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Optimization of Real-Time Control Approach: Number, Placement, and Proportional–Integral–Derivative Control Rules of Flow Control Devices in Distributed Flood Routing

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Abstract: Climate change, through more frequent extreme weather events, and urban sprawl, by increasing runoff, are two critical threats to drainage networks, impacting both public health and property. Augmenting drainage networks to withstand additional stress by enlarging conduits or constructing new detention facilities requires a significant financial investment. The goal of this study is to enhance urban resilience by optimizing real-time control (RTC) systems for drainage networks that optimize the flow control devices (FCDs), which could mitigate the need to invest in major construction costs. RTC is an approach that can help mitigate flooding in urban areas. This study is the first to optimize feedback controllers in SWMM, as well as the first to simultaneously optimize the number, location, and proportional–integral–derivative (PID) controllers for FCDs through two nested genetic algorithms (GAs), and especially within a unified environment (i.e., Python), which led to more efficient management of the process, thereby enhancing the efficiency of urban drainage network optimization. This study examined the impact of optimized RTC on the urban drainage network (UDN) in a part of New Orleans, LA, USA, under 1-, 2-, 5-, and 10-year storm events. The optimized RTC resulted in an improvement of up to 50% in network performance during a design storm. The results demonstrate the applicability in an urban environment where storms, flooding, and financial investments are critical to the management of stormwater drainage.

Keywords: RTC method; optimization; genetic algorithm; PID controllers; FCD; SWMM; UDN

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1. Introduction

Management of drainage networks in urban areas is one of the main concerns of municipalities across the world, since it directly influences the health and comfort of city dwellers. Conventional drainage networks have been designed based on historical precipitation data, and this existing infrastructure does not account for changes in climate, land use, and stormwater or sewage quality. One critical change predicted into the future is larger peak floods due to climate change around the world [1–7]. Increasing the world's temperature has lots of impacts, and one of them is increasing rainfall intensity. Some projected rainfall indices conform to the Clausius–Clapeyron relationship, which suggests an approximately 7% increase in rainfall for each 1 °C of temperature rise; there is substantial evidence indicating that this scaling is influenced by the frequency of extreme rainfall events. In cases involving less frequent, longer-return-period events, even greater increases are observed, leading to a phenomenon known as super-Clausius–Clapeyron scaling [8]. Some models show significant increases in relative percentage change, with a maximum of 70.19% in projected rainfall intensity [9]. Climate change has emerged as a major factor influencing the design of urban drainage systems. More extreme rainfall events, exacerbated by climate change, substantially increase the flood risk in cities.

Changes in land use also contribute to larger floods (i.e., increases in the impervious surfaces). Moreover, if a combined network is considered (stormwater plus sewage water), the problem will be even more aggravated, since increased population has a direct effect on the capacity of the combined networks. Older existing infrastructure, designed for lower flows, is not able to convey the increase in stormwater and will create flooding.

Also, it should be noted that the cities have significant limitations at the outlet point (i.e., wastewater treatment and environmental capacity of the river). Some cities are forced to release wastewater into rivers or nature without sufficient time for the treatment process. Annually, more than 1.2 trillion gallons of untreated sewage, stormwater, and industrial waste flows into United States rivers because of overburdened treatment systems [10].

There are a few methods that have the potential to decrease the outlet discharge in urban areas, including green infrastructure, detention or retention ponds, and RTC. For the existing network or infrastructure, RTC may provide a solution that considers a dynamic stormwater network instead of a traditional one. The RTC system is a reliable and cost-effective methodology [11] that can improve hydraulic performance by utilizing the existing drainage system [12–14].

The RTC method, by using solenoid gates (e.g., sluice gates, slide gates, knife gates, etc.) and sensors, helps to use the free capacity of the drainage network to decrease the outlet discharge of the drainage network. The aim of real-time management of the nodes of a network is to regulate the flow depth continuously in any tributary of the network, based on the data obtained from installed sensors of the drainage network or rainfall forecasts. Thus, by installing sensors and solenoid gates in the drainage network, a static system will be able to respond and adapt [15].

It can be concluded that RTC leads to a more dynamic and, ultimately, reliable stormwater network in terms of flooding, by increasing the detention capacity of the network using the existing capacity of the conduits. Also, this method delivers better water quality at the outlet due to increased detention time. Finally, there are various operational advantages of the RTC method that can be quantified using different metrics. The primary objectives typically include minimizing combined sewer overflows (CSOs) to the environment and reducing urban flooding. These are measured by water volumes, pollutant loads, oxygen concentration in the receiving water, damage cost, or risk. Secondary goals involve reducing energy consumption and operational costs and minimizing actuators' wear and tear to extend their lifespan. Additionally, as suggested by Campisano et al. [16] and Vitasovic [17], operational goals may include preventing sediment deposition in sewers, managing flows during construction or equipment failures, and optimizing flow to wastewater treatment plants (WWTPs) [18].

While numerous advantages of the RTC method have been cited, a crucial issue that significantly influences its performance has not been fully addressed: the selection of flow control device (FCD) locations is critical to the success of an RTC strategy. Moreover, installing an FCD in the right place within the drainage network but without a proper control rule can have an adverse effect on the results of the RTC method. The main aim of this study is optimizing the RTC method in the drainage network in order to find the optimal quantity, placement, and control rules of the FCDs with dynamic wave flood routing.

Previous research efforts have focused on static or steady-state flood routing to simulate drainage network behavior [19,20]. These approaches typically involve simplifying assumptions that treat the network as a series of isolated components, with the hydraulic conditions at each node or conduit assumed to be constant over time. However, such static models fall short of capturing the dynamic interactions that occur within a real drainage network. In reality, the behavior of an urban drainage network is inherently dynamic and interconnected. Any changes at each node can significantly influence the hydraulic conditions at other nodes throughout the network (e.g., backwater effect). For instance, the activation of an FCD at one location can alter flow rates, water levels, and pressures at multiple downstream and upstream nodes. This interconnectedness means that static evaluations are insufficient for accurately assessing the performance and capacity of the network, especially when it comes to implementing FCDs to manage and detain stormwater. Dynamic flood routing, on the other hand, provides a more realistic and comprehensive approach. It accounts for the temporal variations in flow and the complex hydraulic interactions between different components of the network. By simulating the transient behavior of water as it moves through the system, dynamic models can more accurately predict the impact of various control strategies, including the deployment of FCDs. This approach allows for a better understanding of how to optimize the network's capacity to detain water, reduce flood risk, and improve overall system performance. Therefore, it is crucial to move beyond static modeling and embrace dynamic flood routing methods. These methods enable a more accurate and effective evaluation of urban drainage networks, ensuring that the placement and operation of FCDs are optimized in a way that reflects the true behavior of the system under varying conditions. This shift towards dynamic modeling represents a significant advancement in the field of urban stormwater management, offering more reliable and robust solutions for mitigating flooding in complex urban environments.

Previous studies have dealt with the optimization of drainage networks, and the results show an increase in the performance of the RTC by up to 40 percent [14,21]. However, these studies did not employ dynamic wave flood routing, resulting in outcomes that are not clearly articulated or defined. Additionally, not only did none of these studies simultaneously address the optimal quantity, location, and PID settings for FCDs, none of them optimized the number and PID settings of FCDs either. Furthermore, none of these studies integrated the entire optimization process within a single computational environment (i.e., Python), which would lead to more efficient management of the UDN. This fragmentation limits the ability to comprehensively address the complexities of urban drainage systems and undermines the potential for achieving optimal performance and efficiency. This study aims to address the gaps in previous research by conducting the entire optimization process (i.e., identify the optimal quantity, placement, and PID controllers) within the Python environment, including the reading, writing, manipulation, and optimization of the SWMM file. Additionally, this study serves as an evaluation of the RTC method's effectiveness in a flat drainage network (i.e., the slope of the conduits is around 0.0005 ft/ft). The RTC method needs two interrelated main components to ensure its best performance in the drainage networks. The first component involves the identification of optimal locations and numbers of FCDs, and the second component is the best control rules to regulate the FCDs. Therefore, the primary objective of this project is to gain a deeper understanding of these components, namely, the optimal placement, numbers, and control rules of FCDs.

2. Materials and Methods

2.1. Study Area

In this study, the data and maps of a section of the New Orleans drainage network, which were obtained from the New Orleans Sewer and Water Board (S&WB), are utilized to conduct a comprehensive analysis. This work, unlike many previous studies that were conducted on a small watershed with few junctions, conduits, or pumps, was carried out on a large-scale area in New Orleans spanning 281 acres and encompassing 147 subcatchments. The network includes 167 conduits, extending over a cumulative length of 46,072 feet, which serve as the primary channels for stormwater conveyance, with a range of diameters between 1 and 10 ft, and slopes in a range from 0.00023 ft/ft up to 0.06 ft/ft. Additionally, the network features 167 manholes that provide access points for maintenance and monitoring, along with one outfall, which is the final discharge point for the collected stormwater in this study.

