood[10], the "23.7 (2023)" record-breaking heavy rainfall over North China[11] and so on. This has aroused the attention of governments and industry researchers worldwide regarding the safety management of excessive runoff.

The insufficient carrying capacity of Urban Drainage System (UDS) resulted from the lack of drainage facilities, insufficient water retention, inadequate pumping station capabilities and the constrained hydraulic conveyance capacity caused by the sewer blockages, sewer collapse, pump failures, deposited sediments, or solid waste etc. is the fundamental reason why urban areas are susceptible to extreme rainfall events[12-14]. How to improve the carrying capacity of UDS to enhance urban stormwater resilience is a major challenge in urban stormwater management. The green-blue infrastructures (GBI) have garnered a lot of attention as a solution to enhance UDS's resilience in response to extreme rainfall events[15]. The integration of green, grey and blue system (GGB-integrated system) has become a focal point in current research, with primary emphasis on layout optimization and joint scheduling optimization.

In the area of layout optimization, the integration of green system and grey system (namely the GG-integrated system) is the common conduction for better alleviating urban inundation[16-17]. However, the design objective for green infrastructures is usually based on small and medium rainfall events, encountering certain limitations in coping with extreme rainfall events[18-19]. WANG et al. (2020)[20] assessed the status of green infrastructure adoption in China's sponge city projects, revealing that these eco-friendly measures contribute merely 13.8% to the flood control effectiveness of the entire UDS. Natural or artificial water bodies such as lakes, rivers and wetlands (as blue responses) provide the ultimate outlet for excessive surface runoff, which green and grey system infrastructures cannot handle. Water bodies possess substantial potential for urban areas to confront the intricate challenges posed by future environmentally dynamic conditions[21]. LIU (2022)[22] proposed that indicators such as the water surface rate and river network density should be adopted as fundamental metrics for measuring UDS's resilience. Nevertheless, water bodies have not yet been fully integrated into the optimization process[23]. Existing research on GGB-integrated system often suffers from limitations such as small scales and limited scenarios, which do not fully capture the completeness and complexity of actual systems. Additionally, urban river and lake water bodies are not isolated water systems but are closely hydraulically connected to water bodies at regional and watershed scales[24] and river-lake system connectivity is an important aspect of cross regional and cross basin flood control risk management[25]. Thus, urban water body should be further comprehensively considered in the layout optimization of GGB-integrated system. Furthermore, existing research on GGB-integrated system layout optimization typically employs multi-objective optimization methods. However, research tends to focus more on environmental and economic goals while neglecting social and ecological factors. To better balance the roles of green, grey, and blue system infrastructures, future research should incorporate social and ecological processes into the optimization process, thereby achieving synchronous optimization of social, ecological, social, and economic goals.

A major challenge in promoting green and blue infrastructure in urban areas, particularly in highly urbanized regions, is the scarcity of available land[21]. Consequently, the strategy of continuously expanding the scale of green and blue infrastructures is not feasible for implementation. How to utilize existing green, grey and blue infrastructures, how to effectively utilize emergency rainwater storage and discharge functions in urban areas like roads, sunken spaces, and underground areas, and how to realize the connection of various storage and drainage spaces in time and space through optimal scheduling, to cope with the frequent extreme rainstorms in recent years, is a direction worthy of in-depth research.

Optimal scheduling of urban stormwater systems is a complex decision-making process involving multiple layers, multiple objectives, and multiple stages[26]. The key to achieving rapid response and accurate control in such complex systems lies in real-time control (RTC)[27]. RTC strategies can proactively adjust system operations based on monitored state parameters, and they are increasingly being applied to adaptive stormwater management and the enhancement of system resilience[28-29]. However, there are still several shortcomings in applying RTC strategies to the joint scheduling optimization of multiple facilities within the GGB-integrated system. Firstly, existing research often focuses on relatively small plot scales and simple scenarios, which do not adequately represent the complexity of real-world systems[30-33]. Additionally, the UDS's capacity is often inadequate during extreme rainfall events, necessitating more blue-green spaces. Some innovative research has explored the emergency response capabilities of urban spaces such as roads[34-35] and underground areas like underground parking, underground drainage tunnels and detention reservoirs[36-38]. However, the daily functions of these spaces are typically managed by different administrative departments, and there is a lack of effective collaboration mechanisms between these departments, which poses challenges in the emergency use of these urban spaces. Moreover, the optimization control objectives of most studies are quite generic, typically focusing on minimizing total overflow from pipe networks or rivers in the research area. This leads to insufficient safety protection for key infrastructure such as subway stations at finer local scales. Furthermore, most studies develop RTC strategies based on typical design rainfall scenarios, lacking methods for urban stormwater and flood control under real-time rainfall-runoff processes due to the significant uncertainty in meteorological forecasts.

This paper presents a literature review of the layout optimization and joint scheduling optimization for the GGB-integrated system and attempts to construct two comprehensive optimization frameworks to systematically analyze the information related to layout configuration optimization and joint scheduling optimization, and answer the following questions: (1) What are the key steps and methods used in layout optimization and joint scheduling optimization; (2) How different optimization steps affect each other? (3) What further improvements are needed in the future to achieve more scientific optimization for improving the feasibility and effectiveness of practical engineering applications.

2 Layout optimization of GGB-integrated system

2.1 GGB system and its layout optimization framework

The GGB-integrated system is an integrated approach to urban drainage that combines traditional grey system (such as reservoirs, dams, pipes, channels, deep tunnels and pumps) with green system (such as rain gardens and permeable pavements) and blue system (such as lakes, rivers, and wetlands) to manage stormwater runoff in a more sustainable and resilient manner[39-40]. The GGB-integrated system is considered to have great potential in urban areas, as it has not only the resilience and sustainability of green and blue systems, but also the reliability of grey infrastructure on stormwater drainage[21]. The integration of green, grey and blue systems requires evaluating the advantages and disadvantages of the various infrastructures to determine the appropriate combination and strengthening the connections among them to ensure the optimization of the system performance.

The layout optimization involves the efficient and sustainable arrangement of green, grey, and blue systems in urban areas, with the objective of efficiently alleviating urban inundation while promoting environmental resilience and overall sustainability. It involves the construction, renovation, and installation of structural measures (shown in Table 1) based on multi-objective optimization. Numerous researchers focused on the sizing and placement of LIDs[41-42].

Some studies focus on the synergistic effects generated by the combination of LIDs and grey system (e. g., drainage networks, storage tanks), and the combination of LIDs, grey system and blue system (e. g., river networks) under different spatial layouts[40,43-44].

Fig. 1 shows the main steps included in the layout optimization framework of GGB-integrated system. Step 1 analyzes urban inundation situations. Step 2 provides a basis for the selection of green, grey and blue systems. Step 3 determines a set of optimal solutions for the combination of green, grey and blue systems using multi-objective optimization. The decision methods such as Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) commonly assist in making the final decision-making and determining an optimal alternative in practical use (Step 4)[23,45].

2.2 Multi-objective optimization to determinate optimal solutions

Multi-objective optimization algorithms are commonly employed to solve complex problems with multiple conflicting objectives or constraints, which could help planners and decision-makers benefit from assessing the trade-offs implied by the best performing solutions[46]. It has been widely applied in urban stormwater management, including the optimal design of urban drainage networks, the optimal layout of rainwater harvesting systems, and the optimal scheduling of storm water pump stations[47-50].

So far, existing studies have focused more on the layout optimization of green infrastructures especially LIDs and Best Management Practices (BMPs) for urban runoff control, with the parameters of grey infrastructure usually used as invariant condition[21]. For example, YIN et al. (2023) treated the grey system (i. e., pumping station) and blue system (i. e., detention pond and river connection, river dredging) as fixed designs and only optimized the spatial layout and implementation ratio of green system infrastructures[51]. Some studies tried to optimize the GG-integrated system[52-56]. Research on

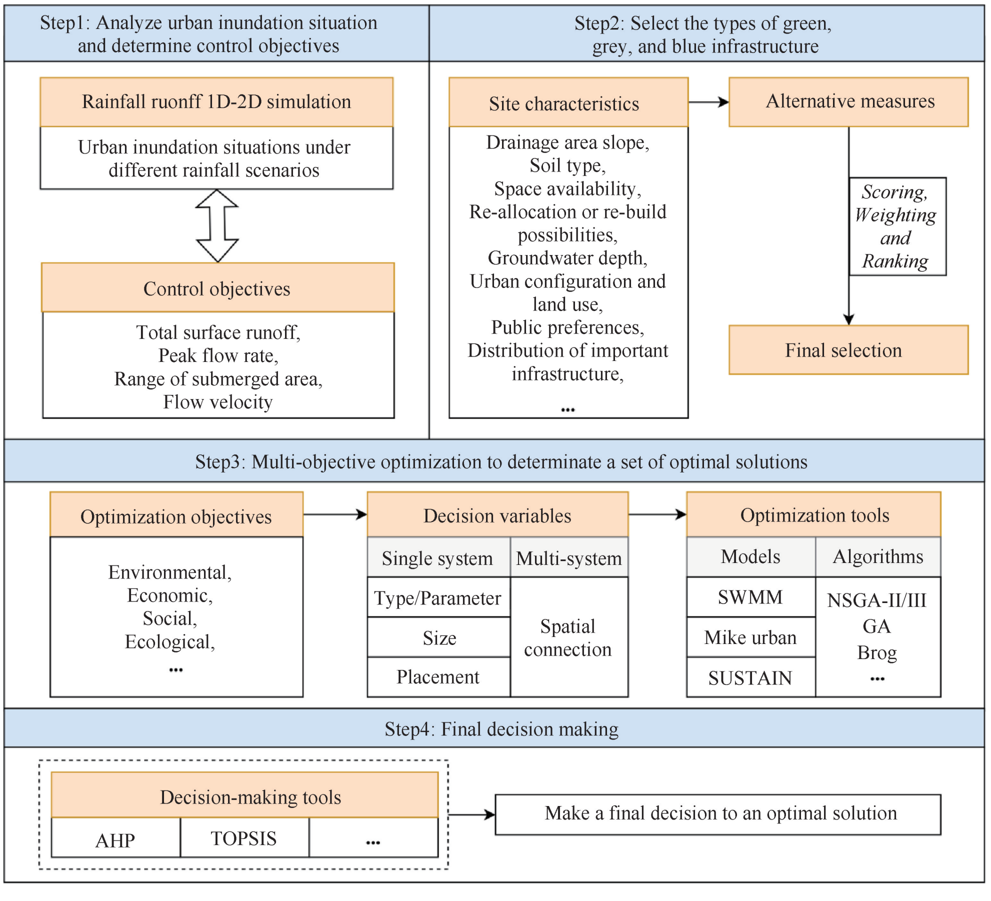


Fig. 1 Main steps included in the layout optimization of the GGB-integrated system

图 1 GGB 融合系统布局优化的主要步骤

integrating blue infrastructures such as rivers, lakes, and reservoirs with the GG-integrated system and optimizing the integral layout of the GGB-integrated system is receiving increasing attention[21,57-59]. Although some studies tried the optimization of the GGB-integrated system, their optimization processes are carried out in two separate steps: the first step optimizes the grey infrastructure applying graph-theory-based algorithm like Hanging Garden Algorithm (HGA), while the second step optimizes the green-blue system applying optimization algorithms such as Genetic Algorithm (GA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) and NSGA-III, which was not under the same multi-objective optimization framework[58-62].

