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CONTRÔLE EN TEMPS RÉEL DES BASSINS D'ORAGE POUR UNE GESTION DURABLE ET ADAPTATIVE DES EAUX PLUVIALES EN MILIEU URBAIN

REAL-TIME CONTROL OF STORMWATER BASINS FOR SUSTAINABLE AND ADAPTIVE MANAGEMENT OF URBAN STORMWATER

Par

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RÉSUMÉ

Le but de cette thèse est de développer et tester des stratégies locales et globales de contrôle prédictif en temps réel (GPRTC) pour un système de gestion des eaux pluviales (SGP). L'hypothèse à vérifier est que le GPRTC des bassins d’eaux pluviales peut améliorer la performance des SGP en termes de qualité et de quantité d'eau. Sur cette base, l'objectif principal de cette thèse est de proposer un cadre décisionnel intelligent pour combiner l’optimisation et des règles de contrôle afin d’améliorer les performances de contrôle qualité et quantité des SGP en temps réel dans le cadre d'une ville intelligente. La résilience globale du système dans des situations critiques, telles que des épisodes pluvieux plus intenses en raison du changement climatique, est discutée en fournissant une analyse comparative des approches dynamique et statique. De plus, la capacité de réduction de l'érosion de l’approche proposée est analysée et les impacts des incertitudes liées aux prévisions de précipitations sur la performance de l’approche de contrôle dynamique sont étudiés. Enfin, un modèle de réseau de neurones hyper-complexe à valeur octonionique (OVNN) est développé. L’intégration de ce modèle aux stratégies de GPRTC permet une estimation plus rapide des débits d'entrée qui doivent être fournis, en temps réel, à la stratégie de contrôle.

Deux bassins versants urbains réels, avec respectivement un et quatre exutoires vers le cours d'eau récepteur, sont choisis pour tester l'applicabilité et l'efficacité de l'approche dynamique proposée. Les résultats montrent que l’approche de contrôle proposée a la capacité d’améliorer la performance des systèmes de gestion des eaux pluviales, en matière de quantité et de qualité, par rapport à une approche de contrôle statique, que ce soit dans des conditions météorologiques normales ou en considérant le changement climatique. L’approche locale offre une réduction moyenne de 76 % des débits de pointe et un temps de rétention moyen de 19 h en climat futur. À l’échelle globale, bien que les critères de performance semblent être affectés par l’augmentation de l'intensité des précipitations en climat futur, l’approche de GPRTC améliore toujours la réduction du débit de pointe et le temps de rétention de l’eau, de 54 % et 14 h respectivement, en présence du changement climatique. De plus, lorsque les prévisions d'incertitude liées aux prévisions de précipitations sont prises en compte, les résultats montrent la capacité de GPRTC à rétablir la fiabilité du système face à des événements imprévus, ce qui permet au SGP de revenir vers un était normal après une défaillance éventuelle.

Mots-clés: Changement climatique, contrôle en temps réel, bassin de rétention, gestion des eaux pluviales, qualité de l’eau, débit de pointe, ruissellement, optimisation, règle de contrôle, ville intelligente

ABSTRACT

The aim of this thesis is to develop and test local and global predictive real-time control (GPRTC) strategies for a network of stormwater management systems. The basic hypothesis to verify is that GPRTC of stormwater basins can improve SWM in terms of water quality and quantity. Based on this, the main objective of this thesis is to propose a smart decision-making to enhance the quality and quantity control performance of the SWM system in real-time as a part of a Smart City. The global resiliency of the system in critical situations such as more intense rainfall events imposed by climate change is discussed by providing a comparative analysis of the dynamic and static approaches. Also, the erosion reduction ability of the proposed approach is analyzed and the impacts of uncertainties linked to rainfall forecast on the performance and robustness of the dynamic control approach is studied. Finally, a hyper-complex Octonion-Valued Neural Network model (OVNN) is developed that performs accurate and rapid rainfall-runoff estimation. The integration of this model to the GPRTC strategies allows faster estimation of inflow rates that should be provided to the integrated optimization rule-based framework in real-time as input data.

Two real world urban watersheds with one and four outlets to a nearby watercourse are chosen to test the applicability and efficiency of the proposed dynamic approach. The results show that the proposed autonomous control approach has the ability to enhance the quantity and quality control performance of the basins for both local and global control approaches, in comparison to a static control approach. Local RTC approach offers an average reduction of 76 % in peak-flows and an average detention time of 19 h under future climate. At the global scale, although the performance criteria are shown to be affected by the increased rainfall intensities in future climate, the proposed control approach still improves the peak flow reduction and detention time of water by 54 % and 14 h, respectively in the presence of climate change. Also, when forecasting uncertainty linked to rainfall predictions is taken into account, the results show the ability of the proposed approach in recovering the system facing unpredicted events which finally enables the resiliency of the stormwater system to bounce back from a failure to normal conditions.

Keywords: Climate change, Real-Time Control, Detention Basin, Stormwater Management, Water Quality, Peak flow, Runoff, Optimization, Control Rule, Smart City

SOMMAIRE DE LA THÈSE EN FRANÇAIS

Les zones urbaines sont confrontées à de nombreux défis pour parvenir à une gestion durable et adaptative des eaux pluviales en présence du changement climatique, de l'urbanisation et de la croissance démographique. Le but de cette thèse est de développer et de tester des stratégies globales de contrôle prédictif en temps réel (GPRTC) pour un système de bassins d'eaux pluviales tout en tenant compte des conditions météorologiques futures. L'hypothèse de base à vérifier est que le contrôle en temps réel prédictif global des bassins d'eaux pluviales, qui permet une gestion dynamique et adaptative des eaux pluviales en milieu urbain, peut améliorer la gestion des eaux pluviales en termes de qualité et de quantité d'eau. L'objectif principal de la thèse est la vérification de cette hypothèse en développant des algorithmes de prise de décision pour le contrôle dynamique des systèmes de gestion des eaux pluviales dans les zones urbaines, tout en tenant compte des conditions météorologiques futures. Plus précisément, les objectifs spécifiques de cette thèse sont de :

- Proposer une approche globale de contrôle dynamique prédictif (GPRTC) afin d'améliorer la performance de contrôle en temps réel, en matière de qualité et de quantité d'eau, du système de gestion des eaux pluviales à l'échelle du bassin versant;
- Analyser de la résilience globale du système dans des situations critiques telles que des épisodes pluvieux plus intenses imposés par le changement climatique;
- Comparer la performance de l'approche globale proposée à celle d'une approche de contrôle statique, à l'aide d'études de cas réels;
- Analyser la capacité de réduction de l'érosion du cours d'eau récepteur rendue possible par l'approche proposée, par rapport à l'approche de contrôle statique;
- Évaluer les impacts des incertitudes liées aux prévisions de précipitations sur la performance et la robustesse de l'approche de contrôle proposée; et
- Évaluer la possibilité d'accélérer le calcul des débits de ruissellement entrant dans les bassins en utilisant un modèle de réseau de neurones hyper-complexe à valeur octonionique (OVNN).

Pour ce faire, des modèles de simulation et des algorithmes de contrôle sont développés et testés. Premièrement, un cadre décisionnel intelligent est conçu grâce au contrôle prédictif en temps réel (CTR) de la vanne de sortie des bassins d'eaux pluviales. Ce cadre permet un contrôle optimal à l'échelle du bassin versant en manipulant la vanne de sortie et en fournissant des points de consigne de sortie optimisés pour les bassins étudiés. Cette méthode de contrôle utilise non seulement les conditions météorologiques observées, mais également des prévisions. La méthode proposée combine l'optimisation et des règles de contrôle afin de réduire l'impact sur le cours d'eau récepteur des débits sortant des bassins d'orage, tant en termes de quantité que de qualité d'eau. La variable de décision est le débit à la sortie de chaque bassin, dont les valeurs optimales sont générées par les algorithmes de CTR développés. Ces débits optimaux sont sélectionnés de manière à éviter les débordements des bassins et à respecter les deux critères de contrôle suivant : 1) le débit de pointe rejeté dans le cours d'eau récepteur est minimisé en contrôlant les débits de sortie des bassins, et 2) le contrôle de la qualité de l'eau est réalisé en maximisant le temps de rétention de l'eau afin d'augmenter la sédimentation des matières en suspension et autres polluants particulaires.