In this study, all detention ponds were deliberately removed from the existing drainage network. This decision was made to allow for a pure evaluation of the RTC system's performance on the conduits of the drainage network. By excluding the capacity provided by the detention ponds, this study aims to assess the effectiveness of the RTC system in managing stormwater solely through the dynamic regulation of FCDs and existing conduit capacities. This approach ensures that the evaluation focuses exclusively on the RTC system's capabilities, without the influence of additional storage provided by detention ponds.

Figure 1 provides a visual representation of the case study area, and Figure 2 highlights the layout of the existing stormwater drainage network with existing detention ponds, including the sub-catchments, conduits, manholes, and outfall.

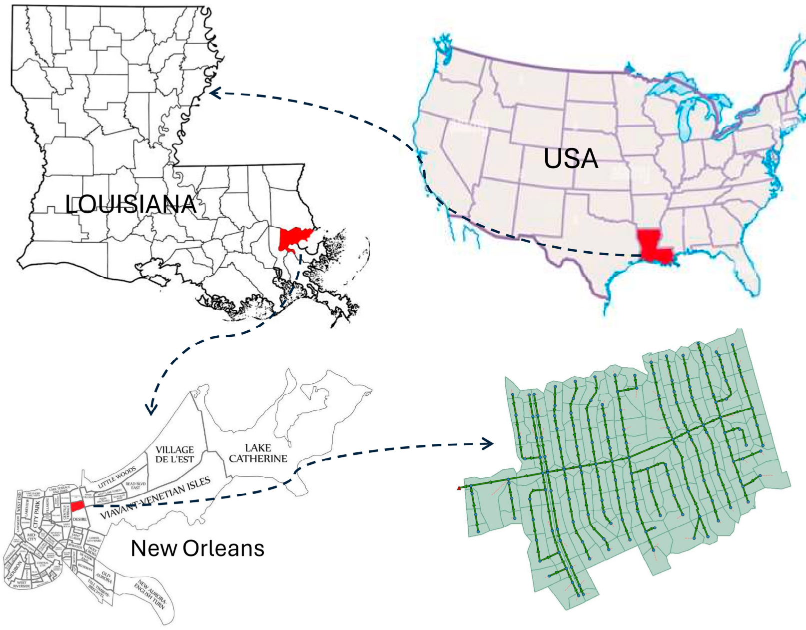


Figure 1. Drainage network case study (New Orleans, LA, USA).

Figure 2. Locations of detention ponds in the existing drainage network that were removed.

The New Orleans urban catchment is a flat drainage network, which was designed based on a 2-year storm [22]. Roughly 96% of the conduits' slope is less than 0.005 ft/ft. Unlike many researchers who have simplified drainage networks into a few conduits and used steady-state conditions [23], in this study, no change was made to the drainage network model (i.e., SWMM file), in order to simplify the calculation, since the aim of this project was evaluation of the RTC method's effects on the performance of a real drainage network, and simplification of this network would not result in the actual outcomes.

2.2. Modeling Tools (SWMM, SWMM_api, and PySWMM)

The drainage network was modeled using a calibrated version of the Environmental Protection Agency's (EPA) Storm Water Management Model (SWMM) [24], which includes junctions, links, and sub-catchments to effectively route floodwaters through the system using a distributed dynamic wave method. The hydraulic and hydrological simulations within the SWMM were executed entirely in a Python 3.11 environment, leveraging the capabilities of SWMM_api and PySWMM, two open-source Python wrappers. These tools facilitate the advanced design and simulation of RTC systems within drainage networks. The SWMM model utilizes several key modules: a storm module, an infiltration module, and a flow propagation module. Each of these modules encompasses multiple modeling options, the specific choices of which are detailed in Table 1.

Table 1. SWMM modeling options.

No	Option	Description
1	Storm Design	Chicago Storm Hyetograph
2	Force Main Equation	Hazen–Williams
3	Infiltration Method	Horton's Equation
4	Routing Method	Dynamic Wave

Urban drainage networks are inherently complex due to their integration of hydraulic and hydrological processes. One of the critical hydrological parameters in catchment areas is the design storm. In the context of the New Orleans drainage system, the design storm is based on a 2-year return period. However, certain areas within the network do not even meet this criterion, highlighting the system's limited capacity and low freeboard [22]. This indicates that the drainage network operates near its maximum capacity, with minimal available free capacity for additional detention, posing significant challenges for optimizing the RTC method. These constraints necessitate the optimization of the RTC method by leveraging the existing free capacity within the conduits, without resorting to structural modifications such as enlarging conduits or constructing detention ponds.

The United States Environmental Protection Agency's Storm Water Management Model (SWMM) is a globally recognized tool for simulating urban rainfall and runoff [25]. In this study, the primary drainage network model was developed using version 5.2.4 of the SWMM, with the Personal Computer Stormwater Management Model (PCSWMM) interface provided by Computational Hydraulics International (CHI). Additionally, the edited version of the input file (i.e., the .inp file of the SWMM engine), generated using Python wrappers (i.e., PySWMM, and SWMM_api), was evaluated using PCSWMM. PCSWMM enhances the capabilities of the SWMM engine by providing advanced graphical tools, simulation management, and analytical features, making it an indispensable resource for water resources engineers and planners. In this research, Kerby's method was used to estimate the time of concentration of the watershed. The Kerby method provides a reliable and effective means of modeling the hydrological behavior for small urban watersheds. It typically generates the lowest time of concentration (TC) values compared to other methods, such as NRCS and the Morgali and Linsley method [26].

$$t_c = 0.828 \times \left[\frac{nL}{S^{0.5}} \right]^{0.467}$$

where t_c is the time of concentration (min), L is the length of the channel from headwater to outlet (ft), S is the average slope (ft/ft), and n is Manning's channel roughness/retardance coefficient.

The time of concentration for the basin was calculated using the Kerby method and found to be 21.5 min. However, for the purposes of this study, this value was rounded to 30 min to align with the recorded rainfall durations from meteorological organizations.

In this study, the Chicago method was used to design storms. The Chicago Storm Design Method, developed by Keifer and Chu in 1957 [27], is a widely used technique for creating synthetic design storms, particularly in urban hydrology [28]. This method is known for its ability to simulate realistic, intense urban rainfall events, which are critical for designing effective stormwater management systems in densely populated areas. The Chicago method relies heavily on intensity–duration–frequency (IDF) curves, which represent the relationship between rainfall intensity, duration, and frequency for a specific location. These IDF curves are derived from extensive historical rainfall data, capturing the statistical characteristics of rainfall events over various periods. In the United States, the National Weather Service has prepared IDF curves for each city, ensuring that accurate and location-specific rainfall data are readily available for this method. One of the key advantages of the Chicago Storm Design Method is its ability to more accurately reflect the peak intensity of urban storms. Urban areas, characterized by high levels of impervious surfaces, experience rapid runoff during intense, short-duration storms. The Chicago method is specifically tailored to account for these conditions, making it highly suitable for urban drainage design. It effectively models the sharp, intense rainfall peaks that are typical in urban environments, ensuring that stormwater infrastructure is designed to handle these critical conditions. Moreover, the Chicago method allows for the customization of storm duration and intensity based on local IDF data. This flexibility enables engineers to create tailored design storms that reflect the unique rainfall patterns and hydrological conditions of specific regions. By adjusting the storm parameters to match the local IDF curves, this method provides a more accurate and reliable basis for designing stormwater management systems. This customization is particularly valuable in diverse climatic regions, where rainfall characteristics can vary significantly.

Many recent studies and observations indicate an increase in both the intensity and frequency of extreme precipitation events. Over the past few decades, the Southeastern United States has experienced a significant rise in hourly rainfall intensity due to global climate change [29]. Additionally, the average duration of rainfall events has decreased as global temperatures have risen. For instance, one of the most severe storms in New Orleans in recent years occurred in 2019, within a span of less than 6 h. Therefore, in this study, a rainfall duration of less than 6 h was utilized, with a specific focus on the urban drainage network.

Given that the time of concentration (t_c) for the selected watershed is equal to 30 min, the storm design duration was set to half an hour for the basin. These events were designed with a rainfall interval of 6 min, providing detailed temporal resolution to capture the dynamic response of the urban drainage network. This approach ensures that the simulation accurately reflects the rapid changes in rainfall intensity and runoff that are typical of urban storms. Storm events for this basin were designed using the PCSWMM (Personal Computer Storm Water Management Model). The design storms, based on return periods of 1, 2, 5, and 10 years, utilized the Chicago method with 6 min rainfall intervals and a duration of half an hour. Figure 3 illustrates the IDF curves generated for these storms, and Figure 4 shows the design storms used in this study for the 1-, 2-, 5-, and 10-year return periods.