This section will systematically analyze the information related to the key components of multi-objective optimization which applied to the planning of the GGB-integrated system, such as optimization objectives, decision variables, optimization tools, and further to answer the following questions: (1) Are there any differences in the key optimization components of multi-objective optimization for the layout planning of the GGB-integrated system compared to the grey system and green system, and (2) What is the current status at each optimization component, and (3) How to achieve more scientific optimization to improve the feasibility and implementation effectiveness of layout planning in future research?

2.2.1 Optimization objectives

In multi-objective optimization, setting the optimization objective is a crucial step as it directly affects the optimization variables, constraints, and final decisions involved in the optimization problem. When defining optimization objectives, it's necessary to guarantee that they are quantifiable and practically achievable. Concurrently, the interplay of different objectives must be considered to discern whether they exist in conflicting or synergistic relationships. Multi-objective optimization is concerned with the optimization of multiple conflicting objectives in multi-objective problems[63-64]. In addressing multi-objective problems, the objective is to identify an acceptable solution that balances all conflicting objectives, grounded in the principle of Pareto optimality[65]. Consequently, multi-objective optimization aims to identify a collection of Pareto optimal solutions, diverging from the pursuit of a single solution as in single-objective optimization[66].

Multi-objectives considered for the layout design of the GGB-integrated system usually involve multiple aspects such as environmental, economic, social, ecological, etc. In previous studies, most of them set two or three conflicting objectives to find the optimal design of the GGB-integrated system. The most popular conflicting objectives are maximizing the effectiveness of runoff control and benefits and minimizing cost (Table 1). Top topics about runoff control-related objectives are runoff volume reduction and system resilience/sustaina-bility[40,43-44,58-59,67], while the cost-related objectives mainly targeted life cycle cost, flood damage cost, capital investment and land occupied reduction[21,59,67-69] and the benefit-related objectives mainly targeted pollutant load reduction, ecological return on investment and co-benefits[39,43-44,68,70-71].

Table 1 Optimization objectives in existing layout optimization research focusing on the GGB-integrated system

表 1 现有 GGB 融合系统布局优化研究中的优化目标

Multi-objective	Specific objectives
Runoff control-related (Maximization)	Runoff volume reduction[43-44,51,68,70] Runoff peak flow reduction[51] Discharge flow reduction of Combined Sewer Overflow (CSO)[69] Flood risk reduction[21] System resilience/sustainability[58-59,67]
Cost-related (Minimization)	Life cycle cost[21,39,43-44,51,58-59,67] Flood damage cost[39,67,71-72] Capital investment[68-69,71-72] Land occupied[21,69]
Benefit-related (Maximization)	Ecological return on investment[68,70] Reduction of pollutant loads[43,68,70] Rainwater reuse rate[72] Environmental benefits[44] Co-benefits (i. e., air quality, buildings, temperature reduction, carbon sequestration, rainwater harvesting and heat stress reduction)[39,71]

2.2.2 Decision variables

In multi-objective optimization, decision variables are usually variant parameters, whose quantification directly affects the values of each objective function, thereby influencing the optimal solutions[45,73-74]. Generally, to enhance the accuracy and practicality of the optimization results, a systematic approach to determining decision variables is required. First, it is essential to clearly define the optimization objectives and identify all factors that may affect the optimization results. From these, screen out those factors that can be directly controlled or adjusted as potential decision variables. The number of decision variables and the information transfer of decision variables with different characteristics can significantly impact the algorithm's convergence and the population's diversity in multi-objective optimization[75-76]. Based on this, the set of potential decision variables should be further refined or grouped considering variable characteristics, practical constraints (e.g., budget, time, and regulatory requirements) and expert opinions. In practical systems, it is usually challenging to accurately determine decision factors due to the fuzzy relationships between decision factors and optimal objectives[77]. Thus, techniques like model simulations[78] and machine learning algorithms[79] can be further integrated to quantitatively assess the impact of each potential variable on the optimization objectives. This systematic process will ultimately determine which decision variables should be included in the multi-objective optimization process, ensuring that they are both feasible and effective.

In the case of urban stormwater management, decision variables would represent the types of infrastructure, their size (volume, area ratio, etc.) and where to locate them. Table 2 shows the decision variables in the existing optimization frameworks of the GGB-integrated system for managing urban stormwater.

Table 2 Decision variables in existing layout optimization research focusing on the GGB-integrated system

表 2 现有 GGB 融合系统布局优化研究中的决策变量

System	Decision variables
Grey	Hydraulic parameters (i.e., pipe diameter, length, slope)[21,43,69]
	Layout parameters (i.e., degree of centralization)[58-59,61]
	The number and location of pumping stations[58,72]
	Volume, location, area ratio of storage tanks[58,67,69]
Green	Type, location, area ratio, number[21,43,68-69]
Blue	Waterway connectivity of river networks[40]
	Length and width of rivers[40]
	Location, volume and area of open detention basins[39,71]

2.2.2.1 Decision variables related to the grey system

Due to the lack of re-allocation or re-build possibilities, it is hard to change the design parameters of the existing pipe networks, therefore, the parameters of grey system infrastructures are usually used as invariant condition not decision variables[21]. However, the fixed capacity of grey infrastructures has limited their abilities to cope with upcoming challenges in a changing environment[80]. Some scholars suggested that the design standard of urban drainage network was generally low, due to the rapid urbanization in China in recent years[20]. Improper size of drainage systems for their treatment volume is a general issue in surface runoff management[81].

For newly planned urban areas or urban areas with renovation plans, optimizing the hydraulic and layout parameters can enhance the capacity of grey infrastructures to manage urban stormwater in the upcoming challenging conditions. The optimized parameters of drainage pipe networks mainly included pipe diameter, length, slope, degree of centralization relevant to the layout of pipe networks and outlets[39,59,71], and the number, location and volume of some key grey facilities such as pumping stations, cisterns and interception treatments[70,72].

2.2.2.2 Decision variables related to the green system

Green system infrastructures, especially LIDs, as a supplement to grey infrastructures for urban runoff control, have been widely adopted worldwide[82]. The type, location, size, design parameter, number and area ratio are key decision variables of green infrastructures, which directly determine the optimization results of layout configurations. In most cases, the selection of potential green infrastructures is the most crucial step that needs to be carried out first. ALVES et al. (2018)[83] provided a four-step selection method, "Screening, Scoring, Weighting, Ranking", of the potential green infrastructures that comprehensively considers rainfall intensity, resulting urban flood risk, site characteristics, performance assessment and local preferences.

2.2.2.3 Decision variables related to the blue system

In existing research, blue system infrastructures mainly involve open detention basins and river networks. Location, volume and area of open detention basins, river length and width, and waterway connectivity are key factors in determining the storage capacity of the blue system for urban runoff control, and thus are the key components in defining the decision variables. Some definitions incorporate blue infrastructure into green infrastructure as they are both natural solutions[84]. The term 'green-blue infrastructure' (GBI) is also commonly used[30,59].

Even though integrating green-blue system with grey system can reduce the demand for construction or renovation of grey system, sometimes construction or renovation of grey system is also necessary. BAKHSHIPOUR et al. (2019)[59] concluded that by adding a green-blue infrastructure, the size of pipes could be reduced by optimization. However, LENG et al. (2021)[43] pointed out that although the optimal design of the GG-integrated system would decrease the weighted average pipe diameters of original grey infrastructure, external uncertainties could offset this effect so that the non cost-effective measures tend to be necessary.

2.2.3 Optimization tools

Optimization tools commonly used in GGB-integrated system layout optimization are usually a coupling of models and optimization algorithms. LERER et al. (2015)[85] identified three groups for optimization tools: "How Much" -tools, "Where" -tools and "Which" -tools according to the types of questions they can assist in answering. "How Much" -tools have different functions, including quantifying hydraulic impacts, hydrologic impacts, water quality impacts, non-flow-related impacts and economic impacts. The layout optimization of the GGB-integrated system usually involves runoff control, economic and ecological-related objectives, which need to be quantified by different models. Specifically, quantifying runoff control-related objectives requires models or coupling models that can simultaneously simulate the grey system (mainly drainage networks), green system (mainly LID practices), and blue system (mainly rivers, lakes, and large storage tanks).

Table 3 shows the frequently used models quantifying runoff control-related objectives and optimization algorithms in the papers appraised, with Stormwater Management Model (SWMM) being the most popular model and NSGA-II and NSGA-III being the most popular optimization algorithms. The combination of SWMM model and NSGA-II/III are most used tool structure[21,51].

NSGA-II is a classic algorithm in the field of multi-objective optimization, suitable for most conventional problems. Many toolboxes and libraries, such as the Python library DEAP (Distributed Evolutionary Algorithms in Python)[86], MATLAB's platEMO platform[87], the R package mco (Multiple Criteria Optimization Algorithms and Related Functions) (https://github.com/olafmersmann/mco. [Online; accessed: 10-09-2024]), and the Java library jMetal (https://github.com/jMetal/jMetal. [Online; accessed: 10-09-2024]), provide implementations of NSGA-II, enabling researchers to use and extend it conveniently. Compared with NSGA-II, NSGA-III, an extension, can better handle multi-objective optimization problems with complex Pareto front shapes (i.e., the distribution of Pareto front solutions) by guiding the evolutionary direction through a predefined set of reference points. In general, multi-objective optimization algorithms generate a series of optimal solutions often named Pareto Front solutions rather than a unique optimal solution[45,62,88]. However, the success of NSGA-III largely depends on the selection of these reference points. Inappropriate reference points may cause the algorithm to converge to an undesirable solution set. In contrast, NSGA-II can perform well without specific reference points. Therefore, for some relatively simple or conventional problems, NSGA-II may be sufficient and more efficient. MATLAB's platEMO platform[87], Pymoo (Multi-objective Optimization in Python) framework[89] (https://pymoo.org. [Online; accessed: 10-09-2024]) and Geatpy (The genetic and evolutionary algorithm toolbox with high performance in python) toolbox[21] (https://github.com/geatpy-dev/geatpy. [Online; accessed: 10-09-2024]) provide implementations of NSGA-III.

Some studies coupled SWMM model with other models such as SUSAIN, MIKE series models to conduct coupling 1D~2D simulation of urban surface, drainage networks and river networks[40,51,72]. Some other optimization algorithms, e.g., GA and Borg Multi-Objective Evolutionary Algorithm (Borg MOEA) were also used[58,72]. GA is easy to implement and has strong global search capabilities, however, its application in multi-objective optimization problems that require balancing multiple conflicting objectives is limited due to its tendency to converge to local optima rather than global optima. Borg MOEA adopts multiple adaptive mechanisms, which makes it more stable in different types of optimization problems. Meanwhile, Borg MOEA can adjust its parameters dynamically during the evolutionary process based on the characteristics of the problem, thus better adapting to different optimization scenarios. In addition, Borg MOEA can quickly converge to high-quality Pareto front solutions in most cases, especially when dealing with complex multi-objective optimization problems. However, compared to NAGA-II and NSGA-III, its computational complexity is relatively higher and more difficult to implement. The clear comparison of the four optimization algorithms mentioned above is shown in Table 4.