Après avoir développé les algorithmes de CTR prédictifs globaux, la performance de la méthode proposée est comparée à celle d'une approche de contrôle statique. Entre autres, la capacité de l'approche proposée à réduire le potentiel d'érosion des cours d'eau récepteurs est évaluée. Deux bassins versants urbains réels, avec respectivement un et quatre exutoires vers un cours d'eau récepteur, sont choisis pour tester l'applicabilité et l'efficacité de l'approche dynamique proposée. Les résultats montrent que l'approche de contrôle proposée a la capacité d'améliorer la performance des systèmes de gestion des eaux pluviales, en matière de quantité et de qualité, par rapport à une approche de contrôle statique, que ce soit d'un point de vue local ou global, de même que dans des conditions météorologiques actuelles ou en considérant le changement climatique. L'approche CTR locale offre une réduction du débit de pointe de 73 à 95 % et des temps de rétention variant de 16 à 30 h dans le scénario climatique actuelles, tandis que, dans les conditions climatiques futures, une réduction moyenne de 76 % des débits de pointe et un temps de rétention moyen de 19 h sont obtenus. Bien que les critères de performance soient affectés par l'accroissement des intensités de pluie en climat futur par rapport au scénario de précipitations actuelles, tant pour le contrôle local que global, l'approche de contrôle globale améliore toujours la réduction du débit de pointe et le temps de rétention de l'eau, de 54 % et 14 h respectivement, en présence du changement climatique. Tous les résultats mentionnés ci-haut sont obtenus en considérant des prévisions de précipitations parfaites. Une analyse supplémentaire a été effectuée pour étudier la performance du GPRTC lorsque les incertitudes liées aux prévisions de précipitations sont prises en compte, en utilisant les données du Système de prévision déterministe à haute résolution (HRDPS) d'Environnement Canada. Les résultats ont montré que bien que la performance de la stratégie de GPRTC dépende de la qualité des prévisions de pluie, l'approche de contrôle proposée a la capacité de rétablir la fiabilité du système face à des événements imprévus, ce qui permet au système d'eaux pluviales de revenir vers un état normal après une défaillance éventuelle.

Enfin, dans la dernière partie de la thèse, un modèle de réseau de neurones hyper-complexe à valeur octonionique (OVNN) est proposé pour estimer les débits à l'entrée des bassins à l'aide de neurones à 8 dimensions définies en fonction de nombres octonioniques. L'intégration de ce modèle aux stratégies de GPRTC développées permet une estimation plus rapide des débits d'entrée aux bassins qui doivent être fournis, en temps réel, à la stratégie de contrôle. La multidimensionnalité des OVNN permet une modélisation précise des processus complexes tout en : (1) réduisant par huit les dimensions des entrées et des sorties; et (2) étendant l'algorithme de rétropropagation traditionnel en ajoutant sept autres dimensions. Ces fonctionnalités conduisent à une approche de solution simplifiée, mais plus précise que les modèles de réseaux de neurones traditionnels. L'évaluation de la méthodologie proposée illustre la capacité des modèles OVNN à produire des estimations précises des débits d'entrée aux bassins avec un temps de calcul réduit, pour le contrôle en temps réel des bassins d'eaux pluviales à l'échelle du système.

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LIST OF ABREVIATIONS

RTC: Real-time control

GPDC: Global predictive dynamic control

CC: Climate change

SWM: Stormwater management

ANN: Artificial Neural Network

OVNN: Octonion-Valued Neural Network

RVNN: Real-Valued Neural Network

QVNN: Quaternion-valued Neural Network

SWMM: Stormwater Management Model

DP-QCR: Dynamic predictive quality control rules

PQ-COP: Predictive quantity control optimization problem

1 INTRODUCTION

Stormwater management in urban areas traditionally seeks to ensure the safety of citizens and to protect public and private property during wet weather. Following the awareness of rapid urbanization and climate change (CC) on physical and chemical characteristics of the receiving waters, the traditional stormwater management systems need to be modified based on these new emerging challenges, more than ever. In spite of the significant efforts made to construct new stormwater management infrastructures in urban areas, a proper coordination between the systems components over the watershed and real-time control (RTC) of the spatio-temporal hydraulic/hydrologic operations could be a promising solution (Kerkez et al., 2016).

Recognizing the need for a change in urban stormwater management traditional paradigm, national and local regulations were integrated to chart a new direction to deal with urban runoff problems. As a result, new objectives were added progressively to the stormwater management traditional objectives, which target the safety of citizens and protecting public and private properties during rainstorms, and also the integrity of the receiving waters. To achieve these objectives, various control structures must be put in place whether at the source (e.g. green roofs or infiltration trenches), over the drainage network (e.g. storage nodes, perforated pipes) or in the downstream areas (e.g. stormwater basins). A stormwater management system in its best form should achieve these objectives by integrating both quality and quantity controls (MDDEP and MAMROT, 2014). On the other hand, although sustainable development of water resources through planning, design and control of stormwater management systems requires public participation, but the main responsibility relies on the decision makers to evaluate the policies and their impacts on the economic, social and environmental changes. Researchers made significant strides to develop efficient tools to support this decision-making process.

Advances in technologies and invention of the Internet of Things (IoT) have enabled pervasive progress in systems components connectivity that allows transitioning the existing stormwater management systems to economic cyber-physical infrastructures that would facilitate RTC of urban runoff dynamics in a sustainable managerial approach as well as enhancing the resilience of urban infrastructure against varying climate. The modern urban areas would oversee the interconnection, aggregation and integration for stormwater collection network while maintaining adaptation, optimality and resilience for its dynamic performance. Reconstruction of stormwater management infrastructures based on new emerging socio-environmental needs also seems a solution; it would place the municipalities in a precarious and costly predicament by posing a limited short-term solution for a large-scale and unsteady problem.

This project aims to develop a global predictive stormwater management framework which is an integrated dynamic optimization and rule-based approach for controlling the stormwater basins over a watershed. As compared to current stormwater management practices, the proposed framework offers three distinct capabilities: 1) it implements emerging dynamics and intelligent control to enable maximal utilization of the network capacity and decide on the optimal control strategy such that the intertemporal socio-environmental criteria are met in terms of water flow volume and quality; 2) it operates in real-time in the sense that it continually receives the historical and observed data as well as the spatio-temporal predicted meteorological data to decide how to manipulate the actuators based on their local system's capacity, preference and compatibility; and finally 3) it has the ability to learn from the historical data to update its input parameters in real-time to get prepared for the upcoming events. This framework is applied to two real-world case studies in the Quebec province in Canada to evaluate its dynamic predictive performance in both local and global scales.

1.1 Global Challenges

Rapid population growth, industrialization and urbanization followed by construction of thousands of square kilometers of impervious surfaces (including buildings, bridges and millions of square kilometers of asphalt roads) in many areas around the world, have posed adverse impacts on the natural environment. These include increased peak flows, water quality degradation, vegetation removal and aquatic habitat extinction, which have led to significant changes in the natural hydrological cycle. Generally speaking, urban development contributes to increased stormwater runoff (both in terms of volume and velocity) by increasing the impervious surfaces. Figure 1-1 illustrates that, as the impervious surfaces develop, the ground loses its ability to infiltrate the water and, consequently, more water remains on the earth surface which transforms into runoff. When the percentage of imperviousness reaches 75 to 100 %, almost 55 % of the annual rainfall volume turns into surface runoff, which can pose many further problems (FISRWG, 1998). This increased amount of runoff not only discharges significant pollutant loads annually into streams (Brombach et al., 2005), but it is the primary cause of sharp peak flows in the receiving watercourses. Figure 1-2 provides a comparison between the flow rates in pre- and post-development areas over a watershed. According to this hydrograph, the same amount of rainfall can cause a higher peak flow in a smaller time period (Figure 1-2) in a developed area, which could lead to more frequent urban flooding, water body erosion, and hydraulic shocks on the receiving streams (Jacopin et al., 2001; Middleton and Barrett, 2008; Muschalla et al., 2014). Last but not least, «from 10% impermeability, the stability of watercourses, as well as the biodiversity and the abundance of the fishes, will begin to be affected» (translated from MDDEP & MAMROT, 2011). To summarize, the impacts of urbanization on natural watercourses can be enumerated as follows (Minnesota Stormwater Steering Committee, 2008; Ministry of the Environment, 2003):

- Changes in hydrological cycle;
- More probable and larger runoff events;
- Changes in the ratio of surface runoff and base flow (more surface runoff and less base flow);
- High velocity flows;
- Changes in stream flow;
- Higher peak flows;
- Decrease in concentration time;
- Higher risk of flooding;
- Changes in water body morphology;
- Erosion;
- Channel bed deformation due to erosion and sedimentation;
- Flood plain augmentation;
- Water quality degradation; and
- Aquatic habitat loss or damage.

All these consequences make the control of stormwater runoff a great challenge for municipalities.