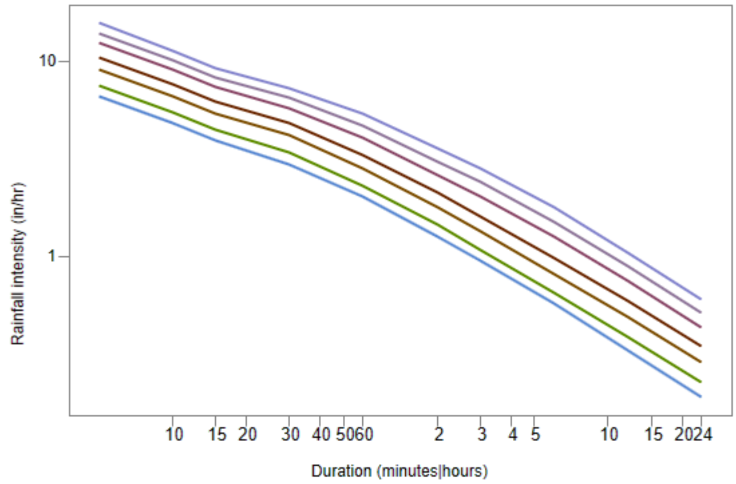


Figure 3. IDF curves for New Orleans (PCSWMM).

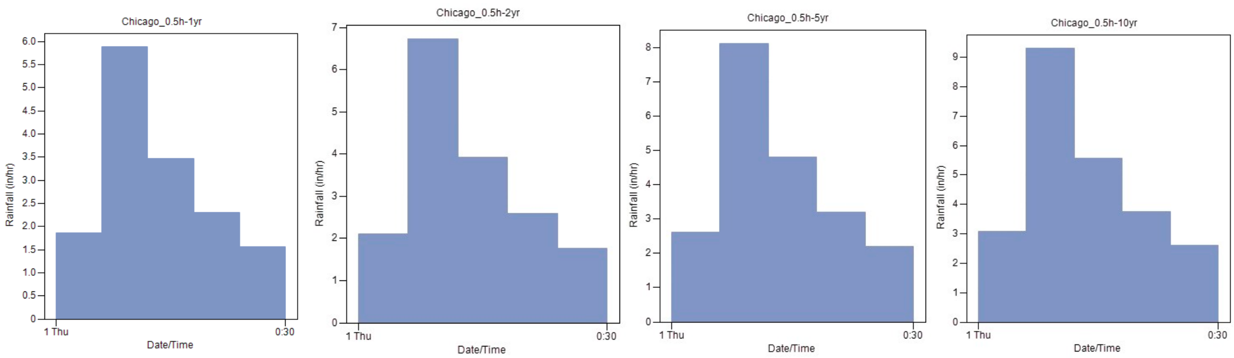


Figure 4. Design storms with return periods of 1, 2, 5, and 10 years, and a rainfall duration of 30 min.

Control Strategies in the SWMM

Control strategies in the SWMM refer to approaches used to manage the operation of UDNs by controlling the flow and water level in FCDs such as gates, weirs, orifices, and pumps. The SWMM can use several types of control rules to manage these devices. The first is rule-based control; this type manages the behavior of FCDs through predefined rules based on real-time system measurements such as water level and flow rate. The second is time-based control; this type controls the FCDs based on a predetermined schedule. For example, a pump may be turned on or off at specific times, regardless of the actual conditions in the system. The third is set-point control, which is a predefined level that the system should maintain, like water levels or flow rates, at specific target values. The fourth is feedback control (PID Control). PID control is a more advanced control strategy that is used to continuously adjust FCDs based on feedback from the system. For example, it can adjust the opening of a gate based on the deviation between a target water level and the current level. PID control rules are widely used in industrial and engineering applications to regulate processes such as gates, weirs, and pumps [30]. In this study, they controlled the flow and levels in drainage systems, helping to prevent issues such as flooding in the drainage networks, by continuously calculating an error value as the difference between a desired setpoint and a measured process variable based on the real-time measurements. The controller then adjusts the process through three mechanisms: Proportional (P): This component reacts to the current error, meaning that it adjusts the control output in proportion to the error at that moment. If the error is large, the correction will be large, and if the error is small, the correction will be small. Integral (I): This component responds based on the accumulation of past errors. It sums up the error over time and adjusts the control output to eliminate any residual error that the proportional term alone cannot correct. Derivative (D): This component predicts future error based on its rate of change. It responds to the speed at which the error is changing, providing a damping effect that helps to prevent overshooting and oscillation. The mathematical representation for these controllers is as follows:

$$u(t) = K_p \cdot e(t) + K_i \cdot \int_0^t e(\tau) d\tau + K_d \cdot \frac{d_e(t)}{d_t}$$

where $u(t)$ is the control output, $e(t)$ is the error at time t, and K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively.

In the SWMM, these rules define how the PID logic controls the hydraulic structures based on sensor data (e.g., water level, flow rate). PID controllers create adjustments in the network based on real-time data, enhance system efficiency, and mitigate the impacts of extreme weather. In this study, through interaction with the SWMM engine, the optimal PID parameters (i.e., K_p, K_i, K_d) were determined for each FCD.

2.3. Optimization Process/Methods

The problems that have been defined in this study (e.g., optimal placement of FCDs) represent a multi-objective optimization problem (MOP) because there are two or more conflicting objectives (i.e., the size of the conduits, the amount of free capacity in the network, hydraulic grade line (HGL), etc.). Unlike single-objective optimization, where the goal is to find the best solution according to one criterion, MOPs seek to find a set of solutions that offer a trade-off among the different objectives. These solutions are known as Pareto-optimal solutions. In many real applications, there exists more than one objective to be taken into account to evaluate the quality of the feasible solutions [31]. Like in this study, there are lots of parameters to be evaluated to select the best place and best control rules for the FCDs. A multi-objective optimization problem can be mathematically formulated as follows:

$$\text{Min } f(x) = [f_1(x), f_2(x), \ldots, f_k(x)]$$

$$\text{subject to:}$$

$$x \in \Omega$$

$$g_i(x) \leq 0, i = 1, 2, \ldots, m$$

$$h_j(x) = 0, j = 1, 2, \ldots, p$$

where f(x) is the vector of objective functions; x is the vector of decision variables; X is the feasible set, defined by the constraints $g_i(x)$ and $h_j(x)$; k is the number of objectives; m is the number of inequality constraints; and p is the number of equality constraints.

In this study, our goals were maximizing the area of the conduit $f_1(x)$, minimizing the hydraulic grade line $f_2(x)$, minimizing the surcharge at the conduits $f_3(x)$, and minimizing the percentage of the conduit filling $f_4(x)$. A solution x^* is Pareto-optimal if there is no other solution x such that

$$f_i(x) \leq f_i(x^*) \;\; \forall i \in \{1, 2, \ldots, k\} \text{ and}$$

$$f_j(x) < f_j(x^*) \;\; \text{for at least one } j.$$

where x can be defined as the conduit name, gate opening size, and number of the FCDs.

Optimization in stormwater management is typically a complex challenge, characterized by nonlinear relationships and nonconvex problem structures, which make it difficult to identify the single best solution [32]. A comprehensive review of the current state of GAs in the planning and management of water resources, provided by Nicklow et al. [33], highlights that evolutionary algorithms (EAs), and GAs in particular, are the most popular and successful optimization techniques for applications in drainage networks [23,33,34]. Accordingly, this study employs a genetic algorithm—specifically, a multi-objective genetic algorithm—to find the Pareto-optimal solutions (i.e., the FCDs' quantity, locations, and control rules). The process of determining the optimal locations of the FCDs within a drainage network can be highly time-consuming and prone to errors without using an optimization engine. For instance, selecting the potential locations among the largest conduits and based on the static storage capacity [21] in the system is possible; however, this trial-and-error approach is inefficient, requiring extensive time to conduct each test and subsequently assess the system's performance and ensure that the new configuration does not cause flooding in the other parts of the drainage network. Additionally, the vast number of potential positions for FCD placement complicates this process further. Therefore, leveraging optimization methods like MOGAs is essential for the efficient and accurate placement of FCDs. These methods significantly reduce the time and effort involved in the optimization process while minimizing errors and ensuring comprehensive system performance.