2.3 Final decision making after optimization

The final decision is a crucial procedure in the entire multi-objective optimization process. The final decision involves combining the optimization results with the actual situation to ensure that the selected solution is not only mathematically optimal, but also the most suitable in practice. Decision-makers need to choose one or several solutions from a set of Pareto optimal solutions obtained from multi-objective optimization for actual implementation. In this process, additional information considering practical applications, decision-maker preferences, and a trade-off analysis of the pros and cons of each potential solution may be considered.

Special decision tools and techniques may be required when making a final decision. Multi-Criteria Decision Analysis (MCDA) is a systematic approach widely used to make optimal final decisions through ranking multiple solutions under defined indicators based on Euclidean distance from the best and worst solutions[67]. Some commonly used MCDA methods include AHP, TOPSIS, Utility Theory, Minimize Regret

Table 3 The frequently used models and optimization algorithms in existing layout optimization research focusing on the GGB-integrated system

表3 现有GGB融合系统布局优化研究中常用的模型和优化算法

Methods and tools (models and algorithms)	Final decision making	References
SWMM + Non-dominated Sorting Genetic Algorithm II/III (NSGA-II/III)	The Pareto Front solutions *	[21, 43-44, 68-69, 71, 88]
	The Pareto Front solutions ⟶Multi-Criteria Decision Analysis (MCDA): TOPSIS method	[67, 70]
SWMM + Hanging Gardens Algorithm (HGA) + Genetic Algorithm (GA) **	An optimized solution set	[61]
	An optimized solution set ⟶ Further decision-making: Determining the most desirable solution through comparison of resilience and sustainability of optimized designs	[59-60]
Coupling model (SWMM + MIKE SHE + MIKE 21 + MIKE 11) + NSGA-II	The Pareto Front solutions	[51]
Coupling model (SWMM + SUSTAIN) + GA	The optimal solution	[72]
SWMM + HGA + Borg Multi-Objective Evolutionary Algorithm (Borg MOEA)	The Pareto Front solutions ⟶MCDA: TOPSIS method	[58]
SWMM + Ideal point method + GA	The Pareto optimal solutions ⟶The optimal solution	[90]
SWMM + HGA + NSGA-II	The Pareto optimal solutions	[62]

Note: * NSGA-II, NSGA-III and Borg MOEA optimization algorithms often obtain a set of optimal solutions, namely the Pareto Front solutions. Further decision-making is required when pursuing the most desirable solution. ** GA is applied to single-objective optimization problems rather than multi-objective optimization problems.

Table 4 Comparison of optimization algorithms NSGA-II, NSGA-III, GA and Borg MOEA

表4 优化算法NSGA-II、NSGA-III、GA和Borg的对比

Algorithm	Objective(s)	Advantages	Limitations
NSGA-II	multi	Efficient, maintains good diversity, and converges well	May struggle with very high-dimensional problems or complex Pareto fronts
NSGA-III	many	Specifically designed to handle many objectives, particularly effective for handling multi-objective problems with complex Pareto front shapes	Be less robust about problems with irregular Pareto fronts. The choice of reference points can significantly affect the quality of the solution. Maintaining and updating reference points will increase the computational overhead
GA	single	Simple to implement, versatile for various types of problems	Not optimized for multi-objective problems, it may require significant modifications to handle multiple objectives effectively
Borg MOEA	many	Robust adaptive mechanisms, faster convergence, scales well with increasing dimensionality and number of objectives	Computationally intensive and more complex to implement

and Weighted Sum Method[58,67,70,91-92]. Some MCDA methods tend to find the most desirable solution, while other MCDA methods may determine some desirable solutions.

In research related to the layout optimization of the GGB-integrated system, the TOPSIS and AHP, as two commonly used methods, are used to determine a most desirable alternative and some desirable alternatives respectively among those Pareto front of solutions obtained by coupling model and algorithm[23,45]. For example, BAKHSHIPOUR et al. (2021)[58] combined SWMM model with HGA and Borg MOEA algorithms to determine the Pareto front of solutions of sustainable urban drainage infrastructure planning (the layout of the GGB-integrated system), and further the TOPSIS method to select an appropriate option among the Pareto front of solutions. LIU et al. (2021)[70] combined SWMM model with NSGA-II algorithm to determine the optimal design solutions (i.e., the Pareto front) of the GG-integrated system, and the AHP method was introduced to further determine selected optimal design solutions considering the socioecological influences of runoff control infrastructure.

2.4 Challenges and future directions

2.4.1 Dynamic optimization considering future uncertainties

Given the uncertainties posed by further climate change and land use change, the optimized layout of the GGB-integrated system necessitates dynamic adjustments. Several strategies including climate prediction models, land use prediction models, multi-scenario analysis and community engagement, may effectively enhance the GGB-integrated system's adaptability to changing environments, ensuring long-term stability and resilience. Specifically, climate change and land use change models can help assess potential future climate scenarios and land use scenarios over the coming decades. Designers can evaluate the performance of different green, grey, and blue infrastructure layout configurations under different combinations of climate scenarios and land use scenarios through multi-scenario analysis[93-94]. This approach helps ensure that the designed GGB-integrated system remains robust and adaptable under various future conditions, enhancing the overall resilience of the system. Community engagement and education also play a critical role. Enhancing community awareness of climate change impacts and involving residents in the construction and maintenance of GGB-integrated system can improve overall societal resilience. Community participation fosters a sense of ownership and responsibility, leading to better long-term outcomes.

2.4.2 Optimization considering dual-purpose design for normal and emergency use

Integrating the concept of dual-purpose design for normal and emergency use into the layout optimization of GGB-integrated system is not only necessary but also strategically important, enhancing urban resilience, optimizing resource use, improving quality of life, and fostering sustainable and adaptable urban environments. Firstly, it enhances resilience by ensuring that the same infrastructure can serve multiple functions during both daily operations and emergencies. For instance, a park designed with permeable surfaces and drainage systems can function as a recreational space under normal conditions and as a flood mitigation infrastructure during heavy rainfall. Secondly, this approach leads to efficient resource utilization by reducing redundancy and maximizing the utility of each component within the system, thereby achieving cost savings and better resource allocation. Thirdly, dual-purpose design improves the overall livability of urban areas by providing recreational amenities during normal times and transforming into critical support infrastructure, such as evacuation routes or temporary shelters, during emergencies. Additionally, it promotes sustainability and adaptability by creating environments that can quickly adjust to changing conditions, ensuring long-term viability and resilience. Furthermore, engaging communities in the planning and design process builds awareness and preparedness, making residents more likely to be prepared for emergencies and actively participate in maintaining these systems. Lastly, the dual-purpose approach can lead to significant economic benefits by reducing the need for separate infrastructure for different scenarios, thus lowering maintenance costs and easing the financial burden on local governments and communities.

Despite the numerous benefits of integrating GGB-integrated system with dual-purpose design, the implementation process may face some challenges from both governmental and public perspectives. From a governmental standpoint, there is a lack of standardized guidelines and regulatory frameworks that can support the seamless integration of these systems. This absence of clear policy directives can hinder the adoption and implementation of innovative infrastructure solutions. Public resistance is another significant obstacle. Some community members may have concerns about the maintenance and long-term sustainability of these projects. For instance, after rainwater retention, poorly maintained underground parking might attract pests due to garbage accumulation, thereby becoming unusable and eroding public trust and investment value. Addressing these challenges requires a multi-faceted approach, including robust policy frameworks, transparent communication strategies, and proactive community involvement to build trust and ensure successful implementation of GGB-integrated systems.

2.4.3 Layout optimization considering spatial scale differences

In the layout optimization of GGB-integrated systems, considering multiple spatial scales (such as basin, sub-basin, urban, drainage areas, and plot) is crucial because different spatial scales influence the determination of optimization objectives and the selection of optimization tools. The "Up-scaling and Down-scaling" theory, also known as "Bottom-Up and Up-Bottom" theory have been applied in LIDs or BMPs optimal placement. Based on the "Up-Bottom" theory, GENG et al. (2019)[95] optimized BMPs at the watershed with the objectives of minimizing costs and minimizing TN and TP loads through the combination of ArcSWAT and NSGA-II. BMPs placement was further optimized at field scale. Based on the "Bottom-Up" theory, GENG et al. (2019)[96] developed a synthesis cost function of BMPs to get the optimal combination between the number of sub-watersheds for BMPs placement, the average sub-watershed size for BMPs placement and the average cost for each BMP, aiming to achieve the most cost-efficient BMPs plans from field to watershed scale. These two studies provided a new perspective on considering scale effects in layout optimization design. However, since their control objective is the reduction of terrestrial non-point source pollution rather than water quantity control, they did not consider receiving water responses and therefore did not incorporate blue infrastructure into the layout optimization. In fact, urban drainage and flood prevention are directly affected by the water levels of urban water bodies, regional water bodies, and watershed water bodies. The layout optimization of grey and green infrastructure should include water response at different scales. ZHANG et al. (2023)[23] recommended down-scaling decomposition of optimization objectives considering receiving water responses. In addition to the water quantity control objective, decomposing macro socio-economic and ecological objectives at the watershed scale to smaller scales can enhance the overall benefits of the GGB-integrated system. This approach also promotes community participation on a local scale and improves the system's sustainability.

2.4.4 Empirical research requirement for practical effectiveness

The optimization layout of the GGB-integrated system currently faces the challenge of high implementation difficulty due to the complexity of urban planning and the need for inter-departmental collaboration. The resulting lack of actual cases poses an obstacle to verify the implementation effectiveness of the GGB-integrated system, which is crucial for validating and refining its theoretical framework and methodology. To address this issue, future research recommends conducting pilot projects in typical cities, including both mountainous and plain cities to test and refine the GGB-integrated system, which will provide valuable real-world data and case studies, enabling researchers to validate and adjust the theoretical framework. Simultaneously, it is essential to conduct long-term monitoring and tracking of the UDS's operational status in these pilot projects. This will establish a comprehensive database to facilitate the assessment and feedback-driven optimization of the GGB-integrated systems, ensuring their long-term stability.