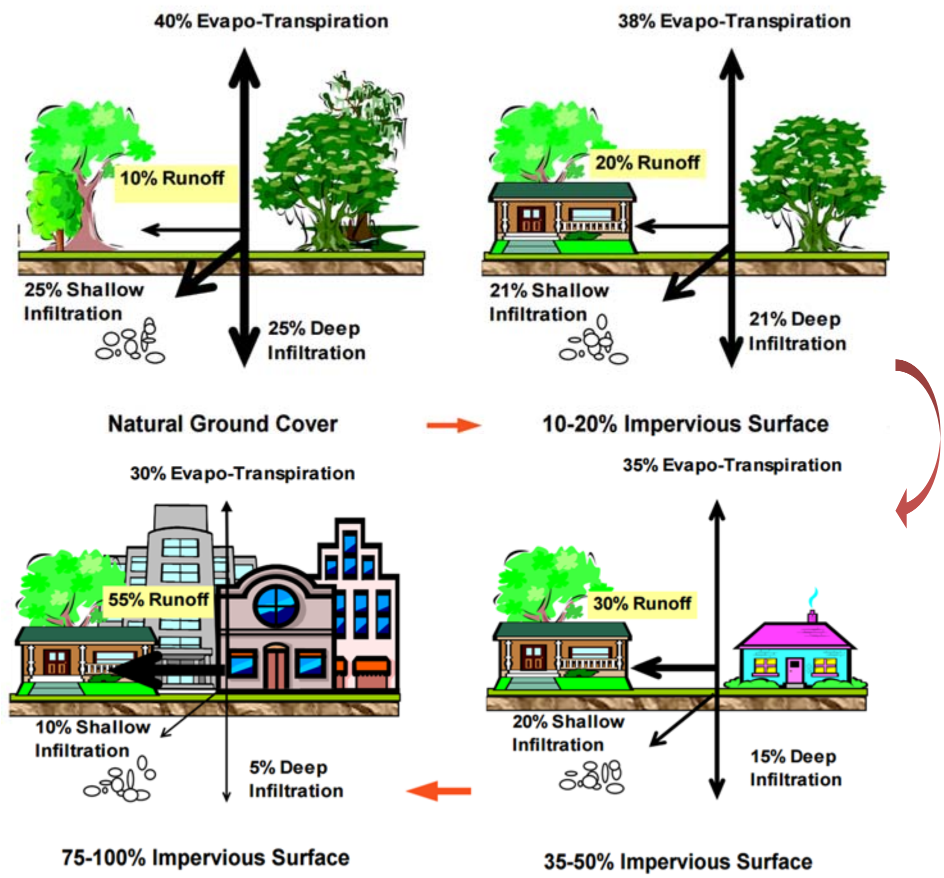

Figure 1-1- The impacts of impervious surfaces on the hydrologic cycle (from OEHHA.ca.gov)

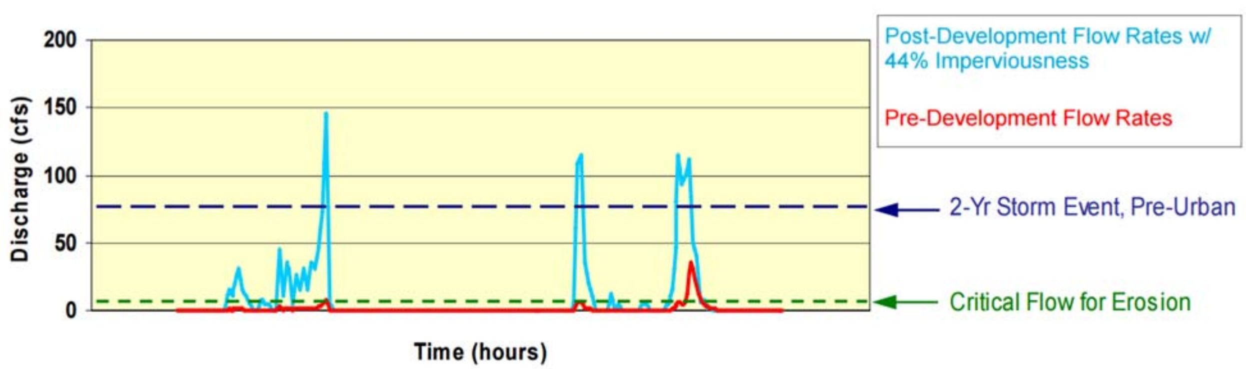

Figure 1-2- Comparison of flow rates hydrographs before and after urbanization (taken from OEHHA.ca.gov)

Beside the rapid urbanization that has significantly altered the hydrologic cycle in urbanized watersheds, climate change (CC) poses additional challenges on urban sustainability by inducing significant changes in precipitation patterns (Guhathakurta et al., 2011). It has been shown that, in several regions of the world, the extreme rain events are becoming more frequent due to CC (Mailhot et al., 2007; Miao et al., 2019; Westra et al., 2013) and that these events will become even more frequent in the future according to the generated projections (Dale et al., 2015; Giorgi et al., 2019). Among others, Guhathakurta, et al. (2011) report noticeable changes in the extreme rainfall events and associated flash floods in recent years in India. Return periods have been changing and now they tend to be shorter for the same intensity (Zorzetto et al., 2016). Furthermore, rainfall trends and drought regime could be affected by climate change in such a way that the intensity of heavy rainfall events over a short period of time is likely to increase significantly (Hegerl et al., 2007). It is reported that in Canada, the intensity and frequency of heavy storm events have been increasing in the last decades due to climate change (Hegerl et al. 2007) and will continue to increase in the future specially over the inland areas (e.g. Ontario and more specifically Southern Ontario, the Prairies, Southern Quebec) (Mailhot et al., 2012). One of the important consequences of this changing climate lies in quicker and more severe urban runoff which results in higher peak flows of the hydraulic system to nearby watercourses (Semadeni-Davies et al., 2008). For example, historical data about the urbanization of a peri-urban area in Swindon, United Kingdom, showed that an increase of the impervious cover from 11 % to 44 % augmented the peak flows resulting from runoff in downstream areas by over 400 % (Miller et al., 2014).

These challenges combined with the growing population in urban areas expose urban area's traditional stormwater infrastructures to a great risk. Severe downpours have significantly increased in terms of frequency and intensity (Giorgi et al., 2019) that are consequently followed by a dramatic increase in the risk of flooding as well as discharging significant amounts of runoff pollutants to the downstream areas across the world. These varying environmental conditions call for a sustainable and adaptive solution that provides dynamic predictive strategies to control urban stormwater.

1.2 Stormwater management systems

Stormwater management aims at solving the stormwater-related issues caused by impervious surfaces and mitigating further consequences of surface runoff. These managerial approaches can be implemented either physically or non-physically, through coordination of various governmental and non-governmental organizations and communities, and may include the optimal control of water quantity, water quality, erosion and sediment, pollution control (i.e. control of water quality), and channel protection (i.e. control of erosion and sedimentation) (Minnesota Stormwater Steering Committee, 2008; MDDEP and MAMROT, 2011).

In recent decades, a multitude of infrastructure and amenities, commonly referred to as "Best Management Practices" (BMPs), have been developed to provide stormwater control. The objectives of these BMPs are to control flow rates (by detention) and/or runoff volumes (by infiltration and/or evapotranspiration and/or storage) as well as to improve the quality of water (by sedimentation). Nowadays, in many regions around the world, these systems have been used to reduce the impacts of urbanization. In North America, the term «Low Impact Development» (LID) has been created to name the practices managing stormwater by mimicking the pre-development natural hydrologic cycle in a given site. These practices allow developing different site design processes including infiltration, evapotranspiration, harvesting, filtration and detention of stormwater (Sameer and Zimmer, 2010). The need for more adaptive and sustainable urban areas has brought attention into the BMPs/LIDs to propose strategies that extract the whole potential of these practices while improving their performances.

Stormwater basins are currently one of the most used BMPs which are physical basins constructed to store the stormwater runoff into their storage temporarily, in order to slowly release the water to the receiving watercourse, ideally at a controlled rate so that the downstream areas are not affected by high rate discharges. These structures are most commonly designed to achieve a static control of the flows discharged into the receiving river. Flow rates received by the inlet pipe of the basin is the input of a stormwater basin, while its outflow rate, as the system output, can be attenuated after a sedimentation process at the outlet pipe, in order to limit discharges to the river. This way, a stormwater basin protects receiving water bodies by decreasing the stormwater flow rates where, besides attenuating peak flows and decreasing erosion rate in downstream areas, the quality of discharged water can be improved through sedimentation.