Optimizing any system requires a thorough understanding of the problem, as the process relies heavily on input parameters and fitness functions. Therefore, it is essential to define these inputs and their relationships before initiating the optimization process. A common method for optimizing urban drainage networks involves integrating a simulation model (i.e., the SWMM) to represent the hydrological and hydraulic processes. This model is combined with an optimization algorithm (i.e., genetic algorithm) to evaluate various alternatives and identify near-optimal solutions [20].

Python wrappers named SWMM_api and PySWMM read and execute the .inp file, which encompasses all elements of the drainage network, including nodes, conduits, outfalls, sub-catchments, detention ponds, time series, etc. Since the SWMM engine can only convert conduits into orifices or weirs, only conduits can inherently be designated as FCDs within the system. Therefore, all conduits are potential locations for the installation of FCDs. Converting a conduit into an orifice or weir within the SWMM substantially reduces its capacity to zero, thereby diminishing the overall detention capacity of the drainage network. In fact, the aim of using the RTC method is increasing the detention capacity of the network, not decreasing this capacity. Furthermore, this conversion changes various hydraulic calculations within the network, including water velocity and time of concentration. To mitigate these adverse effects, if the goal is to automate the entire process, one innovative approach is to introduce a new pipe with a short length (approximately 3 feet) into the network, downstream of any selected conduits, and then convert this new pipe into an orifice or weir, without affecting the main conduit. This method has a lesser impact on the network's hydraulic properties and more accurately simulates real-world conditions. Also, the last conduit connected to the outlet (i.e., outfall in the SWMM) should be exempted, since the newly created conduit in the drainage network is positioned downstream of the existing conduits and cannot be converted into an orifice or weir. At this point, all 166 conduits are ready to be introduced into the genetic algorithm (GA) scripts as potential locations for the installation of FCDs.

The genetic algorithm scripts in this study are designed to be user-friendly and highly customizable. At the initial stage, the user is prompted to specify the GA parameters and the number of locations to be considered for the optimal placement of FCDs. For instance, by default, the script might suggest that 10% of the total number of conduits in the drainage network could be a suitable number for conversion to an FCD. This initial input step is crucial, as it provides flexibility and control to the designers and managers. For example, it can be specified that the program should consider creating up to 10 FCDs within a particular area of the city. This limitation might be necessary due to various factors, such as financial constraints, operational capabilities, or physical space limitations within the urban environment. This customization enables a more efficient allocation of resources and ensures that the proposed solutions are feasible within the given constraints.

In this study, the GA was utilized to minimize the volumes of stormwater discharged into the receiving water body during a 2-year storm event, based on various placements, numbers, and PID controller schemes for FCDs. The effectiveness of the stormwater volume reduction achieved by the FCDs was assessed by integrating hydraulic analysis conducted with the Storm Water Management Model (SWMM) and a Python-based GA. Upon identifying a set of optimal conduits, a subsequent genetic algorithm (GA) was employed, in conjunction with the SWMM engine, to determine the optimal number of the FCDs and optimal PID controllers for each FCD. The process began with the program randomly assigning PID control rules to the initially selected and converted conduits. The performance of these assignments was then evaluated in terms of hydraulic conditions within the drainage network, including water levels, flooding, and the HGL at junctions of the drainage network. If the evaluation met the predefined conditions specified in the Python scripts, the configuration was deemed optimal for both placement and regulation. This configuration was then selected as the first optimal solution. If the evaluation did not meet the required conditions (e.g., increasing the performance of the entire system by more than 1 percent), the input file, which was modified to include an orifice or weir, was reverted to a previous stage before defining the selected conduits as an orifice/weir, and the process would start over. This iterative process continued until the optimal number of FCDs, optimal placements, and optimal PID control rules were identified for the entire drainage network. The GA interacted directly with the SWMM engine within the Python environment to iteratively refine and optimize the solutions. This interaction ensured that each potential solution was rigorously evaluated against realistic hydraulic simulations, facilitating the identification of the most effective configurations for flood mitigation and drainage management. A flowchart of the whole process is shown in Figure 5.

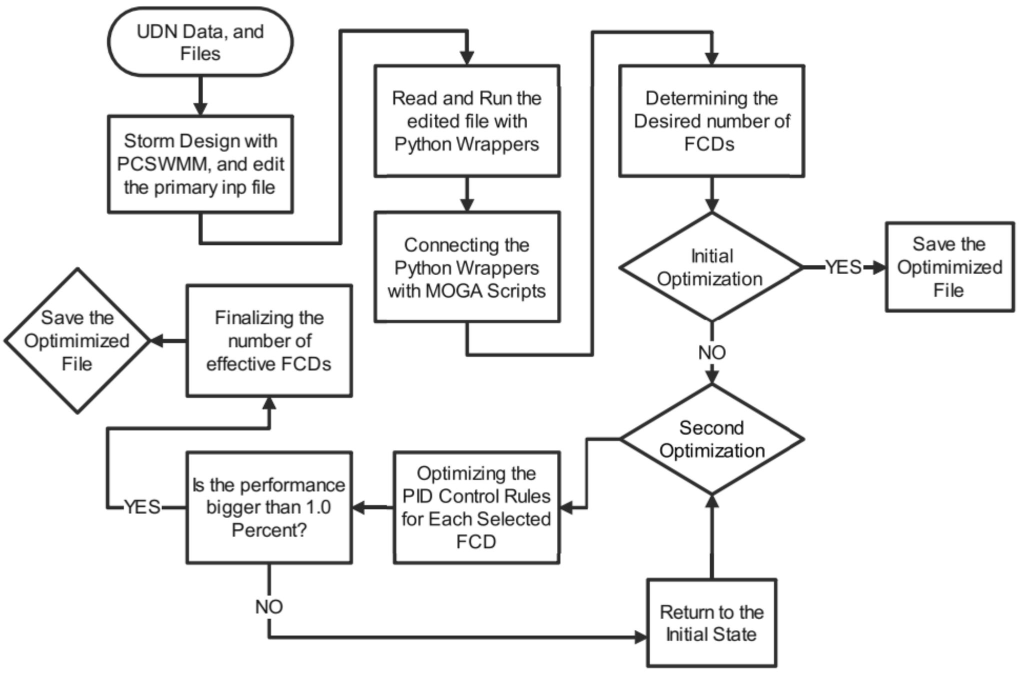


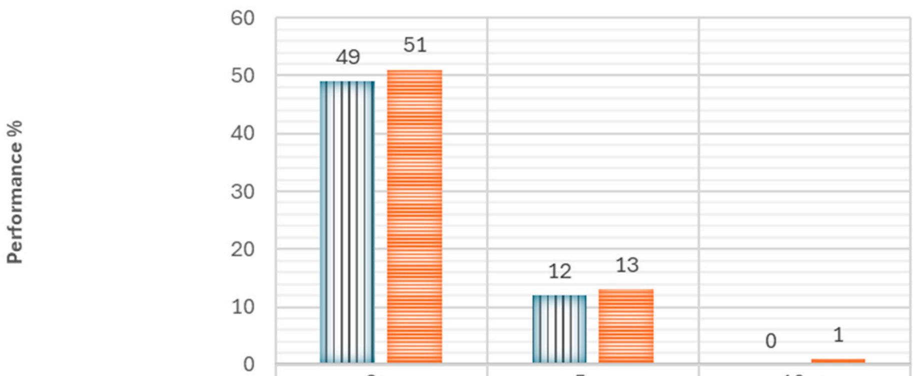
Figure 5. A schematic of the whole process.

3. Results

The primary goal of this research was to optimize the RTC method by determining the optimal location, number, and control rules for the FCDs to retrofit an existing drainage network with a dynamic control system. This system aims to maximize water retention within the network by utilizing the available capacity of the conduits during storm events. By doing so, it reduces the peak flow at the outlet and delays the time to peak flow, allowing the drainage network to handle large floods more effectively. This approach minimizes the need for constructing additional detention and retention ponds and eliminates associated costs.

After defining the design storms and entering the data into the .inp file by using PCSWMM, the SWMM model was executed and optimized using Python wrappers. The optimization was carried out based on the mutual results (i.e., hydraulic and numerical) obtained from the iterative optimization process. In this study, a two-stage nested optimization using a genetic algorithm was employed. At first, suitable points within the network were identified using a primary genetic algorithm with an appropriate fitness function and then passed as optimal points to the second stage of optimization. The primary goal of the initial optimization was to reduce the processing time. In this study, the number of suitable places was determined early in the computations based on the customer's input, and the maximum number of points that could be evaluated and converted into an orifice or weir was set at 20, which represents approximately 12 percent of the total conduits.