3 Joint scheduling optimization of GGB(E)-integrated system

3.1 GGB (E) system and its joint scheduling optimization framework

The GGB(E)-integrated system is the coupling of emergency (E) patch with the GGB-integrated system

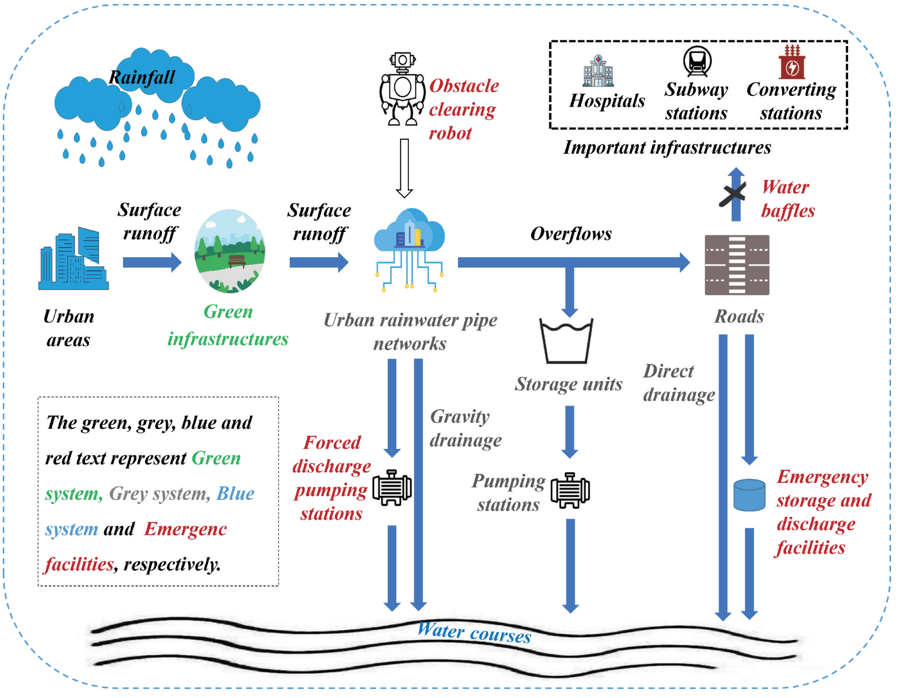


Fig. 2 Concept diagram of the GGB(E)-integrated system

图 2 GGB(E)融合系统概念示意

(Fig. 2). Emergency patch is a sustainable urban planning and design strategy aimed at improving the environmental performance, social welfare, and economic efficiency of cities. It emphasizes solving urban problems through small-scale, decentralized interventions rather than large-scale, centralized solutions[97]. In urban areas, critical infrastructures such as subways, water plants and hospitals play an essential role in ensuring citizens' quality of life, promoting economic development, and maintaining social order. In extreme rainfall-induced flood events, the inundation of these critical infrastructures would lead to substantial economic losses and social impacts. Therefore, it is essential to have emergency response measures for these critical infrastructures.

However, the corresponding protective engineering measures for these critical infrastructures to cope with emergency incidents like floods are scarce. As a result, emergency facilities such as forced drainage pumps, obstacle removal robots, water barriers, etc. are urgently needed. These emergency facilities act as patches for urban stormwater management systems, coupling with the GGB-integrated system to enhance the robustness of urban drainage safety. There is currently a lack of research on emergency facilities for urban storm management.

Central to urban resilience involves enhancing the systems' capacity for absorbing change and maintaining inter-system relationships[98]; yet for real UDS especially for the complex GGB(E)-integrated system, how exactly to improve their adaptability to complex and changing environments to improve the urban drainage safety still requires additional efforts. Adaptability plays an indispensable role in the planning and management of urban response to sudden disasters[99].

Typically controlled in a static manner, traditional stormwater systems often fail to function at their best and may lack the flexibility to adapt to variations due to either climate change or urban development[100]. In contrast to the static management of traditional stormwater systems, joint scheduling, as a non-structural action in mitigating urban floods, is based on the Internet of Things (IoT), Real-Time Monitoring (RTM) data, model simulation, optimization algorithm, data mining, etc., to regulate and control the operation strategies (e. g., the opening and closing of gates and pumps, the inflow and outflow of storage tanks, and the water level of regulating water bodies like wetlands and lakes) of the entire UDS, in order to achieve the most effective and rapid urban inundation prevention and control[30,101]. It is a viable approach to improve urban resilience against flood disasters with a more economically feasible and time effective compared with the construction and renovation of green, grey and blue system infrastructures in urban areas especially in highly urbanized areas.

However, existing research on joint scheduling generally has the following deficiencies: small scale (predominantly plot scale) with overly simplistic topological structures, relatively single controlled system (primarily the flood control scheduling of rivers, lakes, and reservoirs), and significant disparities from actual operational conditions (e. g., neglecting considerations such as sewer blockages and the reduced storage capacity of detention basins due to sediment accumulation)[15,21,30-32]. These shortcomings prevent an accurate representation of the complexity of real-world drainage systems, resulting in schedules that struggle to align with actual requirements and struggle to adapt to varying environmental conditions. In addition, relevant research on joint scheduling is more scenario-based rather than optimization-based[24,101]. Therefore, it necessitates an in-depth exploration of how to optimize the scheduling strategies of green, grey and blue system infrastructures spatially and temporally to flexibly respond to rainfall events of different intensities.

Fig. 3 shows a three-step optimization framework for joint scheduling of the GGB-integrated system to cope with excessive runoff in urban areas in real-time. In step 1, through 1D ~ 2D rainfall runoff simulation and field investigation, the storage and discharge capacity related to urban drainage networks, storage facilities, potential emergency facilities and urban watercourses will be preliminarily evaluated, and the potential storage and discharge units will be determined. In step 2, RTC strategies will be proposed to achieve real-time collaborative control of multi-system storage and discharging units, based on the linkage law of multi-system storage and discharge units. The activation of multi-system storage and discharge units under different rainfall intensity has priority, and the basic order is pipe networks ⟶ pumping stations ⟶ storage facilities ⟶ roads ⟶ emergency facilities ⟶ watercourses. RTC strategies will be combined with simulation models to form the "Model-Algorithm" mutual feedback optimization framework. Based on this optimization framework, a joint scheduling mode library that responds to multiple rainfall scenarios will be generated. In step 3, the joint scheduling mode of multi-system storage and discharge units under an actual rainfall event will be obtained within less than 15 minutes. It is essential to combine the offline decision-making analysis to determine whether the obtained optimization mode will ultimately be implemented.

3.2 Determination of multi-system storage and discharge units

3.2.1 Assessment of current capability of multi-system units

Evaluating the multi-system storage and discharge capacity and identifying the gap between the current capacity and the capacity required to cope with excessive runoff under different rainfall scenarios, are the basis for determining the multi-system storage and discharge units and formulating joint scheduling. The required capacity is not equivalent to excessive runoff, and its definition varies based on different safety requirements. For instance, urban areas with higher safety requirements require a smaller water depth for waterlogging, which in turn requires a larger capacity, and vice versa.

Through field investigations of the design parameters, operational conditions, and impacts of existing storage and discharge systems, a comprehensive evaluation index system (Table 5) is constructed to quantify each system's available storage and discharge capacity. By comparing the designed capacity of each system with their actual performance, those facilities with reduced capacity are identified. Strategies are formulated primarily targeting these identified facilities to enhance their storage and drainage capacity, thereby improving the overall functionality of the system.

3.2.2 Strategies for enhancing the capability of multi-system units

To enhance the storage and drainage capacity of UDS to cope with excessive runoff, a full process "Before-During-After the rains" management strategy should be adopted to improve the urban resilience against flood hazards. Before the rains, Based on rainstorm forecasts, urban inundation analysis and preliminary assessment of

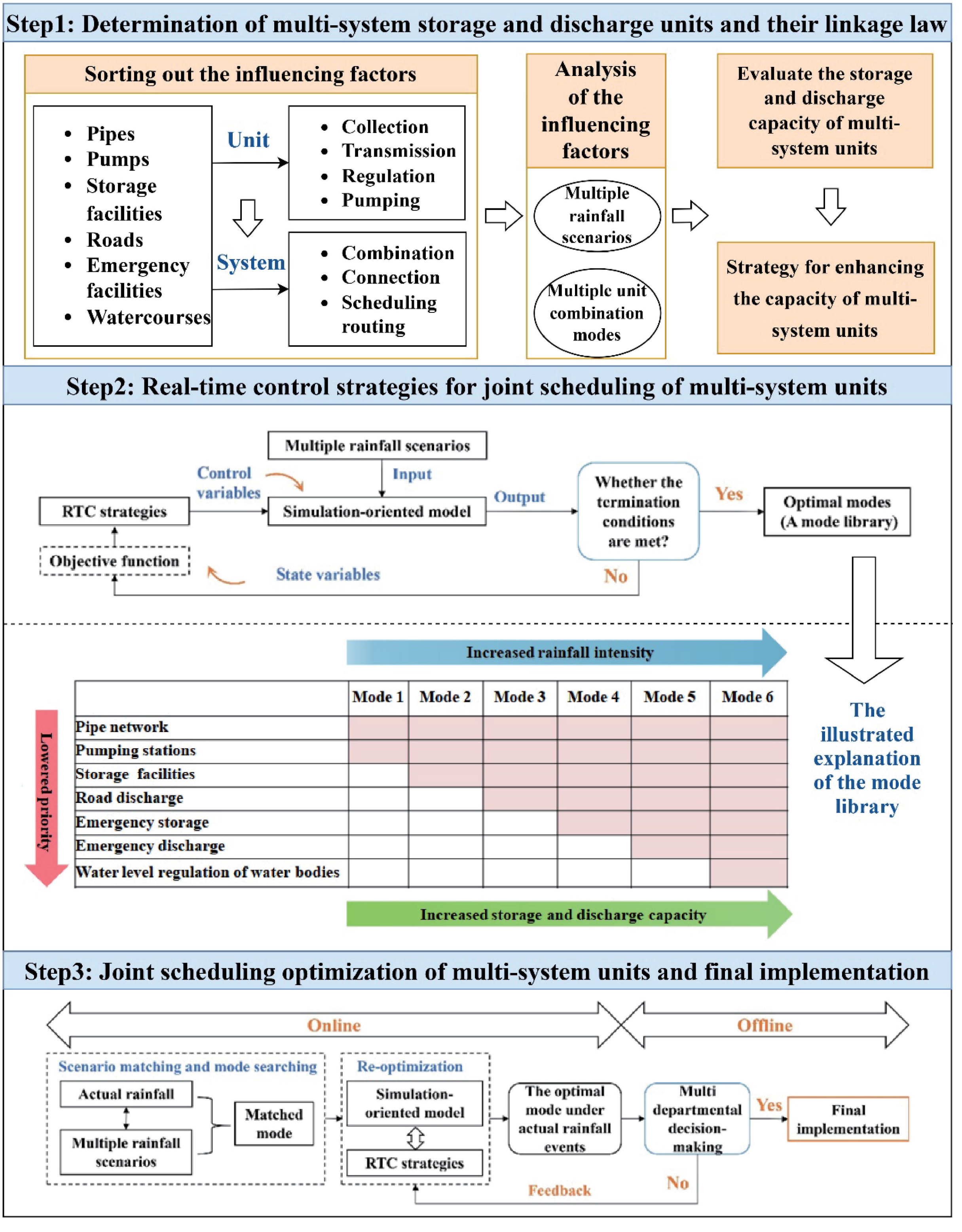


Fig. 3 The optimization framework for joint scheduling of green, grey and blue system infrastructures

图 3 绿灰蓝色系统基础设施联合调度的优化框架

the system's storage and drainage capacity, it is essential to maintain the normal operation of the drainage system through measures such as pipeline dredging and obstacle removal, pumping station maintenance, etc[102-103].