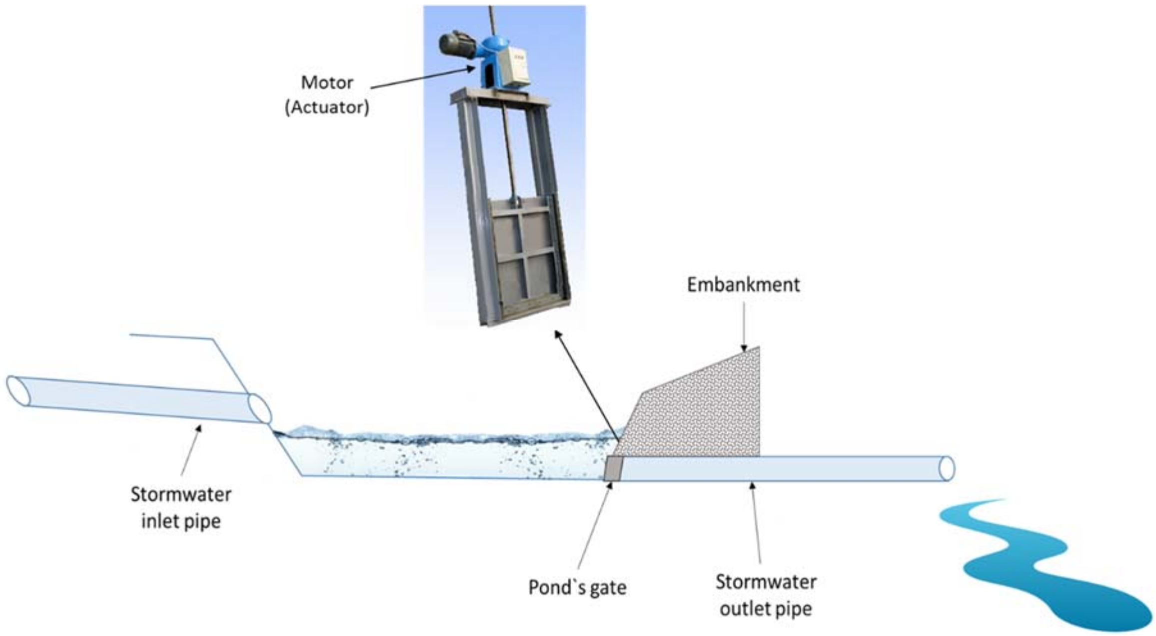

Figure 1-3- Detention basin configuration

1.3 Real-time control

Simply defined, a RTC system performs operations that are controlled dynamically in real-time. In this type of control, the system continuously receives data as input parameters to generate decision set-points based on some predefined processes where a single or a series of tasks over a period of time is being regulated by constant change or progress. All these procedures are realized in small pre-specified time intervals, which are near real-time. In contrast, static control refers to the process of controlling a single or a series of actions whose settings are constant in time and thus not able to adapt to the observed situation. In this thesis, by static control we mean a system which works without time considerations, while a dynamic control corresponds to a RTC in which the control system performs on-line. Stormwater management (SWM) can benefit from various RTC modeling techniques to control the performance of flow regulation devices in both combined sewer and stormwater networks. As this approach has the ability to enhance the performance of existing facilities, it is not always necessary to construct new infrastructures to meet new requirements, which would lead to significant savings (Colas et al. 2004). Generally, RTC systems can be distinguished regarding to their control level or data type. There are two levels in terms of spatial extent of control called global and local, and two other levels in terms of temporal data type as reactive and predictive (Duchesne et al., 2004). The combination of these different levels determines the level of complexity, performance and benefits of the system that result in four different combinations as local reactive, local predictive, global reactive and global predictive control. For example a local reactive RTC is when all the actuators (a system component which is responsible for manipulating another system component like a mobile gate) perform based on the set-points that are generated using the input parameters of the past and actual system data. Hence, in such systems, the level of control is less complicated than other types of RTC (Figure 1-4). On the contrary, the level of control in a global predictive RTC is relatively more complex where the control facilities should be provided with the data from all the system components to establish an integrated collaboration between the existing actuators (Figure 1-5). In this type of control, besides the historical and observation data, the prediction data of the input parameters are employed to generate the decision set-points for all the actuators at the global level. This helps the system realize its global objectives through an effective collaboration between its local operations while considering the future condition of effective parameters.

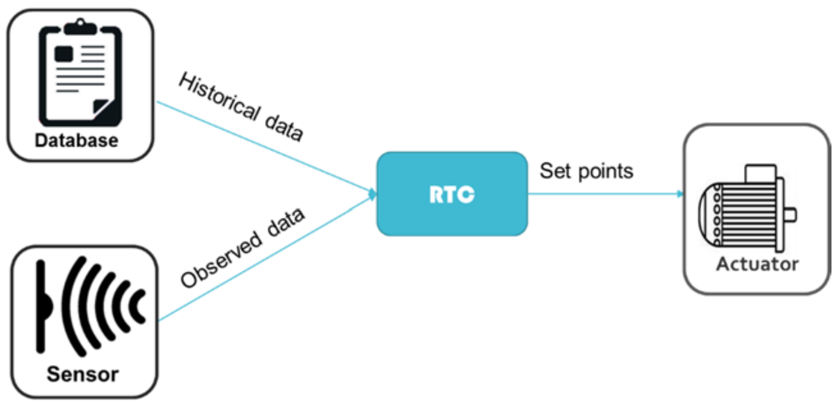

Figure 1-4- A local reactive real-time control system consists of one single actuator

Recent technologies facilitate the implementation of RTC in stormwater management systems. In these approaches, despite conventional controls, real-time hydrologic states and rainfall predictions can be employed to provide the system with decision-making strategies to efficiently modulate the flow rates in stormwater management infrastructure (Marsalek, 2005; Wong and Kerkez, 2018). Employing RTC strategies for these infrastructures brings flexibility to the urban stormwater management systems. A dynamically managed system that considers predicted data, besides actual and historical data, is able to adapt itself to variations of environmental conditions.

Advances in technology and automatic systems have led to the development and implementation of “smart” stormwater systems, which perform computerized control to continuously modify themselves to adapt to changing inputs (Kerkez et al., 2016). In this regard, S*ustainability in SWM Systems*, as one of the key elements of smart cities, can be realized by equipping stormwater management infrastructures with RTC strategies. A RTC sustainable stormwater management not only seeks the restoration of the natural hydrological cycle in urban areas, but aims at providing an adaptive performance according to environmental variabilities. Sustainable management of stormwater must therefore be at the heart of urban development. According to the guide from MDDEP and MAMROT, (2011; free translation): «One of the fundamental principles of stormwater management should be to preserve or reproduce the natural hydrological cycle as much as possible, using different techniques and practices, not only for relatively high flows but also for flows associated with more frequent rain events». To this aim, stormwater management infrastructure needs to be controlled in real-time to tackle the emerging global challenges and their combined impacts in the most effective way, to provide enhanced operational control systems that compensate the inefficiencies of conventional stormwater management systems.

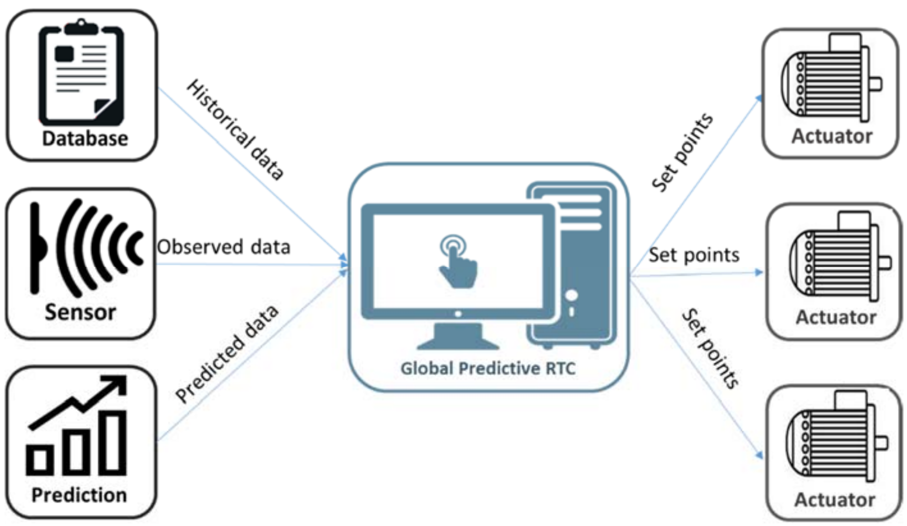

Figure 1-5- A global predictive real-time control system consists of multiple actuators and a remote control center

1.4 Limitations of current practices

One of the primary challenges arising in present stormwater management systems is their inability to provide a dynamic solution to the present evolving challenges (Kerkez et al. 2016). While sustainable urban development relies on the design of advanced urban planning systems, dynamic stormwater management infrastructures are among urban systems that can play an important role in facing varying environmental challenges. In addition, increasing extreme climatic events and growing population have increased the need to evolve the stormwater management systems so that it is essential for the urban stormwater management systems to perform dynamically and adaptively.

Another significant challenge engaged with SWM systems is that, in most cases, they are designed and operated locally, irrespective of the operation of other structures, or the conditions of other components in the watershed. In this regard, the U.S. Environmental Protection Agency (EPA) reports that past practices of controlling the stormwater management systems on a site-by-site basis have been inadequate, raising the need to implement the stormwater control measures as a whole system that incorporates modern stormwater management goals at watershed-level (Rossman and Huber, 2016). A recent study (Wong and Kerkez, 2016) concludes that integrating the entire watershed at system-level and feedback with the operational-level decisions is still an open research area and investigations are needed to design management systems that are adaptable and robust to climate change. Despite the advances in technology, global digitally-enabled environmental systems have rarely been investigated. Employing smart systems and Internet of Things (IoT) techniques, municipalities are now able to retrofit their traditional stormwater infrastructures with sensors, actuated control valves and dynamic gates to allow an adaptive performance for controlling the urban stormwater runoff against the changing environment (Kerkez et al., 2016). This has led to the definition of smart stormwater systems that aggregates the observed and predicted data over the watershed for real-time monitoring and control of urban stormwater.

While optimality is a key concept in modern smart cities where automated components interact with each other, in the context of SWM, achieving optimal operations is an important limitation of the existing infrastructures that mostly consider some simple rules to identify what actions need to be taken at the outlet of the drainage network (e.g. Gaborit et al., 2012). More specifically, there is a lack of practical solutions to enhance the system-wide optimal performance efficiency of built stormwater management infrastructures; optimized solutions that provide the system with an enhanced quantity and quality control performance against the varying environmental conditions and help in defining optimal feedbacks at the operational-level that satisfy intertemporal socio-environmental needs.

1.5 Research objectives, contributions and thesis outline

The purpose of this study is to introduce a global real-time control approach for an adaptive and sustainable management of urban stormwater, focusing specifically on the operational objectives of stormwater basins over a watershed. The central idea of this project is to investigate a novel stormwater management control framework which is predictive, sustainable and adaptive, that balances network flow dynamics incorporating the environmental, meteorological, and hydraulic/hydrologic requirements in real-time. This novel SWM architecture (Figure 1-6) involves hydraulically linked flow optimization routines across a two-layer hierarchy of stormwater sewer networks: watershed-scale and local-scale. A real-time quantity control optimization algorithm is joined with quality control rules to meet the requirements of municipal regulations with different performance criteria. The proposed distributed architecture accommodates runoff dynamics into the watershed network that is currently connected to a cloud-based data of system parameters, environmental states and generated set-points to enable transferring from a static-state network to an adaptive, distributed and dynamic network. Moreover, the proposed distributed optimization and control paradigms provide an economic alternative to the cost prohibitive urban infrastructure replacement solution.