After evaluating the two methods through multiple tests (i.e., more than 20 separate runs)—one involving the selection of primary conduits (i.e., by using the primary genetic algorithm) to be examined within the program, and the other considering all conduits as potential locations for FCD installation—the results demonstrated that, with initial optimization using the genetic algorithm, the optimization time could be reduced to less than 5% of the normal state. Meanwhile, the quality and results of the two states differed by less than 2%, which is negligible. Figure 6 compares the results of the two scenarios, with and without initial optimization. Therefore, utilizing pre-optimization could enhance the model's execution efficiency by up to 20 times without significantly compromising the quality of the results. This is particularly important for optimizing large-scale networks. For instance, without initial optimization, each run could take over 25 h, whereas with initial optimization, the execution time for each optimization was reduced to 2 h. Therefore, two nested genetic algorithms were employed to optimize the locations, numbers, and PID control rules. It is noteworthy that, in this study, a six-core computer with a processing speed of 3.4 GHz and 64 GB of RAM was used.



	2 yr	5 yr	10 yr
With Pre-Optimization	49	12	0
Without Pre-Optimization	51	13	1

Figure 6. Comparison of performance of the models with and without initial optimization.

Next, the performance of the optimized RTC system across different storms was compared. It should be noted that the flood routing method in the SWMM was set to the dynamic wave method in order to obtain more realistic results from the city's drainage network. Additionally, another limitation was added to the genetic algorithm: any FCDs that did not contribute to a flood reduction of more than 1 percent were automatically excluded by the scripts as suitable locations for installing orifices or weirs. This process enhanced the performance of the entire system by disregarding low-impact FCDs.

All optimization scripts were written in such a way that the RTC system would not cause flooding in any part of the network. If this aspect was not included in network management and the installation of FCDs, the RTC system could easily lead to flooding in various other parts of the network. This is because creating any weir or orifice in the existing network will result in increased water levels at different points in the network, and if these increases and decreases in water levels are not managed intelligently, they can easily cause flooding elsewhere in the drainage network. Therefore, it seems that any use of the RTC method without using optimization is completely ineffective or must involve extensive, time-consuming trial and error.

The performance of the RTC system is based on the amount of free space within the drainage network's conduits, since the foundation of using the RTC method lies in utilizing the available capacity within the conduits of the drainage network. Hence, it was essential to assess the amount of free space in the drainage networks affected by each storm before proceeding. As noted earlier, in this study, the effects of four synthetic storms on the drainage network were analyzed. As shown in Table 2, the percentage of temporary flooding at various points in the drainage network due to each of the four studied storms was evaluated. It can be said that, with a reduction in the percentage of temporarily flooded points in the network, an improvement in the performance of the RTC system can be expected. In the following sections, the results of the simulation of the drainage network under the four mentioned storms, both naturally (without using the optimized RTC system) and with the use of an optimized RTC system, are demonstrated.

Table 2. The percentage of temporary flooding.

Events	The Percentage of Flooded Junctions
10 Years	100%
5 Years	70%
2 Years	30%
1 Years	10%

3.1. Impact of a 10-Year Storm

As shown in Table 2, due to a ten-year storm in the drainage network, referring to the SWMM results, all junctions experienced temporary flooding. Therefore, there was no free space available for the RTC system to use during critical moments in order to enhance the performance of the drainage network. The performance of the optimized RTC system under this storm was evaluated, as shown in Figure 7, and the optimized RTC was unable to improve the network's performance, since with the creation of any weir or orifice the optimization model encountered flooding errors and was unable to improve the performance of the drainage system.

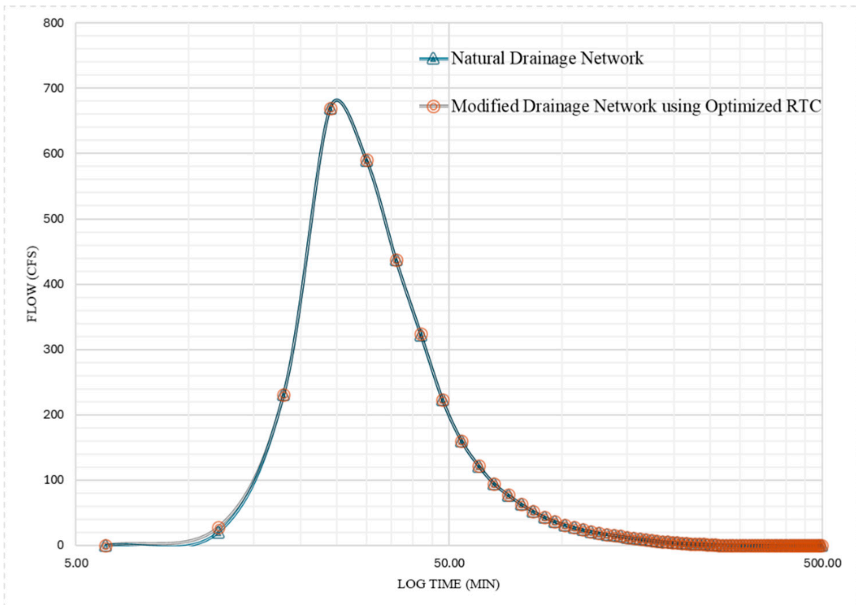


Figure 7. Hydrographs at downstream conduit: comparison with and without RTC system for 30-min rainfall duration and 10-year return period.

3.2. Impact of a 5-Year Storm

As shown in Table 2, 70% of the junctions in the drainage network experienced temporary flooding during the simulation by the SWMM. The results, as shown in Figure 8, indicated that the optimized RTC system can enhance the UDN's performance by up to 12% during a 5-year storm. Additionally, a reduction in peak flood levels and a delay in the peak time by approximately 5 min were observed. Thus, it can be concluded that an optimized RTC system could effectively delay the flood peak time and reduce its magnitude.

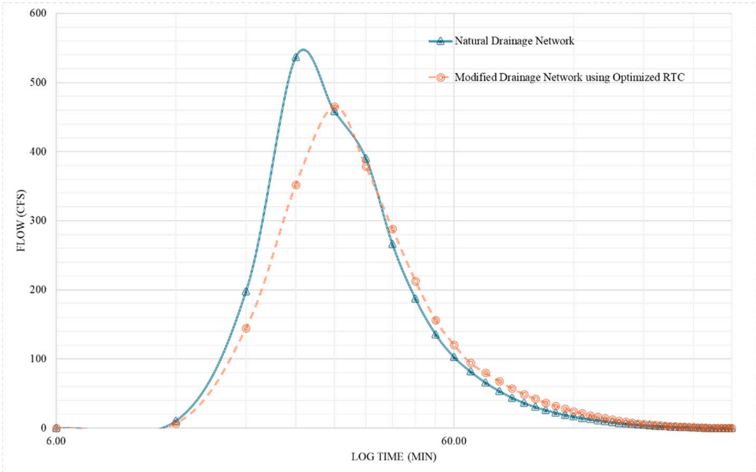


Figure 8. Hydrographs at downstream end conduit: comparison with and without the RTC system for 30-min rainfall duration and 5-year return period.

Moreover, as shown in Figure 9, the RTC system effectively reduced the flow velocity before the peak time, which can help mitigate damage to the UDN during floods. After passing the peak flood time (i.e., 30 min), the RTC system caused a slight increase in the flow velocity, which could help prevent post-peak sediment deposition. This, in turn, can reduce numerous problems associated with sediment accumulation in UDNs after big floods. Overall, it can be stated that the RTC system is capable of controlling and balancing the flow velocity to improve the system's performance in combating sediment deposition. This is also evident in the reduction in flow depth before the flood peak time by up to 11 percent (Figure 10). In essence, the RTC system can decrease the flow depth to improve flow conditions before the peak time and, after the peak, increase the flow depth in a balanced manner, leading to reduced post-flood sediment deposition.

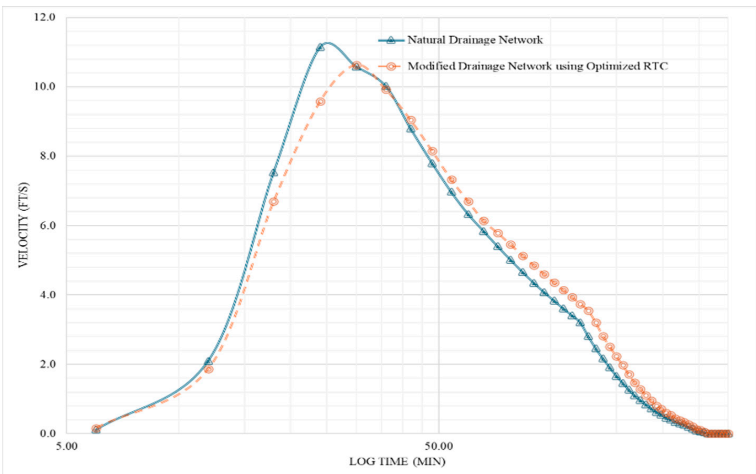


Figure 9. Velocity vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 5-year return period.