Currently, there is a lack of research focusing on enhancement of in-pipe storage capacity. In practical drainage systems, operational failures such as structural damage and sedimentation blockages can result in a

Table 5 Evaluation index system for capacity of multi-system storage and discharge units

表 5 多系统蓄排单元能力评估指标体系

Storage and discharge units	Evaluation indicators	Indicator characteristics	
		Design parameters	Affected by
Drainage networks	Collection capacity Transmission capability Storage capacity	■ Design parameters ■ Number and type of inlets	■ Sediment accumulation ■ Blockage ■ High water level
Pumping stations	Carrying capacity	■ Design parameters	■ Carrying capacity of main inflowing and outflowing pipes ■ Flood prevention and power supply guarantee level
Road as drainage channels	Transmission capacity Storage capacity	■ Road grade ■ Section design parameters	■ Maximum allowable depth and velocity of accumulated water for safe passage ■ Infrastructure distribution on both sides of the road
Storage spaces (e. g., storage tanks, overground sunken spaces or underground spaces)	Storage capacity	■ Design parameters ■ Emptying methods	■ Vertical entrance routing ■ Vertical water blocking height ■ Emptying strategy
Watercourses	Acceptance capacity Storage capacity	■ Water surface area ■ Key control water levels (ecological, flood control)	■ River operation regulation ■ Upstream and downstream coordinated scheduling

reduction in the hydraulic conveyance capacity of pipelines. LUO et al. (2022)[104] optimized the use of in-pipe storage space with improved dynamic programming (DP) considering the time lag of flow routing, which indicated the optimal use of in-pipe storage space can significantly improve the performance of UDS. LI et al. (2023)[105] found that considering the pipe network drainage made the reduction of demand storage capacity for 75% total rainfall control rate, ranging from 90.1% under 0.25-year return period to 60.0% under 50-year return period, compared with un considering the pipe network drainage.

Blue and green system infrastructures can enhance UDS's resilience during failure conditions or insufficient drainage capacity[15]. As required, the storage space can be increased by regulating urban river level[101]. The urban river level has a significant impact on urban flood risk. WANG et al. (2022)[106] found that higher water level can lead to an increase in urban flood volume and flood duration. Alternatively, submersible overground sunken spaces, underground spaces can also be utilized as emergency storage spaces[107-108].

During the rains, based on real-time monitoring data such as water level and flow velocity, intelligent controls are mainly carried out on drainage networks, roads and sunken spaces or underground spaces to improve storage and drainage capacity. For the drainage network, pumps and drainage measures are automatically activated as needed. The structural (e.g., proactive pump operation) and nonstructural measures (expansion of the discharge pump capacity) contribute to improving UDS's resilience[109]. For roads, when the water depth and flow velocity reach safety warning thresholds, access is restricted to both pedestrians and vehicles, utilizing them as overflow channels. HU et al. (2023)[110] developed stability threshold surfaces related to the water depth, flow velocity, and flow orientation for prototype vehicles exposed to flooding. ZHU et al. (2023)[111] studied the hydrodynamic instability of pedestrians in floodwaters and proposed an upgraded threshold formula of flooded people in terms of velocity and depth that account for turbulence. These studies help to provide deterministic safety warning trigger for vehicles and pedestrians. Moreover, the critical traffic lifelines, such as entry and exit routes, important rescue routes, etc. should be excluded for extra-excessive runoff diversion. There is currently a lack of research on the evaluation index system for determining whether a road is suitable for extra-excessive runoff diversion.

For underground spaces that are not submersible such as the subway systems and basements, safety protection measures, including the installation of water shields, should be implemented. Earlier, sandbags were commonly used for constructing or reinforcing flood prevention measures to protect subway entrances and other critical infrastructures[112]. However, filling and carrying of sandbags require substantial manpower and time that are often limited during flood events. In comparison, the installation of a flood barrier at the entrance or onto a doorway represents a more efficacious, trustworthy, and sustainable approach for ongoing protection[113]. SHIN et al. (2021)[114] compared the risk of flooding in the underground space for a case without a water shield (a fixed height of 0.5 meters) with that determined for a case with an installed water shield; the results showed that by installing water shields at the entrances of the underground space of a large apartment complex, the flood risk was lowered due to that the movement of inflow water was slowed. Compared to a fixed height flood barrier, a foldable water shield that can automatically adjust its height based on real-time water level monitoring may be a more promising application. GUO et al. (2023)[113] investigated the performance of the proposed air-inflated rubber dam as flood barrier at the subway entrance through numerical studies and laboratory model tests; this study only considered the static water pressure featuring different floodwater heights and did not consider dynamic flood conditions with substantial flow velocities and turbulence and floating trash that is more realistic. For general sunken spaces such as urban concave bridge areas and the sunken green spaces in parks, they are submersible after restricting both pedestrian and vehicle access, so they can be utilized for emergency storage. However, there is currently a lack of relevant research.

After the rains, storage facilities should be promptly restored to their storage capacity. Damaged facilities should be repaired timely to ensure the continuous operation efficiency and reliability of the entire system.

3.3 RTC strategies for joint scheduling of multi-system units

Urban stormwater management has undergone a transformation from passive control to active control. Passive control, also known as static control, primarily relies on predesigned static engineering measures to control surface runoff and is a piece-wise capital improvement of passive infrastructure systems[115]. Passive control determines the layout configuration of engineering measures mainly based on historical rainfall data and experience, lacking the ability to respond to sudden extreme rainfalls. It has been confirmed that passive control is less effective than active control for mitigating flood[31,115-116].

Active control utilizes advanced control systems and algorithms for dynamic decision-making based on RTM data of key system parameters such as rainfall, water levels and flow rates. Active control is an economically effective method for controlling urban runoff, which focuses more on economically utilizing the storage capacity of existing stormwater systems rather than continuously expanding and constructing expensive and land-intensive infrastructures[117]. The progress of smart cities and hydrologic informatics has promoted the application of low-cost sensors and actuators (e.g., remotely controlled valves and pumps) in UDSs to enable online monitoring and real-time data transmission, providing promising tools and methods for achieving active control of UDSs[118].

The joint scheduling of urban drainage system is a complex decision-making process involving multiple levels, multi-objectives, and multi-phases[119]. RTC can achieve rapid response and accurate control of complex systems[27]. Compared to passive control, a major advantage of RTC is its ability to utilize available information (e.g., environmental monitoring, weather forecasting) and adjust system operation based on real-time status[28]. RTC strategies are increasingly being applied to adaptive urban stormwater management and resilience enhancement[29].

Table 6 shows the commonly used RTC strategies and their comparison with the passive control strategies. RTC strategies can generally be divided into reactive control strategies and predictive control strategies. Rule-based Control (RBC) is a reactive RTC strategy, while Model Predictive Control (MPC), Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) are predictive RTC strategies.

Compared with passive control strategies, the advantages of RBC mainly lie in its pre-intervention and timely response. RBC can identify potential issues through real-time monitoring of the system's status and preset deterministic rules for various actuators such as gates and pumps. For example, the opening and closing status, flow rate, and other operating parameters of each actuator can be automatically adjusted based on changes in the water level, flow rate, and other status parameters of key monitoring points in the system. Through these pre-intervention measures, the drainage system can respond promptly to environmental changes and maintain stable operation. In contrast, static control strategies typically rely on fixed settings, which may make them ineffective in responding to unforeseen environmental changes.

Compared with RBC, MPC, RL and DRL are optimization-based approaches, and have advantages in predictability. MPC primarily includes three key components: predictive model, rolling optimization, and feedback correction. The predictive model is used to forecast the system's behavior based on the nowcasting precipitation data over forecast time horizons (e.g., 90 min, 12 h, 24 h, 36 h, 48 h, 7 d)[30,100,120-121]. In the component of rolling optimization, the optimal control actions can be determined at each time step based on the current system state. Optimization can be solved using numerical techniques such as quadratic programming (QP) or nonlinear programming (NLP). In the feedback correction component, the system state is continuously updated in real-time, and the control strategy is adjusted to correct any deviations. These enable the system to adapt to potential future scenarios and act before current and upcoming events occur[117,122-123]. RL aims to train an agent to learn and optimize its behavior through experimental trials and relatively simple feedback, thereby effectively controlling a given environment. RL controls actuators based on the current state and immediate feedback, rather than directly predicting future states. But it can learn a strategy based on the current state through its agents, which can consider potential future states to guide decision-making[31,124]. DRL is a field of RL that aims to solve the problem of excessive state space ("curse of dimensionality") in RL by integrating deep learning. This integration enables DRL's application to complex models and large-scale systems[125].

Despite the benefits of RTC, it may encounter potential risks and failures, which need further consideration to enhance its robustness. For instance, the effectiveness of MPC strategies may be compromised due to the inherent measurement and forecast uncertainty in real-world applications. CHEN et al. (2024)[126] evaluated the impacts of the uncertainty of rainfall forecasts on MPC performance for urban drainage management and revealed MPC performance remains close to optimal when forecast uncertainty levels are between 0.1 and 0.3, but deteriorates significantly at uncertainty levels from 0.3 to 0.5. Many studies have proposed improved MPC considering rainfall forecast uncertainty. The research primarily focuses on two aspects. One aspect aims to enhance the system's adaptability to the uncertainties in rainfall forecasts. In this case, the uncertainty of rainfall forecasts still exists. For example, SVENSEN et al. (2021)[127] applied the chance-constrained MPC (CC-MPC) based on different stochastic scenarios to the SWMM model of the Astlingen benchmark network. There were four stochastic scenarios, which only considered the uncertainty in the runoff inflows generated by forecasted rainfalls. The first scenario considered the probability confidence level variations (60% ~ 100%) of the inflow forecasts. The second scenario considered the bound on the uncertainty defined by actual inflow and standard deviation. The third and fourth scenarios considered scaled bias and offset bias affecting the expectation of the inflow forecasts. They compared the operational behavior of CC-MPC with the conventional MPC with deterministic forecast and found that in most scenario simulations, the performance of CC-MPC was close to that of the deterministic MPC with perfect forecasts. OH et al. (2023)[121] utilized an online sensor data assimilation with Extended Kalman Filtering (EKF) to calibrate the MPC prediction model. This makes MPC robust to the uncertainty of prediction models, and further robust to the uncertainty of main inputs of prediction models like forecasted rainfall.