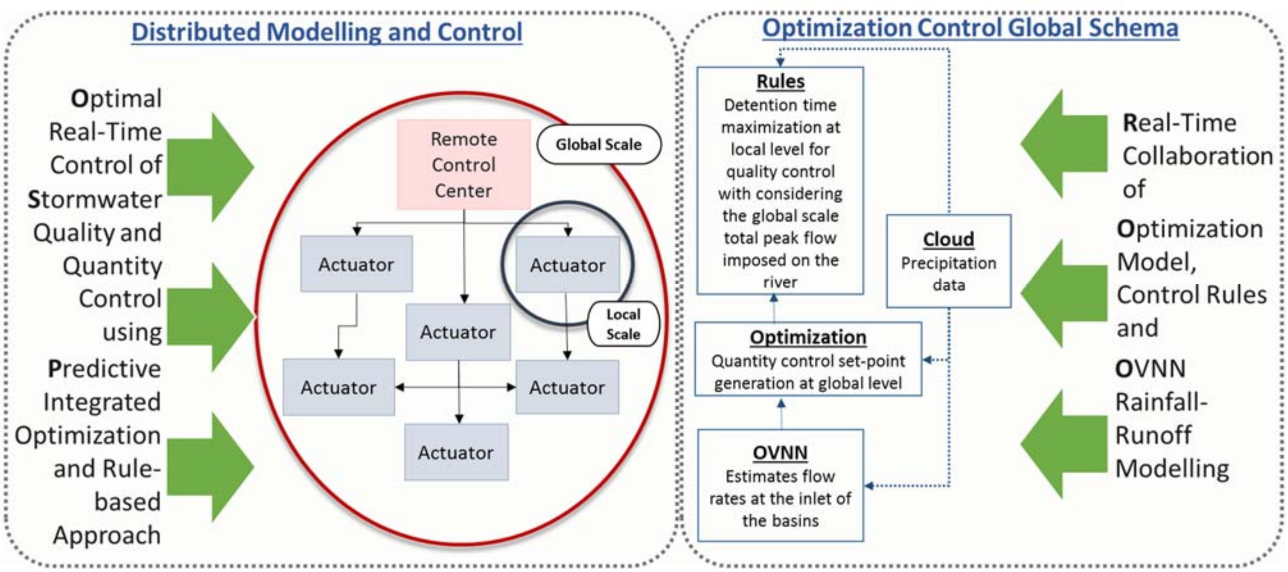

Figure 1-6- Global schema of the proposed smart real-time control approach at two levels

The developed optimization rule-based approach is run at each time-step and in real-time in order to generate the required outflow rate set-points for a few time-steps ahead and provide a short-term predictive control for the studied system. Since the quality control rules perform based on the prediction precipitation data of the next 48 hours, the generated set-points at each time-step has the ability to respond to the upcoming rain events over the future two days. The hypothesis is that this framework enhances the performance of existing SWM infrastructure with smart control algorithms over two levels and adds flexibility to the stormwater management network by managing the flow appropriately between the system components. Both the local level management and the system-wide management are in collaboration and the performance of locally generated set-points is tested at the global scale to decide whether to proceed with the actual state of the system at the present time-step or the global optimization should be performed. It should be noted that the proposed dynamic control approach is developed for parallel stormwater basins where no flow sharing is considered between them. The studied stormwater basins drain the runoff received from their associated network and do not receive any flow from other basins. In addition, a rainfall-runoff model, octonion-valued neural network, is embedded into the proposed optimization framework to facilitate real-time system runoff estimation and allow defining smaller time-steps to generate flow set-points at each local controller. This approach can be summed up through three sets of core contributions, each with several specific objectives as follows:

- **Design of an integrated optimization and rule-based algorithm for predictive RTC of stormwater basin at local level via long and short-term flow planning**

The main novelty of this phase is the introduction of the first predictive RTC algorithms that enables optimizing the performance of a single stormwater basin in terms of water quantity while maximizing the detention time for enhanced quality control, employing observed and predicted precipitation data. This allows an adaptive and predictive performance against actual and upcoming rain events. In addition, the performance of the proposed integrated optimization rule-based approach will be examined in presence of climate change to provide an adaptive measure as an alternative to the construction of new infrastructure. The specific objectives of this contribution can be enumerated as:

- To propose a predictive RTC control strategy for stormwater basin outflows aiming at minimizing peak flows and maximizing detention time at the local scale;
- To evaluate the performance of the proposed integrated RTC strategy on a case study stormwater basin;
- To assess the outcomes of integrating quality control rules to the quantity control optimization model for the studied stormwater system;
- To test the impacts of climate change on the RTC strategy’s performance; and
- To carry out a comparative analysis of the results obtained with the dynamic integrated RTC approach versus those of a traditional static approach.

- **Developing a smart framework for system-level control and optimization of urban stormwater, uncertainty analysis and erosion control**

The aim of this part is to extend the local-level integrated optimization rule-based strategy to a smart holistic control framework at the watershed level. Such global control framework should be capable of reducing the peak flow rate imposed on the receiving watercourse by balancing the outflow rates from all the stormwater basins over the watershed while considering the network capacity and water detention time at each local system. Hence, a dynamic flow rate optimization will be realized where the predicted precipitation data along with historical and observation data will be employed to decide on the best flow planning strategy at the system level. Besides, since the rainfall predictions are always associated with forecasting errors, an uncertainty analysis will be carried out to assess the global resiliency of the proposed dynamic strategy in uncertain situations. More specifically, the objectives of this part are:

- To propose a global predictive dynamic control (GPDC) approach to enhance the quality and quantity control performance of the stormwater management system in real-time at the catchment scale;
- To analyze the global resiliency of the system in critical situations such as more intense rainfall events imposed by climate change;
- To investigate the challenges of the proposed global approach by evaluating the comparative performance of a real catchment case study under dynamic and static approaches;
- To analyze the erosion reduction ability of the proposed system-level approach compared to the static approach; and
- To evaluate the impacts of uncertainties linked to rainfall predictions on the performance and robustness of the proposed control approach.

- **Improved real-time flow rate estimation by developing a multi-dimensional artificial neural network algorithm**

The main novelty in this part is the presentation of an octonion-valued neural network for rainfall-runoff modeling as a tool to provide input data for the proposed global control optimization framework. Developing such algorithm offers a significant reduction in complexity of the rainfall-runoff estimation using physical-based models like SWMM (Rossman and Huber, 2016) while generating accurate and fast predictions of the inflow rates based on the rainfall data sets provided. In summary, the specific objectives of this part are as follows:

- To design an 8-dimentional neural network by defining the perceptions in octonion-valued domain in order to estimate the runoff rates from the rainfall data, as a complex hydrological process;
- To perform a comparative analysis between the results obtained using the developed octonion-valued neural network and those generated by the physical-based simulation model in terms of accuracy and computational efficiency; and
- To investigate the advantages of employing an octonion-valued neural network for real-time rainfall-runoff modeling over the quaternion-valued and real-valued neural networks.

Four scientific papers and one conference paper were written based on these contributions. They have been integrated into this thesis and are summarized below:

1. Shishegar, S., Duchesne, S., & Pelletier, G. (2018). Optimization methods applied to stormwater management problems: a review. Urban Water Journal, 15(3), 276-286. **(Published)**

This paper provides a comprehensive review of the literature on optimization techniques applied to the stormwater management problems. Since more than eighty references were investigated in this study, four different categorizations were considered for the studied problems in the literature based on: 1) the control approach that can be either static or dynamic; 2) the urban drainage type that can be either combined or separate sewer; 3) the uncertainty consideration that includes deterministic and stochastics approaches; and finally 4) the objective function which can be either quantity, quality or cost. At the end, the research gaps and directions for further studies were provided based on this review of related state-of-the-art.

2. Shishegar, S., Duchesne, S., & Pelletier, G. (2019). An integrated optimization and rule-based approach for predictive real-time control of urban stormwater management systems. Journal of Hydrology, 577, 124000. **(Published)**

In this scientific paper, an integrated predictive real-time control optimization and rule-based approach were proposed to provide an adaptive and sustainable management strategy for stormwater basins at the local scale. The proposed approach in this paper minimized the peak flows imposed to the receiving watercourse during wet periods while maximizing water detention time in the basin by four designed rules to realize sedimentation during dry periods. The combination of these two quantity and quality control approaches is implemented on a rolling horizon approach, which enables dynamic scheduling of outflows at the outlet of a single stormwater basin.

3. Shishegar, S., Duchesne, S., Pelletier, G., & Ghorbani, R. System-Level Stormwater Management Optimization: A Smart Predictive Framework. Journal of Environmental Management. **(Submitted on May 2020).**

This paper extends the predictive RTC algorithm to a global scale to upgrade the conventional stormwater management system with a smart system-level adaptation measure. The global performance of the proposed algorithm is evaluated in presence of climate change and an erosion analysis is performed to evaluate the impacts of employing this developed strategy on mitigating the erosive potential of the receiving watercourse. In addition, the uncertainty associated with precipitation prediction is investigated in this paper that provides a better understanding of the dynamic control approach sensitivity to forecasting error and its ability to generate resilient control strategies for the stormwater basins over the watershed.