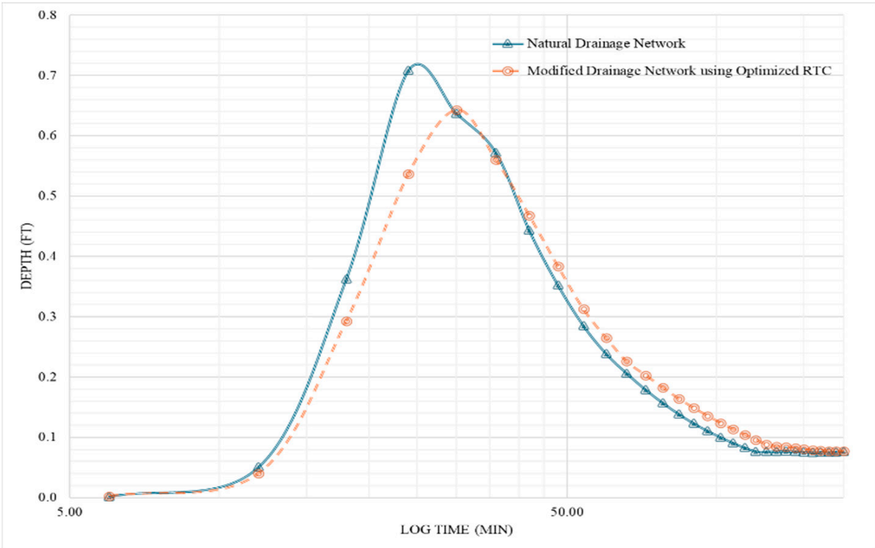


Figure 10. Depth vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 5-year return period.

3.3. Impact of 2-Year and 1-Year Storms

As shown in Figure 11, the impact of the optimized RTC system on managing a 2-year storm, which served as the design storm for the existing UDN, was thoroughly evaluated. The analysis revealed that, as depicted in Table 2, a 2-year storm led to temporary flooding in approximately 30% of the UDN's junctions, compared to a 5-year storm, which caused temporary flooding in 70% of the UDN's junctions. This comparison highlights the improved conditions in terms of available capacity within the network's conduits under the 2-year storm scenario. The results depicted in Figure 11 further demonstrate that the optimized RTC system achieved a 50% reduction in flooding, a significant accomplishment that underscores the RTC system's effectiveness in enhancing the resilience of the drainage infrastructure. This success is consistent with the findings of previous studies [14,21], confirming the reliability and efficiency of the optimized RTC system in mitigating flood risks within urban drainage networks.

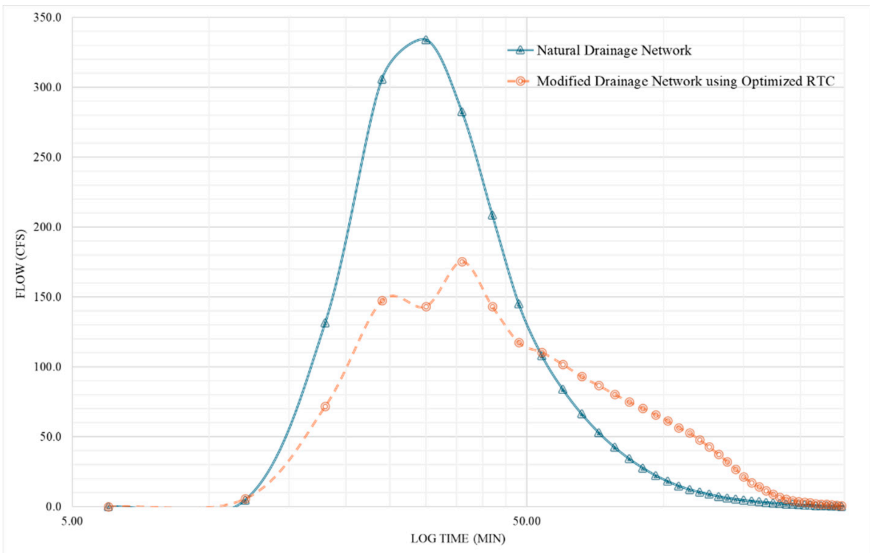


Figure 11. Hydrographs at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 2-year return period.

In the case of a 2-year storm, the optimized RTC system successfully delayed the peak time by 8 min, which represents an approximately 25% delay, considering that the original flood peak occurred within 30 min. This delay demonstrates the system's effectiveness in managing stormwater during critical periods. Furthermore, as illustrated in Figure 12, the RTC system was able to control and improve the flow conditions during the first 50 min of the storm. As mentioned earlier, after managing and delaying the peak flow, any subsequent increase in discharge (i.e., after the first 50 min) does not negatively impact the UDN. This provided a significant advantage for the UDN when compared to the more intense conditions observed during a 5-year storm. The benefits of the RTC system are further supported by the data shown in Figures 12 and 13. According to Figure 13, the optimized RTC system reduced the flow depth by up to 35% during peak times. This substantial reduction in flow depth highlights the system's ability to mitigate critical conditions within the city's drainage conduits, thereby enhancing the overall resilience of the drainage infrastructure.

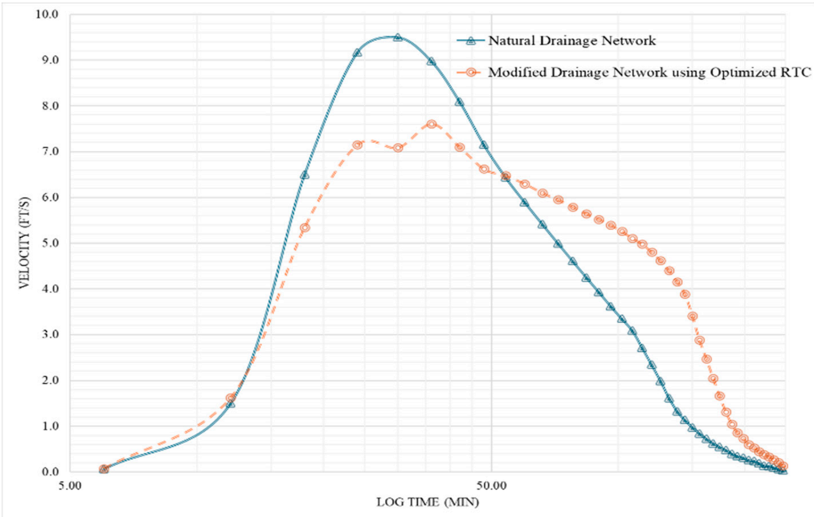


Figure 12. Velocity vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 2-year return period.

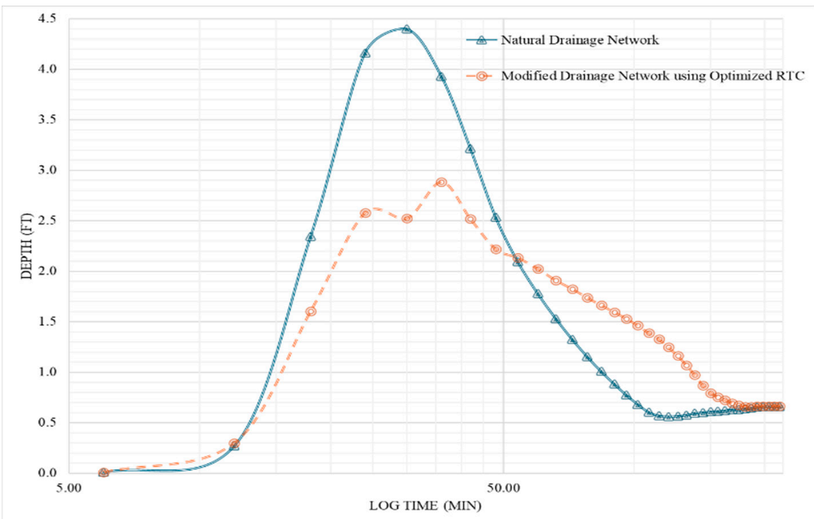


Figure 13. Depth vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 2-year return period.

In this study, a 1-year flood event was also analyzed to assess the performance of the optimized RTC system under conditions smaller than the design flood for the New Orleans drainage network. As shown in Table 2, approximately 10% of the network points experienced temporary flooding during the 1-year flood. The results, illustrated in Figure 14, indicate that the optimized RTC system was able to reduce the flood peak by 8% during this event. However, it is important to note that, in this scenario, the RTC system did not cause a delay in the peak time. This outcome can be attributed to the relatively lower flow rate associated with a 1-year flood, which is insufficient to activate the RTC controllers and significantly alter the performance of the drainage system. Additionally, such an intervention is generally unnecessary, as the network is designed to handle up to a 2-year flood event without experiencing significant flooding. The drainage system's ability to manage these smaller events with ease is further corroborated by the data presented in Figures 15 and 16, which show the network's robust performance under these conditions.