The other aspect aims to improve the accuracy of the rainfall forecast. Extending the forecast time horizons for upcoming rainfall events would allow RTC systems to perform pre-storm releases well in advance at a lower, more natural rate[120]. Although Numeric Weather Prediction (NWP) can forecast rainfall events with horizons of up to 7 days readily available, more efforts need to be made to improve forecast accuracy and reduce forecast uncertainty to make rainfall forecasts better serve the RTC system[120]. WANG et al. (2019)[128] used seasonality coherent calibration to improve forecast accuracy by postprocessing the received NWP. Recent advances in machine learning-based methods also offer a feasible approach for rainfall forecasts. For example, JAFARI et al. (2023)[129] developed an adaptive input data-clustered Artificial Neural Network (ANN)-based method to achieve 30 minute ahead rainfall forecasts. To improve forecast accuracy, they incorporated rainfall fluctuations over finer temporal resolutions than the forecast horizon as additional predictors and results showed significantly enhances the effectiveness of the forecast model. REZAEI et al. (2024)[130] combined the deep learning-based Long Short-Term Memory (LSTM) model and the hybrid Particle Swarm Optimization-assisted Support Vector Regression (PSO-SVR) model to achieve 10 minute ahead rainfall forecasts. Using forecasted precipitation data as the main input, the simulation results of the drainage system control simulation model showed significant reductions in flood volumes and peak flows.

In addition, RTC performance is also sensitive to the failures of hardware components such as sensors and actuators, as well as communication failures between the devices spatially distributed in a catchment-scale system. Recent advances in enhancing reliability of UDS's RTC systems focus on system fault-tolerant design, sensor fault detection, monitoring data repair, decentralized control, etc. For example, LUO et al. (2024)[131] proposed a multi-criteria optimization method for the GG-integrated system with real-time control rules, optimizing both economic cost and system performance under normal and system failure conditions. Failure probabilities and losses were quantified using homogeneous Poisson process models and a machine learning-based surrogate model, respectively. This approach significantly improved system resilience to equipment and structural failures. PLEAU et al. (2022)[132] proposed an innovative real-time sensor fault detection approach based on the statistical properties of redundant measurements herein to improve the operation and maintenance of urban drainage systems. HE et al. (2023)[133] proposed a new deep learning model, which combines One-Dimensional Convolution (Conv1D) and Gated Recurrent Units (GRU) to improve the accuracy of abnormal monitoring data repair caused by sensor failures and network instability. ZHANG et al. (2023)[124] proposed a decentralized control strategy based on a cooperative Multi-Agent Reinforcement Learning (MARL) algorithm called value decom-position network (VDN), which coordinated the decentralized control agents through centralized training. The decentralized multi-agent structure ensures that communication failures of one agent do not affect other agents. This makes MARL enhance the overall coordination of decentralized agents to achieve better performance than a fully decentralized strategy. When observation communication failures, MARL can enhance communication robustness with a smaller performance loss than the centralized strategy. In practical applications, it is typically necessary to utilize multiple strategies simultaneously to maximize the robustness of RTC systems.

Table 7 presents some software tools with control modules applied in urban stormwater management, some of which can achieve heuristic control, e. g. EPA-SWMM, Mike Urban CS, but are unable to perform complex control logic and real-time optimization control. Some research studies combine SWMM with evolutionary algorithms to achieve real-time optimization control functions. For instance, ABOU et al. (2018)[139] used EPA-SWMM hydrologic-hydraulic simulation engine and GA to optimize the time-state schedules for the actuators

Table 6 RTC strategies and their comparison with passive control strategies

表 6 RTC 策略及其与被动控制策略的比较

Characteristics	Passive control strategies[31,116,134]	RTC strategies			
		RBC[30,31,135]	MPC[30,31,116,120]	RL[31,124,135]	DRL[136-138]
Pre-intervention	No	Yes	Yes	Yes	Yes
Timely response	No	Yes	Yes	Yes	Yes
Predictability	No	No	Yes	Yes	Yes
Optimization-based	No	No	Yes	Yes	Yes

Table 7 Software tools with control modules applied in urban stormwater management

表 7 应用于城市雨水管理的具有控制模块的软件工具

Software tool	Open source
InfoWorks ICM[30]	No
EPA-SWMM[139-142,146]	Yes
PCSWMM[100,147-148]	No
XPSTORM[149]	No
MatSWMM[150]	Yes
PySWMM[124,151-152]	Yes
Mike Urban CS[153-154]	No
CSOFT[155]	No
CityDrain[156]	Yes
MOUSE[157]	No
CORAL[158]	No
Simuwater[33,144]	No

of UDS through MPC strategy. JAFARI et al. (2018)[140] and LI et al. (2022)[141] determined the optimal operation rules of drainage facilities within the shortest response time based on SWMM and Particle Swarm Optimization (PSO) algorithm. SADLER et al. (2019)[142] developed the swmm_mpc, one of state-of-the-art open-sourced MPC software, which utilizes the EPA-SWMM computing engine and the hotstart file provided by PySWMM to simulate MPC for UDSs. SUN et al. (2020)[143] presented an MPC-enabled SWMM implementation of the Astlingen RTC benchmarking network.

The commonly used 2D-1D hydrodynamic platform InfoWorks ICM's built-in RTC editors support creating MPC logic, providing a powerful engine to model control actions according to water level conditions and variations in rainfall intensity[30]. Simuwater, developed by North China Municipal Engineering Design & Research Institute Co. Ltd., Tianjin (China) in 2020, is a promising software tool applied in urban stormwater management. Simuwater can perform water quantity-water quality simulations of the entire process "source-network-plant-river" at the community, urban, and watershed scales, with RTC functions[144]. Simuwater can create RTC logic independently or in combination with SWMM and control systems such as OVATION[33].

Although these software tools have contributed to the increasing applications of RTC in real-world systems, the computation time of the predictive model calculation greatly hinders its further development. To improve MPC computational efficiency, CHEN et al. (2024)[145] proposed two surrogate models, the water tank-water balance model 1 and 2, to replace SWMM as the predictive model for MPC, with 26% fewer calibration parameters, shorter computation time and the accuracy in meeting scheduling requirements.

3.4 Joint scheduling optimization of multi-system units

The construction of smart management and control platforms can help the true implementation of scheduling strategies achieve. Fig. 4 shows the structure of a platform for intelligent control of urban runoff through the joint scheduling of multi-system storage and drainage units. The platform consists of application software (including OS clients and the simulation model), the Supervisory Control and Data Acquisition (SCADA) server and field devices (including sensors, the Remote Terminal Unit (RTU), Programmable Logic Controller (PLC) and actuators). The SCADA server is the main control center responsible for processing information and making decisions[32,139]. The simulation model simulates the UDS's operating status and RTC strategies, and transmits data and control commands (i.e., the resulted optimal time-state schedules) to SCADA server. The SCADA server sends control commands to the RTU/PLC. RTU/PLC are data acquisition and control units which are mainly used to collect and upload sensor measurements and execute the control commands received from the

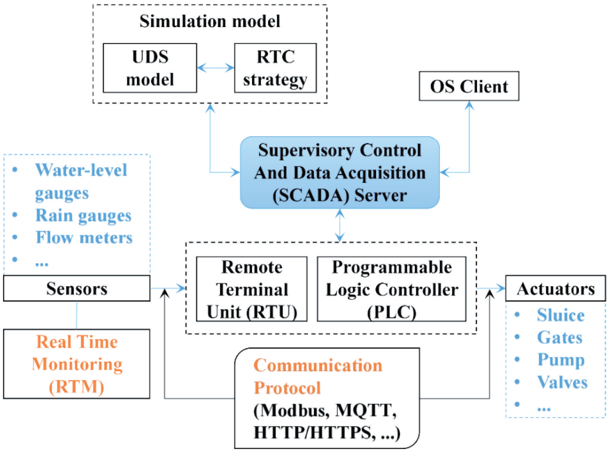


Fig. 4 The platform structure for intelligent control of urban runoff through the joint scheduling of multi-system storage and drainage units

图 4 多系统蓄排单元联合调度实现城市径流智能调控的平台结构

SCADA server to make management decisions for UDSs include which actuators (e.g., sluice gates, pumps, valves, etc.) should change, when to change them, and to what setting they should be changed[142].

Different types of sensors are used to monitor the operations of UDS. These can be water-level gauges, rain gauges, flow meters, etc., which constitute a RTM system, directly contributing in RTC applications and helping engineers to understand, evaluate and improve the operation of the UDS[139]. Modbus, MQTT, HTTP/HTTPS protocols are applied as the communication protocols in this system, connecting the sensors and actuators to the RTU/PLC.

The simulation model consists of two parts, namely the UDS model and the RTC strategy, which is the key component of the platform, issuing control commands to the SCADA sever and achieving the joint scheduling of multi-system storage and discharge units. The generation of optimized joint scheduling modes involves two main steps, namely, the generation of the mode library under multiple rainfall scenarios (Step 1) and the generation of real-time joint scheduling mode based on scenario matching (Step 2). The mode library is generated by utilizing mutual feedback between the RTC strategy and the UDS model (Fig. 5a). Firstly, the UDS model is utilized to conduct rainfall-runoff simulations under various rainfall scenarios (e.g., 5, 10, 20, 50, and 100 year return periods), thereby resulting in the acquisition of state variables, mainly including the locations of waterlogging points and their associated water depths and flow velocities. These state variables are used as inputs to the RTC strategy, which utilizes GA to automatically optimize and output the optimal control variables. Control variables encompass specific control objects and action attributes, such as the height of gates, the opening status of valves, and On/Off status, flow rates of pumps, and flow distribution ratio of diversion wells. Consequently, the optimal joint scheduling scenario for each rainfall scenario is obtained, and the optimal scenarios corresponding to various rainfall scenarios forms the mode library.

When an actual rainfall occurs, the rainfall scenario that is most like the actual rainfall is identified by comparing the three indicators of rainfall volume, intensity, and process. The mode corresponding to the rainfall scenario is matched in the library and re-optimized to obtain the optimal mode under the current actual rainfall (Fig. 5b). Ultimately, it is essential for multiple departments collaboratively to determine offline whether the optimal mode generated online should be implemented.