4. Shishegar, S., Ghorbani, R., Duchesne, S., & Pelletier, G. Rainfall-runoff modelling using Octonion-Valued Neural Network. Potential journal for submission: Hydrological sciences journal.

In this paper, a multi-dimensional octonion-valued neural network is proposed for rainfall-runoff forecasting. The proposed network is a data-driven model that provides fast and accurate flow rate estimation for real-time control processes. Comparison of the generated data using the developed octonion-valued neural network to those of a physically based approach like the stormwater management model (SWMM) was performed to investigate the efficiency of the proposed approach in terms of run-time and accuracy in estimating runoff discharges.

2 LITERATURE REVIEW

This chapter will provide a comprehensive review of stormwater best management practices, different control approaches, and methods for rainfall-runoff estimation. This chapter will be concluded with a published paper on optimization methods applied to stormwater management problems where a discussion on the research gaps is provided based on which this thesis project is motivated to propose the smart global predictive RTC strategy.

2.1 Problems associated with stormwater management systems and the proposed solutions

As elaborated before, stormwater management systems face some global challenges that require effective managerial policies, whether by upgrading their physical components, determining new control methodologies or promoting enhanced decision-making strategies.

Flooding, as one of the problems that stormwater management systems have been engaged with, is a direct hydrological consequence of urban development. Flood protection is considered as one of the major challenges in stormwater management (Ministry of the Environment 2003). Changes in stream response to storm events and greater hydraulic efficiency of urban conveyance elements lead to increased peak stream flows (Ministry of the Environment 2003). As one of the objectives of stormwater management systems is to minimize the risk of loss of life and property damages due to urban floods, many researchers have worked on this issue (e.g. (Mobley and Culver, 2014; Sun et al., 2011; Travis and Mays, 2008; Yeh and Labadie, 1997). Yeh and Labadie (1997) proposed a watershed-level approach for the integrated design of stormwater detention basins in order to achieve an efficient urban flood control strategy. In their study, that investigates the SWM systems at design-level, the optimal layout and sizing of detention basins were considered as the effective factor on the global performance of stormwater basins. A dynamic programming algorithm alongside with a multi-objective genetic algorithm (GA) was employed to optimize the problem. Travis and Mays (2008) also utilized dynamic programming techniques to identify the optimal location and sizing of retention basins. They claimed that taking retention basins as flood control ponds to mitigate flooding provides a more flexible model (Travis and Mays 2008). In another publication by Sun et al. (2011), a general framework was proposed for an optimal flood risk-based storm sewer network design, which is capable of taking future flood risks into account. Different from the Yeh and Labadie study (1997), the stormwater system layout was predefined. Yet, the pipe size and slopes are the decision variables that allow the identification of the appropriate design level by providing a trade-off between the construction cost and flood risk reduction. Mobley and Culver (2014) payed attention to detention pond outlet control structure design to develop a series of flow controls that reduce the ecological impact on the stream caused by urbanization while satisfying peak flow constraints. In this study, the detention pond design criteria was taken from Rossman and Huber, (2016) and design guidelines published by the Denver Urban Drainage and Flood District (DUDFCD, 2001), where one of the principal goals of a detention pond is the reduction of the post-development peak release rates to their pre-development levels.

Figure 2-1 illustrates how pollutants move with stormwater in separate sewer networks (NGSMI, 2005). According to this figure, it is important to have some stormwater facilities next to the receiving watercourse that treats stormwater runoff and/or helps reducing the generation of pollutants at their source. Otherwise the runoff carrying pollutants of roadways, constructions, parking lots and building roofs during wet periods, discharges directly to a receiving water, which can lead to further problems, as stated before.

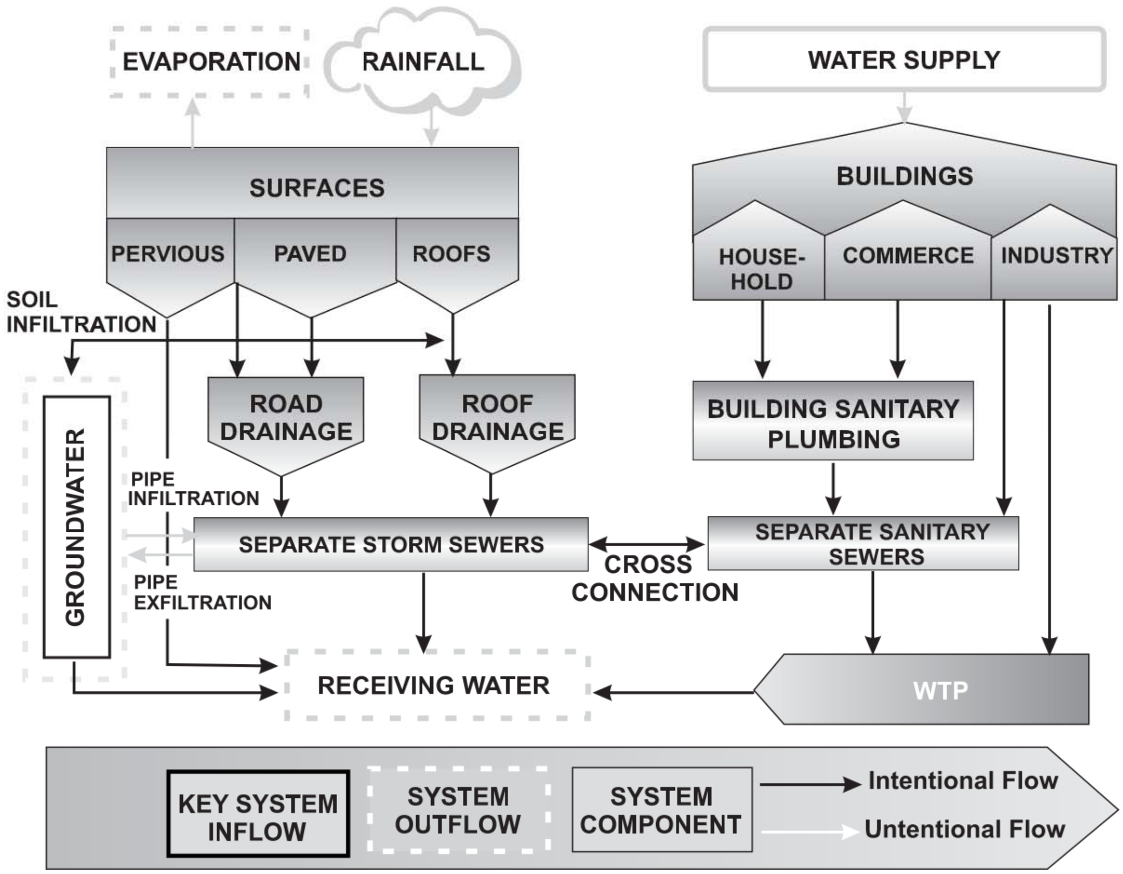

Figure 2-1- Pollutants sources and their movements in separate stormwater sewer systems (taken from *Butler et al. (2000)*)

Total suspended solids (TSS) reduction is thus another important stormwater management system objective, which provides post-development treatment of stormwater runoff (Middleton and Barrett, 2008). In this regard, Papa, et al. (1999) explained that in order to obtain an efficient pollution control performance of stormwater ponds, two opposing factors should be considered: improved pollutant sedimentation over longer detention times and decreased volume of runoff, that can be captured and treated by the pond. Hence, two parallel mathematical formulations are presented for pollution control performance of a dry basin for two scenarios where: (i) a volume resulting from a predefined design storm is to be captured by the pond, and (ii) the designer is free to select the storage volume of the pond. The achieved optimal design criteria of each case was analyzed to determine the best pollution control performance resulting from a design storm approach (Adams et al., 1987).

(Shammaa et al., 2002) provided a literature review on the factors and criteria that affect the TSS removal in a stormwater basin where beside detention time and volume, the pond geometric characteristics like length to width ratio, pond depth, bottom grading and side slopes are also important factors in TSS sedimentation. However, it is reported in this review that, unfortunately, many of these factors are not being considered in the pond designs, which leads to less efficient performances. For example, after analyzing two stormwater basins in Edmonton, it was found by (Shammaa et al., 2002) that the detention times in these ponds were too short for sedimentation and that the pollutant removal operation was not as effective as it should be. (Middleton and Barrett, 2008) report that to enhance the pollutant removal efficiency of stormwater management facilities, the outlet control can be modified to increase residence time in the basins. A further study (Muschalla et al., 2014) suggests equipping stormwater basins with dynamic sluice gates or similar actuators to first increase retention time and then attenuate peak flows to the receiving river. To do so, a real-time approach was applied to control the outlet sluice gate, which resulted in an effective solution for TSS and hydraulic shock reduction imposed on the river. More studies on RTC application will be presented in Section 2-2.