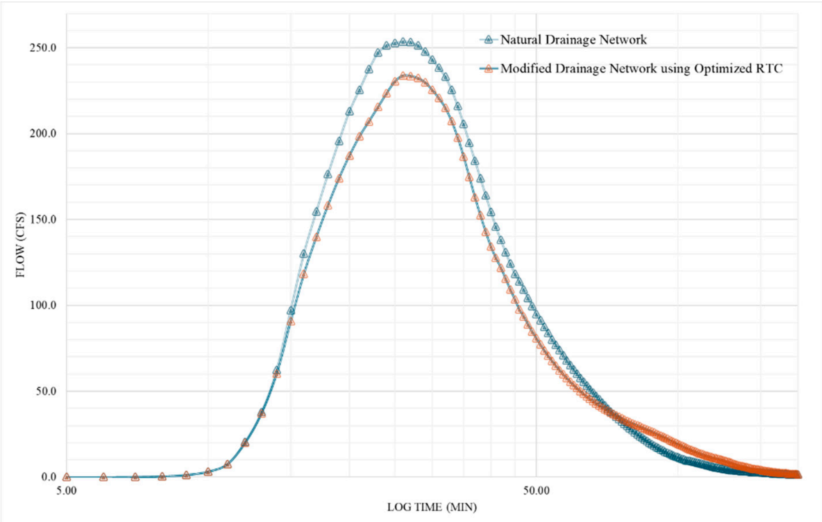


Figure 14. Hydrographs at downstream end conduit: comparison with and without the RTC system for 30-min rainfall duration and 1-year return period.

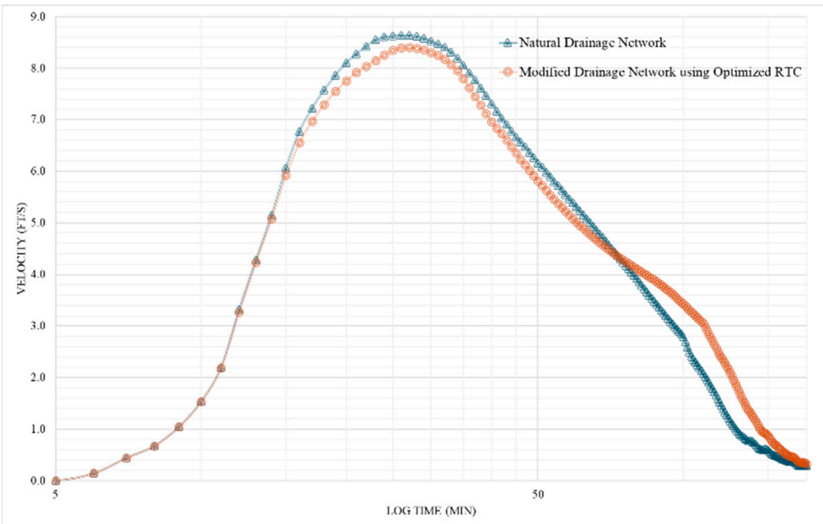


Figure 15. Velocity vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 1-year return period.

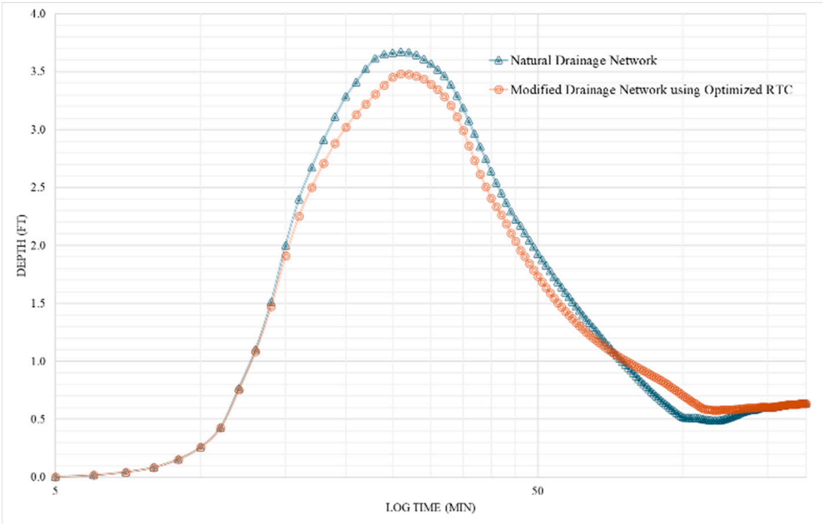


Figure 16. Depth vs. time at downstream conduit: comparison with and without the RTC system for 30-min rainfall duration and 1-year return period.

The locations and final number of orifices selected for installation during the 2-year return period are presented in Figure 17 and Table 3. As previously mentioned, the initial optimization algorithm identified 20 orifices as the optimal locations for the installation of FCDs. In the subsequent step, the final algorithm simultaneously determined the most effective PID controller settings for each FCD while also evaluating the performance of these devices in terms of their ability to reduce flooding. Through this process, the algorithm refined the selection, ultimately choosing 13 orifices to be implemented in the system (Figure 17). This optimization not only ensured the strategic placement of the FCDs but also enhanced the overall efficiency of the flood control system.

Figure 17. Placement of the final orifices in the optimized RTC system; 2-Year return period.

Table 3. The results of the GA: name and number of orifices, and amount of orifice opening.

No.	Orifice Name	Amount of Orifice Opening
1	DPS04_35406_a	0.723492703
2	DPS04_34958_a	0.432305127
3	DPS04_34590_a	0.340279824
4	DPS04_34610_a	0.709111527
5	DPS04_35317_a	0.615080009
6	DPS04_34588_a	0.486044229
7	DPS04_34515_a	0.168070492
8	DPS04_36189_a	0.818414757
9	DPS04_35321_a	0.73724803
10	DPS04_35320_a	0.720034622
11	DPS04_36175_a	0.745877744
12	DPS04_35325_a	0.951866165
13	DPS04_35407_a	0.609437972

The varying performance percentages of the RTC method in a drainage network for different flood return periods can be explained by understanding how the RTC systems interact with different flood magnitudes and frequencies. During 5-year and 10-year floods, the drainage system operated in such an overloaded state and was so full of water that there was no space left for the RTC system to function. Therefore, it can be conclusively stated that the best performance of the optimized RTC system occurs when it operates based on the design flood, since in the design storm enough freeboard and safety factors are considered for the UDN, and the RTC system can use this free space in the best manner. That is, if a drainage system is designed for a 100-year flood, the optimized RTC can improve its performance by up to 50%. This, in turn, can effectively control the flood discharge in cities.

4. Conclusions

A GA script was developed to optimize the number, location, and control rules of the FCDs by using the water level data, along with flow control gates interacting with a calibrated SWMM engine to increase the in-pipe capacity to reduce the flood volume downstream. The performance of the RTC system is directly dependent on the amount of available free capacity within the pipeline network. This was tested by examining four floods with different return periods on the New Orleans network. The results indicated that when the design flood (which was a 2-year flood for the studied drainage network) is used, the optimized RTC system can improve flow conditions, reduce the peak flood discharge by up to 50%, and delay the peak time by up to 30%. It was also found that the optimized RTC system can reduce the peak discharge of a 5-year flood by up to 12%. The optimized RTC system also showed some success in reducing the peak discharge for return periods shorter than the design flood, achieving an 8% reduction in peak discharge. In summary, for lower-intensity events, the infrastructure itself may handle the load adequately, reducing the visible impact of the optimized RTC. For moderate events (e.g., the design storm), the RTC can optimize flows and storage effectively, showing a significant performance increase of up to 50 percent. For high-intensity events, the limitations of the physical infrastructure in terms of free capacity to retain water diminish the effectiveness of RTC, as it cannot fully mitigate the larger volumes of water. Understanding these dynamics can help refine and improve RTC strategies for different flood scenarios.