Table 8 summarizes several RTC-enhanced drainage solutions that utilize MPC, RBC or RL approaches to achieve flood control and water quality improvement. The control scale is more focused on smaller plot scales, while implementation of RTC at larger watershed scale has

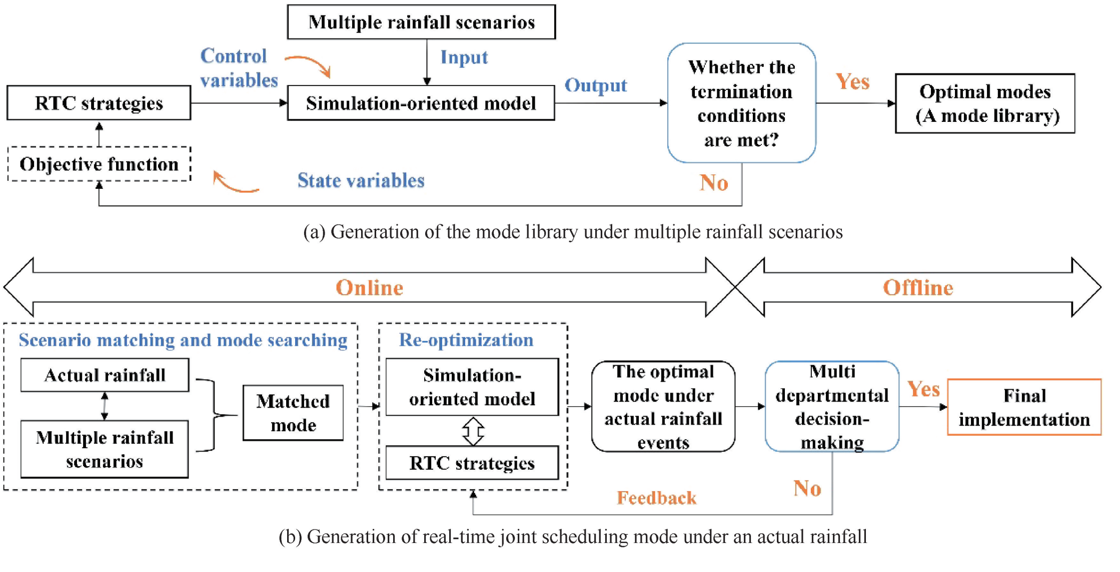


Fig. 5 Construction of the mode library and generation of a real-time mode for joint scheduling of multi-storage and discharge units

图 5 多蓄排单元联合调度的预案库构建与实时方案生成

Table 8 Summary of recent research on RTC-enhanced urban drainage solutions

表 8 城市排水解决方案中应用 RTC 的最新研究总结

System	RTC strategies	Models	Application location (size)	Optimization objectives	Control step
SS[100] *	MPC	PCSWMM	A detention basin in a Canadian city (162 ha)	Minimize the outflows from the basin to watercourses	Each 5 minute
SS[30]	MPC	InfoWorks ICM	A closed-watershed landscape site in Beijing's Tongzhou District, China (30 ha)	Minimize energy consumption caused by device operation and overflow control	Each 5 minute
SS[135]	RBC, RL	EPA SWMM	Hague area of Norfolk, Virginia USA (0.37 ha)	Minimize the total flooding throughout the stormwater system, maintain target pond depths, and minimize the export of TSS from the ponds	Each 15 minute
SS[121]	MPC	EPA SWMM	An urban watershed located in Ann Arbor, Michigan, USA (400 ha)	Maximize pollutant removal and minimize flood	Each 15 minute
SS[139]	MPC	EPA SWMM	A stormwater network of a critical sector at the Lille University campus, France (30 ha)	Flood mitigation by increasing the retention tank capacity without modifying any network's elements	Each 10 minute
SS[101, 159]	RBC	EPA SWMM	the Jin'an area in Fuzhou City, China (5401)	Flood control	Unkonwn
CSS[154] **	MPC	Mike Urban	The Lyngholm cloudburst project in Copenhagen, Denmark (224 ha)	A trajectory of control actions for the inflow of stormwater to the combined sewer system to mitigate CSO	Each 5 minute
CSS[32]	MPC	EPA SWMM	A sewer system of the eastern part of Casablanca, Morocco (4160 ha)	Minimize CSOs by maximizing the treated volume of polluted water at the WWTP	Each 30 minute
CSS[124, 160]	RL, MARL, MPC	EPA SWMM	A combined sewer system in Chaohu City, China (2645 ha)	CSO reduction and flood mitigation	Each 10 minute
CSS[144]	GA-based RTC	Simuwater	A combined sewer system in a Chinese city (900 ha)	CSO reduction	Each 5 minute

Notes: * SS means Stormwater systems. ** CSS means Combined sewage systems.

received some attention, albeit less frequently[32]. The main control objects are actuators such as sluice gates, pumps and valves. Control actions such as adjusting the height of gates, the opening status of valves, and On/Off status of pumps are usually executed in each 5, 10, 15 or 30 minute step, based on the monitoring water level and pollutant concentration data, to control the inflow and outflow of inlets of the sewer/stormwater system, diversion wells and detention ponds.

3.5 Challenges and future directions

3.5.1 Optimization considering future uncertainties

Future climate change and urbanization bring numerous uncertainties, including the increased frequency of extreme weather events, population growth, and changes in resource demand. Joint scheduling optimization, by incorporating uncertainty analysis, can develop more robust and flexible scheduling plans, ensuring that systems maintain stable and effective operations in changing environments. This paper suggests two promising methods, robustness pathways and adaptation pathways, for developing robust, resilient, and sustainable urban stormwater management strategies that can adapt to future uncertainties (Fig. 6).

Robustness pathways involve designing joint scheduling systems that can perform effectively under a wide range of potential future conditions. This approach emphasizes the incorporation of flexibility, redundancy, and adaptability to ensure the system maintains its functionality and resilience across various scenarios. For the GGB(E)-integrated system, based on different future rainfall scenarios and urbanization scenarios, multiple rainfall-urbanization combination scenarios can be formed. Under each combination scenario, a corresponding optimal scheduling strategy would be generated, and the optimal scheduling strategies under multiple combination scenarios ultimately form a joint scheduling contingency plan database. Adaptation pathways focus on developing phased strategies that can evolve over time in response to new information and changing conditions. This approach emphasizes continuous learning and adjustment based on the results and feedback of the previous phase to generate the next phase's strategy,

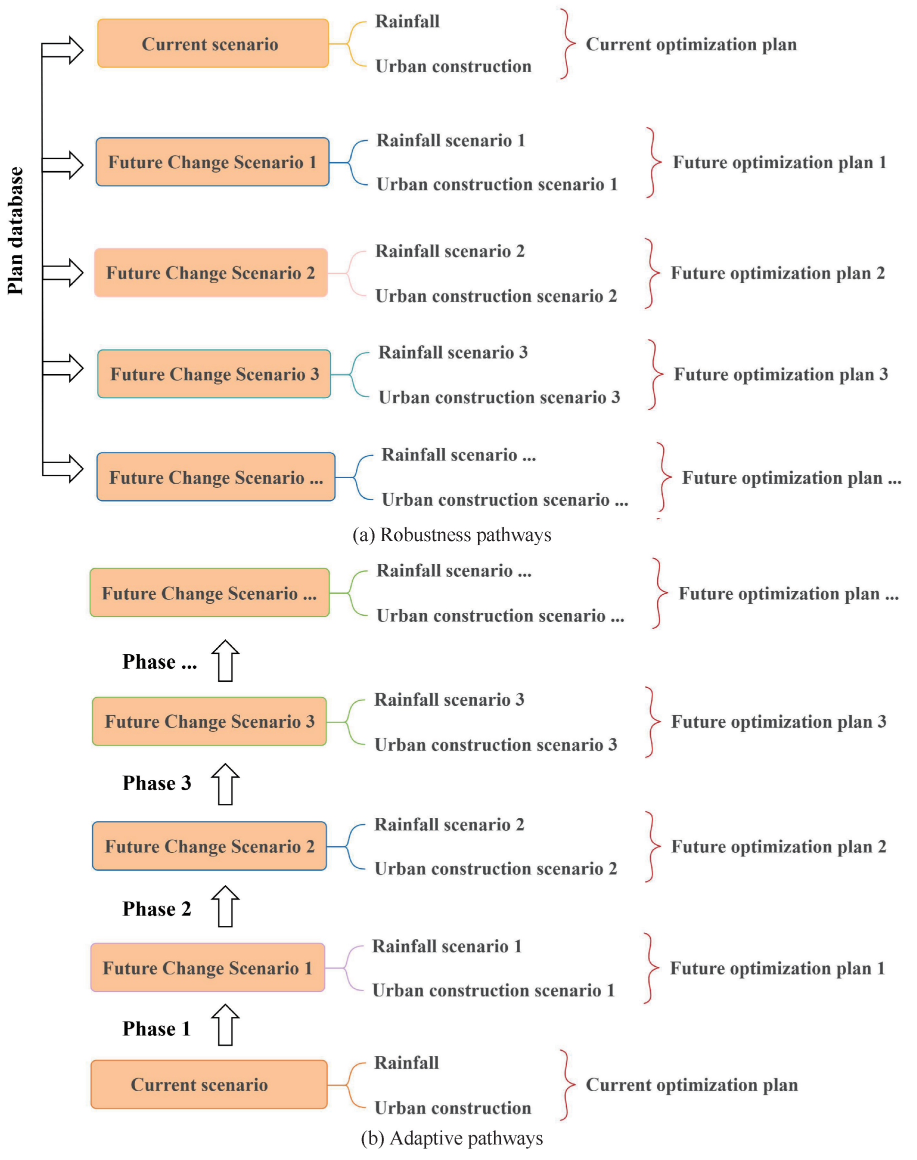


Fig. 6 Robustness pathway and adaptive pathway methods for the optimization strategy design of the GGB(E)-integrated system to address future uncertainties

图 6 应对未来不确定性的 GGB(E)融合系统优化策略设计的鲁棒性路径和自适应路径方法

thereby ensuring that the system remains effective and efficient. The interval between the previous phase and the next phase can be long-term or short-term, such as between events or between years.

3.5.2 Optimization considering mute feed effect of flood and waterlogging in different scales

Due to the inclusion relationship of geographic spatial locations and hydrological connections, there exists a mute feed effect of flood and waterlogging in urban, sub-basin and basin scale[24]. The construction and operation of flood prevention and drainage projects at one scale can directly impact flood and waterlogging conditions at the other two scales. To improve the drainage resilience of urban areas in response to extreme rainfall events, it is very important to consider the mute feed effect of flood and waterlogging in the joint scheduling optimization of multi-system storage and discharge units.

Coupling watershed flood model and urban waterlogging model is a feasible way to study the mute feed effect of flood and waterlogging in urban, sub-basin and basin[24,161]. Coupling models can be divided into nested models and hierarchical models (Fig. 7). The nested model integrates the runoff model, urban drainage network and river network hydrodynamic models, which embeds the urban waterlogging model as a sub-model of the watershed flood model. Commonly used models such