Another problem associated with stormwater management systems is that their construction requires significant investments to cover the land cost, initial construction cost and maintenance cost. In this regard, (Klenzendorf et al., 2015) report that active control of already constructed stormwater management systems enables a significant enhancement in their performance at a relatively lower cost than new constructions. In another study by Bartos, et al. (2018), it is elaborated that although many stormwater management objectives were previously realized by statically controlled infrastructures, retrofitting these systems with remotely-controlled components can provide the systems with the same benefits while reducing costs, expanding the control domain and adding adaptation capabilities to these infrastructures.

Another challenge in controlling the performance of stormwater systems is that, a single stormwater system was considered as the main issue in most of the studies with operational level considerations. However, considering the local operation of a system rather than that of a whole network can result in solutions, which are not optimal at the global level. For example, a locally optimal retention time in a single stormwater basin may cause a peak flow reduction at the local scale but the final hydrograph in the downstream receiving watercourse can be affected by the flows from other upstream areas that can cause critical conditions in the whole network. So, in order to achieve an efficient flow regulation plan, it is necessary to consider the network of pipes and detention basins located over the entire watershed to implement stormwater control measures at watershed-level (Rossman and Huber, 2016).

2.2 Stormwater best management practices

Several studies have addressed the importance of the BMPs and proposed a variety of techniques for their effective application mostly at the design level. For instance, the optimal design of the placement and size of detention basins for the control of flood in urban areas using a genetic algorithm (GA) (Yeh and Labadie, 1997), the runoff control in stormwater basin design, site by site, using dynamic programming (Behera et al., 1999), the efficient design of BMPs as series to prevent localized flooding (Villarreal et al., 2004), the pollution load reduction by optimizing the detention time of a stormwater pond (Papa et al., 1999), the development of a multi-criteria decision-making analysis to choose the most efficient BMP in terms of economic, social, environment, technical, hydraulic and maintenance criteria (Martin et al., 2007) and the design of a detention basin outlet to minimize alteration in the natural flow regime through simulation-optimization methodology (Mobley and Culver, 2014). All the above approaches provide solutions to better utilize different types of BMPs. In recent decades, stormwater basins in particular have become one of the most used BMPs that are mostly studied locally, irrespective of the operation of other structures or the conditions of other components in the watershed. In 1998, Walker investigated a stormwater pond in Adelaide to examine a method to determine the pond's residence time and the temporal distribution of its inflows. This method was developed to calculate the long-term residence time distribution based on the basin's behavior during inflows of varying amplitudes (Walker, 1998). To do so, both steady state and non-steady flow conditions were considered and then, the results from both cases were combined to achieve an overall residence time distribution for the stormwater basin and model the efficiency of the basin in terms of stormwater pollutants removal. Some researchers have considered the location of stormwater basins over a watershed as the effective factor in the overall performance of the stormwater management systems (e.g. Sebti, et al. 2016; Reichold, et al. 2010; Peng et al., 2016; Lee et al., 2012). Zhen, et al. (2004) utilized a long-term simulation approach to effectively identify an enhanced stormwater pond implementation plan. In this study, the sediment accumulation and resuspension effect were considered as the performance criteria of the detention ponds which were evaluated through the Agricultural Non-Point Source Pollution model (AnnAGNPS) framework (Zhen et al., 2004). This framework not only allows users to examine the treatment efficiencies of a group of several stormwater control facilities, but also provides a robust and cost-effective design of stormwater treatment systems. In another study by Sebti, et al. (2014), an optimization model was developed for selection and placement of retention ponds along with three other types of structural BMPs (green roofs, infiltration trenches and vegetated depressions). The objective function was to minimize the total cost of BMPs, subject to the constraints of (1) draining infrequent heavy rainfall without surcharging the conduits; and (2) driving frequent small rainfall into the water treatment plant without overflows.

Besides the design level, stormwater management basins have also been studied from the operational perspective (Gaborit et al., 2012; Middleton and Barrett, 2008; Muschalla et al., 2014; Oxley and Larry, 2014; Papa et al., 1999; Park et al., 2012). In this regard, Gaborit et al., (2012) investigated several enhanced RTC scenarios in order to optimize the operation of a dry detention pond located near Quebec City, Canada. TSS concentration removal was taken as the control performance criteria, which was evaluated by manipulating the output valve of the basin. The results of this study showed a significant increase in TSS removal efficiency from 46 % to 90 % in all scenarios. In another study (Ngo et al., 2016), the operation of detention ponds for minimizing the downstream flood damages was taken into account. To this purpose, the optimization techniques was coupled with the flood routing model using EPA-SWMM to obtain the optimal pumping schedule and the crest depth of a weir in order to minimize the maximum water level at the downstream control location. The evaluation of the optimal solution on the historical rainfall data of Seoul, South Korea, followed by severe flood events in 2011, showed significant flood mitigation in the studied watershed area.

2.3 Real-time control methodologies

There are numerous studies focusing on the control of stormwater basins mostly on static control strategies. However, the investigation of the systems controlled in real-time is an area of growing interest. In earlier RTC of water system studies, the application of Model Predictive Control (MPC) to prevent flooding in downstream areas was investigated, where the use of optimization algorithms for dynamic control of urban drainage systems was promoted (De Keyser et al., 1988; Niewiadomska-Szynkiewicz et al., 1996). In further stages, other objectives were considered such as minimization of combined sewer overflows (Duchesne et al., 2004), maximization of the pollutant load reduction (Hoppe et al., 2011) and also performance optimization of the regulating devices installed in urban drainage systems (Pleau et al., 2005). Also, a few research efforts have been directed towards the development of stormwater basins RTC strategies, but they are mostly rule-based methods, like the ones in Gaborit et al. (2012) or in Bilodeau, et al. (2019), where several control rules have been developed for real-time control of the outflow rate of stormwater basins. This was realized by manipulating the outlet valve of dry detention ponds based on several automatic reactive RTC scenarios identified by customized thresholds. Although the corresponding results showed improved pollution load volume removal efficiency from 46 % to 90 % in Gaborit et al. (2012), the proposed scenarios are not necessarily optimal and are applicable only on the studied basin. In another study by Jacopin et al. (2001), some on/off regulations were designed to develop operational management practices for stormwater detention basins. These operational local reactive control rules depend on local hydraulic conditions to control flows during heavy storm events and pollutants sedimentation during smaller more frequent events. Generally, adding control rules to the outlet of stormwater basins brings the ability to adapt to weather conditions; however, integrating optimization techniques into the definition of control set-points provides even more dynamic solutions to stormwater management problems that are applicable to different types and sizes of problems. In spite of limited efforts to study the performance of stormwater management systems in real-time, there is still a lack of a universally integrated system for stormwater management structures at the operational level that performs optimally under varying environmental conditions (e.g., urbanization, extreme storm events, runoff dynamics, etc.). Stormwater basins are among the stormwater management structures that can be controlled in real-time to exploit their potential for adaptive management of urban runoff. The RTC optimization of stormwater basins from the operational level perspective is still an emerging area of interest and most of the existing literature on optimization of stormwater management systems have addressed these systems only from the design level perspective. In this regard, (Wong and Kerkez, 2016) suggest retrofitting stormwater infrastructures with sensors and digital control systems to tackle varying meteorological conditions and runoff dynamics. In a recent study by Wong and Kerkez (2018), using internet-connected sensors on an urban watershed, a control algorithm was developed to manage the operation of valves and gates at the catchment scale. The authors showed that by controlling only 30 % of all watershed sub-systems, it was possible to achieve an adaptive performance in terms of flood mitigation and flow rate attenuation. In another study, Kerkez et al. (2016) proposed connectivity and intelligence as two key factors of adaptive control of stormwater management systems. Recently, Mullapudi et al. (2017) proposed a modelling framework for the simulation of smartly controlled stormwater ponds. To do so, the real-time operation of stormwater basin gates and valves was investigated. They reported that the biggest limitation of existing simulation approaches is their ability to simulate system-wide impacts of real-time control. Hence, they targeted their study on both local and global scales and evaluated performance of the system in terms of pollutant removal efficiency in both scales. Results showed two major benefits of system-wide control compared to the local approach; firstly a 15 % reduction in wetland effluent concentration and, secondly, a reduction in downstream hydraulic loads which has the potential to reduce the downstream erosion too. Generally, by deploying various field sensors, mobile gates and remote valves, it is possible to transform conventional stormwater management systems into a globally-controlled smart infrastructure that collects the observation data of the water quantity and quality over the network along with precipitation data to store them into the cloud database. In the cloud, data is maintained and backed-up remotely for further distribution over the network. A system-level control framework is required to properly process these data and furtherly generate some control set-points for the system operations to manage system flow dynamics for sustainable management of urban stormwater infrastructures.

2.4 Rainfall-runoff modeling

In stormwater management studies, the estimation of runoff as a critical parameter has always been of great interest. The studies on rainfall-runoff modelling are ranging from theoretical black-box methods to very detailed process-based simulation models. In this regard, the rainfall-runoff modelling approaches can be categorizes in two types: data-driven system-based methods and physically based mechanistic methods. Data-driven methods are built upon the linear/non-linear relationship between the input and output parameters without requiring any detailed understanding of the complex internal processes (Kalteh, 2008). Artificial neural networks (ANNs) are the state-of the art of this type of runoff estimation approaches that has been widely presented in the stormwater management literature. In contrary, in physically based models, a high number of parameters about the spatial and temporal characteristics of the watershed is needed to provide a deep understanding of the physics related to the hydrological processes for the mechanistic modelling of runoff (EPA, 2008). Among various physically based models, the stormwater management model (SWMM) is one of the tools with the ability to dynamically simulate the stormwater runoff and flow rates over an urban drainage network from specified rainfall series (Rossman and Huber, 2016).