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References

1. Edenhofer, O.; Pichs-Madruga, R.; Sokona, Y.; Seyboth, K. Special Report on Renewable Energy Sources and Climate Change Mitigation (SRREN). 2011. Available online: https://www.uncclearn.org/wp-content/uploads/library/ipcc15.pdf (accessed on 1 May 2011).
2. Kordana, S. The identification of key factors determining the sustainability of stormwater systems. In *Proceedings of the E3S Web of Conferences, Semarang, Indonesia, 14–15 August 2018*; EDP Sciences: Les Ulis, France, 2018; Volume 45, p. 00033.
3. Piro, P.; Turco, M.; Palermo, S.A.; Principato, F.; Brunetti, G. A Comprehensive Approach to Stormwater Management Problems in the Next Generation Drainage Networks. In *The Internet of Things for Smart Urban Ecosystems*; Springer: Cham, Switzerland, 2019; pp. 275–304.
4. Sun, C.; Joseph-Duran, B.; Maruejouls, T.; Cembrano, G.; Meseguer, J.; Puig, V.; Litrico, X. Real-time control-oriented quality modelling in combined urban drainage networks. *IFAC-PapersOnLine* **2017**, *50*, 3941–3946. [CrossRef]
5. Lee, J.G.; Selvakumar, A.; Alvi, K.; Riverson, J.; Zhen, J.X.; Shoemaker, L.; Lai, F.-H. A watershed-scale design optimization model for stormwater best management practices. *Environ. Model. Softw.* **2012**, *37*, 6–18. [CrossRef]
6. Grebel, J.E.; Mohanty, S.K.; Torkelson, A.A.; Boehm, A.B.; Higgins, C.P.; Maxwell, R.M.; Nelson, K.L.; Sedlak, D.L. Engineered infiltration systems for urban stormwater reclamation. *Environ. Eng. Sci.* **2013**, *30*, 437–454. [CrossRef]
7. Bloorchian, A.A.; Ahiablame, L.; Osouli, A.; Zhou, J. Modeling BMP and vegetative cover performance for highway stormwater runoff reduction. *Procedia Eng.* **2016**, *145*, 274–280. [CrossRef]
8. Martel, J.-L.; Brissette, F.P.; Lucas-Picher, P.; Troin, M.; Arsenault, R. Climate change and rainfall intensity–duration–frequency curves: Overview of science and guidelines for adaptation. *Int. J. Hydrogen Energy* **2021**, *26*, 03121001. [CrossRef]
9. Halder, S.; Saha, U. Future projection of extreme rainfall for flood management due to climate change in an urban area. *J. Sustain. Water Built Environ.* **2021**, *7*, 04021012. [CrossRef]
10. Ahuja, S. *Water Reclamation and Sustainability*; Elsevier: Amsterdam, The Netherlands, 2014.
11. Schütze, M.; Campisano, A.; Colas, H.; Schilling, W.; Vanrolleghem, P.A. Real time control of urban wastewater systems—Where do we stand today? *J. Hydrol.* **2004**, *299*, 335–348. [CrossRef]
12. Bach, P.M.; Rauch, W.; Mikkelsen, P.S.; McCarthy, D.T.; Deletic, A. A critical review of integrated urban water modelling – Urban drainage and beyond. *Environ. Model. Softw.* **2014**, *54*, 88–107. [CrossRef]
13. Beeneken, T.; Erbe, V.; Messmer, A.; Reder, C.; Rohlfing, R.; Scheer, M.; Schuetze, M.; Schumacher, B.; Weilandt, M.; Weyand, M. Real time control (rtc) of urban drainage systems–a discussion of the additional efforts compared to conventionally operated systems. *Urban Water J.* **2013**, *10*, 293–299. [CrossRef]
14. Fradet, O.; Pleau, M.; Marcoux, C. Reducing CSOs and giving the river back to the public: Innovative combined sewer overflow control and riverbanks restoration of the St Charles River in Quebec City. *Water Sci. Technol.* **2011**, *63*, 331–338. [CrossRef]
15. Kerkez, B.; Gruden, C.; Lewis, M.; Montestruque, L.; Quigley, M.; Wong, B.; Bedig, A.; Kertesz, R.; Braun, T.; Cadwalader, O.; et al. Smarter Stormwater Systems. *Environ. Sci. Technol.* **2016**, *50*, 7267–7273. [CrossRef] [PubMed]
16. Campisano, A.; Ple, J.C.; Muschalla, D.; Pleau, M.; Vanrolleghem, P. Potential and limitations of modern equipment for real time control of urban wastewater systems. *Urban Water J.* **2013**, *10*, 300–311. [CrossRef]
17. Vitasovic, Z. Real Time Control of Urban Drainage Networks, Washington, DC, USA: United States Environmental Protection Agency (US EPA) and Office of Research and Development. 2006. Available online: https://www.iwapublishing.com/sites/default/files/ebooks/9781780408972.pdf (accessed on 18 August 2011).
18. Lund, N.S.V.; Falk, A.K.V.; Borup, M.; Madsen, H.; Mikkelsen, P.S. Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management. *Crit. Rev. Environ. Sci. Technol.* **2018**, *48*, 279–339. [CrossRef]
19. Kroll, S.; Weemaes, M.; Van Impe, J.; Willems, P. A methodology for the design of RTC strategies for combined sewer networks. *Water* **2018**, *10*, 1675. [CrossRef]
20. Eulogi, M.; Ostojin, S.; Skipworth, P.; Shucksmith, J.D.; Schellart, A. Hydraulic optimisation of multiple flow control locations for the design of local real time control systems. *Urban Water J.* **2021**, *18*, 91–100. [CrossRef]
21. Eulogi, M.; Ostojin, S.; Skipworth, P.; Kroll, S.; Shucksmith, J.D.; Schellart, A. Optimal Positioning of RTC Actuators and SuDS for Sewer Overflow Mitigation in Urban Drainage Systems. *Water* **2022**, *14*, 3839. [CrossRef]
22. Ardurra. Comprehensive S&WB-City of New Orleans Stormwater Management Model (SWMM), Consulting Engineers Report 2019. Available online: https://www.swbno.org/documents/Reports/July%2010%202019%20Rainfall%20Event%20Modeling%20Report.pdf (accessed on 1 September 2019).

23. Mounce, S.R.; Shepherd, W.; Ostojin, S.; Abdel-Aal, M.; Schellart, A.N.A.; Shucksmith, J.D.; Tait, S.J. Optimisation of a fuzzy logic-based local real-time control system for mitigation of sewer flooding using genetic algorithms. *J. Hydroinform.* **2019**, *22*, 281–295. [CrossRef]
24. Rossman, L.A. Storm Water Management Model User's Manual Version 5.1. 2015. Available online: https://www.epa.gov/sites/default/files/2019-02/documents/epaswmm5_1_manual_master_8-2-15.pdf (accessed on 18 August 2015).
25. Urban Hydrology for Small Watersheds (Technical Release 55). 1986. Available online: https://www.nrc.gov/docs/ML1421/ML14219A437.pdf (accessed on 1 February 2019).
26. Krakowie, U.R.W.; Wałęga, A.; Cupak, A.; Amatya, D.M. Center for Forested Wetlands Research USDA Influence of time of concentration on variation of runoff from a small urbanized watershed. *Geomat. Landmanag. Landsc.* **2015**, *2*, 7–19.
27. Keifer, C.J.; Chu, H.H. Synthetic storm pattern for drainage design. *J. Hydraul. Div.* **1957**, *83*, 1332-1-1332-25. [CrossRef]
28. Chen, J.; Li, Y.; Zhang, C. The effect of design rainfall patterns on urban flooding based on the Chicago method. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4245. [CrossRef]
29. Brown, V.M.; Keim, B.D.; Black, A.W. Climatology and trends in hourly precipitation for the southeast United States. *J. Hydrometeorol.* **2019**, *20*, 1737–1755. [CrossRef]
30. Ogata, K.; Brewer, J.W. *Modern Control Engineering*, 5th ed.; Prentice-Hall, Inc.: Hoboken, NJ, USA, 2009; pp. 681–751.
31. Lust, T.; Tuyttens, D. Variable and large neighborhood search to solve the multiobjective set covering problem. *J. Heuristics* **2014**, *20*, 165–188. [CrossRef]
32. Shishegar, S.; Duchesne, S.; Pelletier, G. Optimization methods applied to stormwater management problems: A review. *Urban Water J.* **2018**, *15*, 276–286. [CrossRef]
33. Nicklow, J.; Reed, P.; Savic, D.; Dessalegne, T.; Harrell, L.; Chan-Hilton, A.; Karamouz, M.; Minsker, B.; Ostfeld, A.; Singh, A.; et al. State of the Art for Genetic Algorithms and Beyond in Water Resources Planning and Management. *J. Water Resour. Plan. Manag.* **2010**, *136*, 412–432. [CrossRef]
34. Abdel-Aal, M.; Shepherd, W.; Mounce, S.; Ostojin, S.; Schellart, A.; Shucksmith, J.; Skipworth, P.; Tait, S. Alleviating the risk of sewer flooding using fuzzy logic in a real time control system–an experimental study. In Proceedings of the 8th International Conference on Sewer Processes and Networks, Rotterdam, The Netherlands, 31 August–2 September 2016.