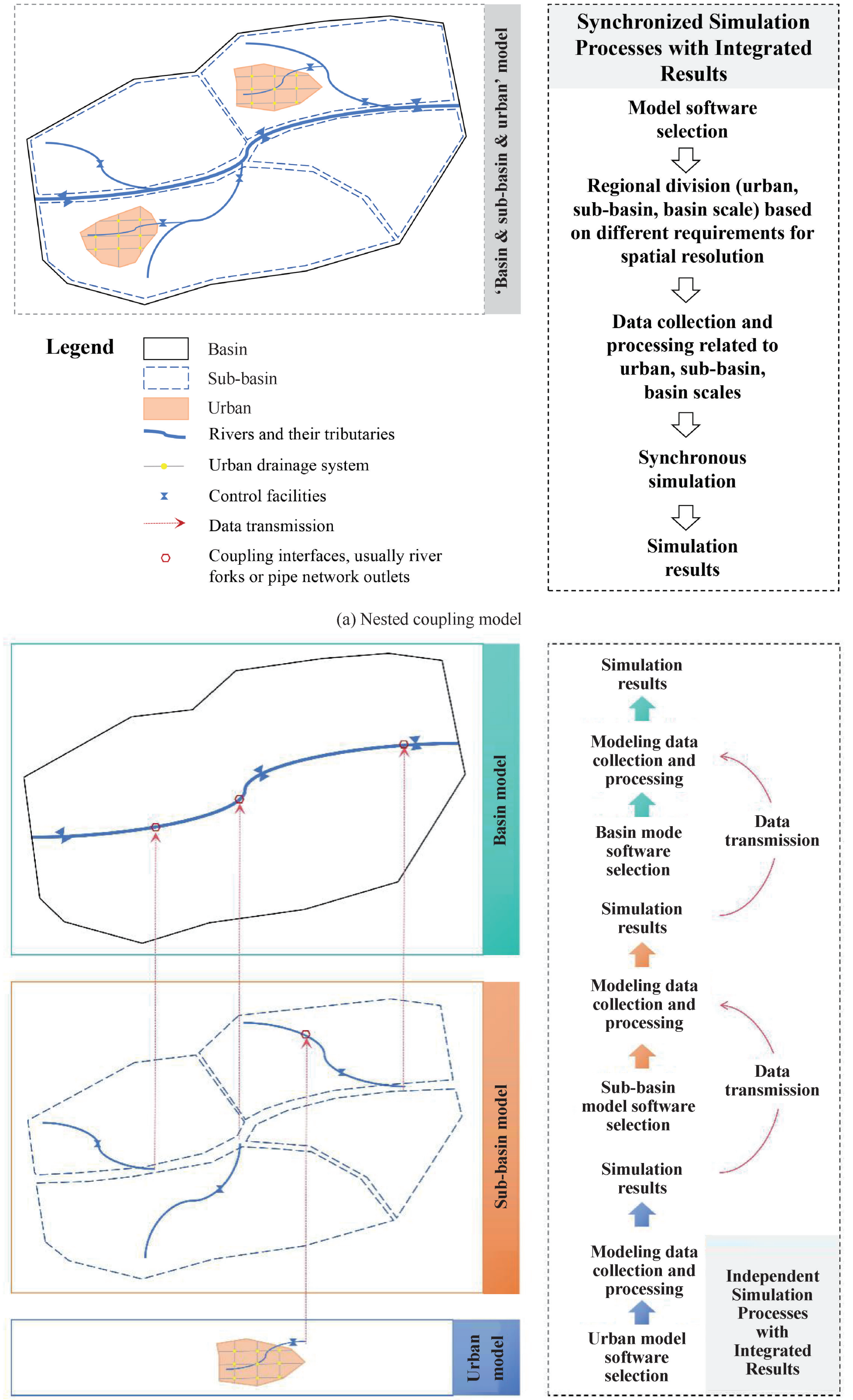


Fig. 7　Coupling of watershed flood model and urban waterlogging model

图 7　流域洪水模型与城市内涝模型的耦合

as MIKE FLOOD, PCSWMM, InfoWorks ICM and XPSTORM all have nested coupling structures or provide coupling interfaces. The nested structure can maintain the consistency of the overall model on a large scale, while providing higher accuracy simulations in local areas (urban area). For example, LIU et al. (2023)[162] applied the Grid-based Runoff Generation Model (GRGM) to forecast flood, which divided the entire area into a unified spatial grid cells of 10 × 10 m and distinguished between watersheds and urban areas through differences in runoff generation patterns. LI et al. (2023, 2024)[24,163] coupled a watershed runoff model and a river network hydrodynamic model to study the mute feed effect of urban waterlogging and watershed flood, as well as the standard syntaxis of urban drainage and sub-basin flood standards.

The hierarchical model adopts a multi-level modeling strategy, that is, using different types of models at different geographical scales, which can effectively solve the problem of scale differences and improve the accuracy and applicability of the overall model. The hierarchical model connects different levels through specific interfaces and data exchange mechanisms. Currently, multi-scale model coupling still faces challenges in the conversion and consistency of parameters, boundary conditions, and time steps across different scales, as well as computational resource demands and result robustness.

3.5.3 Establish an information sharing and feedback platform

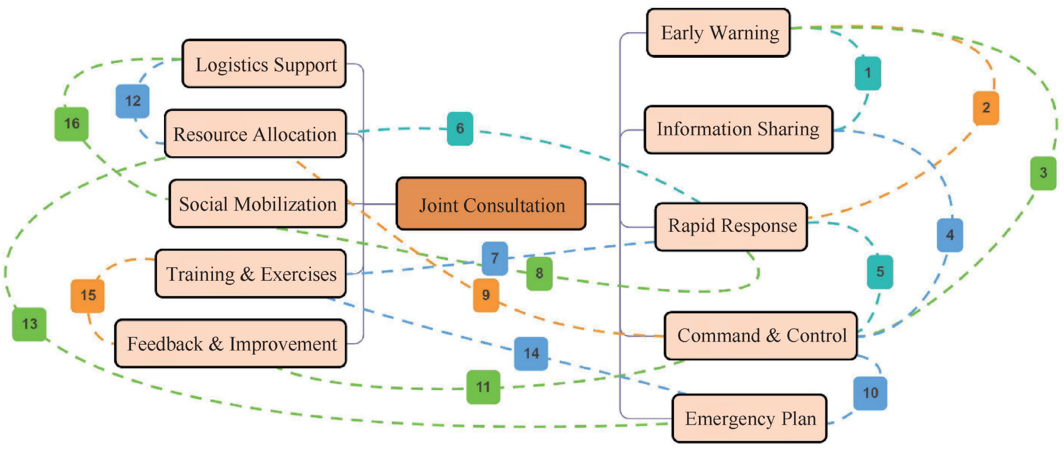
The GGB(E)-integrated system requires a multitude of data to serve as evidence for problem identification, model validation, and final decision-making. In this context, the establishment of an open platform for sharing urban information data is imperative. With the support of monitoring systems and equipment, real-time information sharing across departments and regions can be achieved, breaking the information cocoon and integrating various urban hydrological, meteorological, geographical and other information. This contributes to enhance response speed, optimize resource allocation and improve the accuracy and scientific basis of decision-making.

In addition, through the application of the Internet of Everything (IoE) and a Big Multimedia Data (BMD) approach, the system solution can provide effective services for the public and relevant departments, such as timely notification of warning and forecasting information, guidance of risk locations, refuge areas, evacuation routes, etc., especially in emergency situations. This to some extent responds to the People-Centered Smart Cities (PCSC) concept advocated by UN-Habitat since 2018, which is a multi-stakeholder approach for urban digital policy making, encouraging the digital rights for citizens, collaborative development through sharing, and technological and data sovereignty (https://unhabitat.org/digitalcitiestoolkit/#).

3.5.4 Decision execution via multi-departmental collaboration

The multi-system storage and discharge units are managed by different departments, including water resources, meteorology, transportation, emergency management, housing and construction, etc. Through interdepartmental collaboration, better information sharing, resource allocation, and task coordination can be achieved, thereby enabling a rapid response to heavy rainfall events and reducing losses. Fig. 8 illustrates 16 potential interdepartmental collaboration mechanisms involving pre-, during-, and post-rainfall stages.

Before heavy rainfall events, the emergency management department should convene a joint consultation meeting with meteorology, water resources, water affairs, and traffic management departments. The meeting should focus on the trend analysis and early warning forecasts of rainfall and floods and deploy relevant response measures. Under the guidance of the early warning information, relevant departments promptly initiate emergency response, mobilizing emergency rescue forces and supplies. During heavy rainfall events, all relevant departments should implement the specific measures deployed. Especially, public security, rescue and medical departments should be on-site to carry out emergency rescue operations, evacuate residents, and handle secondary disasters. Power supply, telecommunications, and water supply departments should ensure that backup systems are in place to maintain basic services. In addition, real-time updates on rainfall and flood conditions should be shared continuously. Communication channels must remain open to ensure all departments are informed and can adjust their strategies accordingly. After heavy rainfall events, all relevant departments should reconvene to assess the emergency response effectiveness, identify issues, and propose improvements. Through this structured process,



Description of Collaboration Mechanisms between Different Systems			
1	Early warning information transmission	9	Command & Control system command resource allocation
2	Warning information triggers response	10	Command & Control system makes decisions based on emergency plans
3	Warning information for command system decision-making	11	Command & Control system provides feedback
4	Real-time data for command system decision-making	12	Logistics support system ensures resource supply
5	Rapid response teams receive instructions and execute tasks	13	Resource allocation system allocates resources according to emergency plans
6	Rapid response teams receive resource support	14	Validate emergency plans through exercises
7	Rapid response teams enhance professional capabilities	15	Provide feedback through exercises
8	Rapid response teams are supplemented by social forces	16	Social forces provide additional support

Fig. 8 Interdepartmental collaboration mechanisms

图 8 跨部门协作机制

departments can enhance their overall response capabilities and minimize the impact of future heavy rainfall events.

4 Conclusions

This paper systematically reviews the current status of the GGB-integrated system for urban excessive runoff regulation in two aspects: layout optimization and joint scheduling optimization. Based on the gaps between the current status and practical application requirements, this paper proposed comprehensive optimization frameworks for layout optimization and joint scheduling optimization with the expectation of serving to solve practical problems.

The multi-objective optimization approach is mainly utilized to determine the layout configuration of the GGB-integrated system for mitigating urban inundation. The objective of optimization is mainly focused on runoff control, which is followed by cost-related objectives, and then ecological benefits-related objectives. The combination of model and algorithm "SWMM+NSGA II/III" may be the most promising tool for obtaining a set of Pareto optimal solutions. The MCDA methods, mainly TOPSIS and AHP, are further applied to determine an optimal solution for practical applications, prioritizing the best cost-effectiveness. The key components of the layout optimization process mentioned above mainly focus on the layout optimization of the GG-integrated system and LID planning, while the blue system infrastructures have not fully considered into optimization. Some studies, while incorporating retention ponds or water bodies into the optimization, are limited by their small research scale and simple scenarios, which do not adequately represent the complexities of the real-world systems. Based on these, this paper proposes innovative strategies and methods, involving responses to future uncertainties, the incorporation of blue infrastructure in optimization framework, and a comprehensive consideration of the impacts of multiple scales and multiple objectives on optimization outcomes, to enhance the feasibility and effectiveness of the GGB-integrated system in practical applications.

Coupled simulation models and RTC strategies are commonly used for joint scheduling optimization of UDSs. MPC is probably the most successful RTC strategy due to its adaptability in handling complex systems that require considering multiple objectives and constraints simultaneously. Current research on the application of RTC strategies to UDSs is mostly limited to the plot scale, with more attention paid to the control of individuals or small facilities, rather than the entire system. There is a lack of methods to automatically determine the regulation of multi-system facilities in real time based on the actual rainfall-runoff process. Furthermore, there is no consideration of emergency facilities for extreme situations, leading to a lack of practical engineering feasibility for real-world systems. To overcome the gaps and improve the robustness of GGB (E)-integrated system, this paper proposes a comprehensive joint scheduling optimization framework for multi-system storage and drainage units. This framework is dedicated to employing innovative strategies and methods to enable complex urban drainage systems to rapidly respond to variable rainfall events, thereby maximizing urban drainage safety.

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(责任编辑　王海锋)