In recent decades, by advances in technologies and emergence of real-time control systems, the use of data-driven models in various hydrological processes has become of great interest including flood prediction (Berkhahn et al., 2019), climate change studies (Daliakopoulos and Tsanis, 2016) and rainfall-runoff modelling (Kan et al., 2015; Tayyab, 2019). In this regard, Kan et al., (2015) introduced a hybrid data-driven model by developing an ensemble ANN for rainfall-runoff forecasting employing event-based simulations in non-updating time-steps mode. Although this approach provides a high accuracy estimation of the runoff, it is not practical to be employed in real-time control systems due to its inability to provide fast runoff estimations. Nayak, et al. (2005) proposed a fuzzy computing approach for real-time forecasting of flood. As data-driven models are highly dependent on the input parameters, a sensitivity analysis was carried out to evaluate the performance of the model under consideration of different combinations of input variables. Recently, the real-valued ANN models have been developed to higher dimensional numerical domains based on which several hyper-complex techniques have been proposed to model the high-dimensional nonlinear processes (Saad Saoud and Ghorbani, 2019) among which, Octonion-Valued Neural Networks (OVNNs) are proved to be one of the most promising approaches of hyper-complex ANNs. In stormwater management studies, high spatio-temporal variability of precipitation patterns, complexity of the underlying physical processes, and large quantity of parameters to characterize the watershed for the prediction of runoff rates make this problem relatively complex. Although many studies have employed ANN for runoff forecasting (Chen et al., 2014; Kalteh, 2008; Tayyab, 2019), the application of multi-dimensional ANNs have rarely been carried out. Chapter 5 provides a more detailed review of the methods applied to rainfall-runoff modelling in the literature.

2.5 FIRST SCIENTIFIC PAPER: Optimization methods applied to stormwater management problems a review

French title:

Revue des méthodes d'optimisation appliquées aux problèmes de gestion des eaux pluviales

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Authors contributions:

The authors confirm contributions to the paper as follows: All authors designed and developed the study conception and literature classifications. Shadab Shishegar studied the related literature to each classification, generated the results, and drafted and prepared the manuscript. Sophie Duchesne and Genevieve Pelletier as the supervisors of the project, provided many useful articles to investigate in the literature review and by giving practical advices significantly enhanced the quality of the paper. All authors reviewed the paper and approved the final version of the manuscript.

ABSTRACT

Stormwater management essentially aims at controlling the surface runoff in order to reduce water pollution, restore ecosystem integrity, and preserve the environment. Application of operations research for controlling stormwater management systems has been increased in recent years. This paper reviews and discusses several optimization problems associated with this field and tries to identify the knowledge gaps. Some of the developed commercial software tools are also presented. Having evaluated the relevant state of the art, we have noticed that there is an upward trend towards sustainability of the stormwater management systems to deal with climate change. Despite this progress, there are still many areas to further develop stormwater management models, many of which relate to uncertainty identification, real-time control, and the proper formulization of multi-objective problems.

Keywords: stormwater management; optimization; climate change

2.5.1 Introduction

Rapid population growth, industrialization, urban development and consequently the scarcity of high quality water resources are issues that induce researchers to employ mathematical optimization methods as one of the most effective methods to design solutions for different water related issues such as watershed degradation, pollution, water scarcity, sewer overflows, floods and drought.

Stormwater management in urban areas traditionally seeks to ensure the safety of citizens and to protect the public and private property during wet weather. Following the awareness of the impacts of stormwater drainage on physical and chemical characteristics of the receiving water, other objectives were gradually added to these traditional objectives. Thus, stormwater management activities may include the optimal control of water quantity, water quality (including nonpoint source pollution control and natural area protection), and erosion and sediment control (channel protection) (Committee 2008, MDDEP and MAMROT 2011). A stormwater management system can achieve its objectives by integrating all these types of controls. On the other hand, planning, design and control of stormwater management systems for sustainable development of water resources require the public participation; however, the main responsibility relies on the municipal decision makers to evaluate the policies and their impacts on the economic, social and environmental changes. Hence, researchers try to use the best tools available to make the best decisions. As tensions and disputes over water-related issues are growing, many researchers are currently engaged in finding practical solutions for these issues. In this regard, both hydraulic and hydrological aspects of rainfall-runoff processes have been widely considered, including surface runoff in either urban or natural settings, water transportation through rivers and drainage networks, and stormwater related infrastructures such as conventional pipes and Best Management Practices (BMPs). In all these aspects, the optimal design and operation have been of great importance.

In all cases, mathematical modeling can be an effective way to optimize the system performance which is in direct relation to its components (Behera et al., 1999). Generally, a mathematical optimization model tries to find the value for its decision variables which results in “the best” outcome for its objective function(s), without violating the constraints. A simple mathematical optimization model can be defined as:

$$\max\ (\min\ )\ f(x) \qquad (1)$$

Subject to

$$g_i(x)\{\leq, =, \geq\}\ b_i \quad \forall i \in I \qquad (2)$$

$$x_j \in S \quad \forall j = 1,2, \dots, n \qquad (3)$$

Where x is a set of decision variables, $f(x)$ is the function that defines the objective of the problem, $g_i(x)$ represents all the functions that together with b_i, the boundaries, and S, as the set constraints on x, determine the problem constraints. It should be noted that a problem can have more than one objective function. In this case, besides $f(x)$ other functions will be added to the objective function part of the model. The goal of a mathematical optimization model is to minimize or maximize the objective function(s) while satisfying all the constraints.

Optimization problems can be categorized according to different criteria such as (Frontline Solvers, 2016):

Based on the functions: Linear programming (LP), Quadratic programming (QP) and Non-linear programming (NLP)

Based on the decision variables: Continuous programming, Discrete programming including Integer programming (IP) and Binary programming (BP), and finally Mixed integer programming (MIP)

Based on the constraints: Constrained programming and Unconstrained programming

Based on convexity of functions: Convex optimization and Nonconvex optimization

Stochastic programming and Deterministic programming

Single objective optimization, bi-objective optimization or multi-objective optimization.

There are numerous other forms of optimization problems that are not included in the classification above, such as Bound constraints programming, Quadratic programming with quadratic constraints (QPQC), Non-linear least square programming, Non-smooth problems (NSP), and many others which are not as common as the aforementioned types.

In stormwater management area, depending on the target problem, most of the optimization approaches are found to be non-linear programming mostly because of the non-linear behavior of the processes themselves. Also, in some cases the continuously changing nature of the environmental phenomenon and the heterogeneity of the parameters in creation of a natural situation can impose non-linearity. For instance, in a reservoir system optimization problem, the complexity of the variables and processes like unregulated inflows, system demands, net evaporation and hydrologic parameters, leads to a complex non-linear programming problem (Labadie, 2004). However, a non-linear programming problem can be solved using different algorithms depending on the degree of non-linearity of that optimization problem (Pleau *et al.* 1998), in many cases, linear programming is preferable to simplify the mathematical resolution.

This paper aims at providing a survey of literature in stormwater management issues that employ optimization methods to achieve an effective solution. To do so, a thorough categorization of these problems is presented to provide a better understanding of the current research issues and the criteria involved in the investigation of the problem. The outline of the paper is as follows. Section 2 presents the study purposes. Section 2.5.3 explains the methodology used to collect the literature and then identifies the scope of the review and the different perspectives that are investigated in the research. In section 2.5.4, a summary of stormwater management optimization studies and their models characteristics is provided in the form of a table, according to the proposed classification in section 2.5.3. Later in section 2.5.4, a detailed survey of literature is presented separately for studies based on control approach, uncertainty consideration, and the objective functions associated to the studied stormwater management optimization problems. The concluding remarks with some further study suggestions are provided in section 2.5.5.

2.5.2 Study goals

In this review article the goals are:

- To collect an extensive list of scientific researches in the field of stormwater management using optimization methods,
- To facilitate the access to a variety of relevant references for researchers,
- To identify the research gaps and indicate the major shortcomings in the literature, and finally,
- To propose further studies for the advancement of this area of research.

2.5.3 Methodology

Studies on different optimization problems found in the field of stormwater management are investigated in this review. To gather the related literature, the SCOPUS database was searched by using the search terms “optimization” AND (“stormwater management” OR “urban drainage”). Totally, 334 documents were found after limiting the search to the years 1986-2017. These documents cover a broad range of journals on environmental science and engineering as some of them are shown below (Table 2-1).

While surveying these studies, we focused on reviewing the optimization problems related to stormwater management and identifying the prominent related research questions. To this aim, we present various strategies proposed in the literature and investigate the most significant objectives conducive to manage stormwater systems.

Furthermore, these studies will be investigated to propose areas where the models could be improved. To this aim, we have distinguished the stormwater management optimization models from four perspectives: i) the stormwater management approach including combined or separated sewer networks, ii) the control approach which can be either static or dynamic, iii) the uncertainty considerations, and iv) the objective function, that could be defined in terms of quality, quantity and/or cost. Figure 2-2 expands the different perspectives of the survey to classify the previous published literature into several groups.

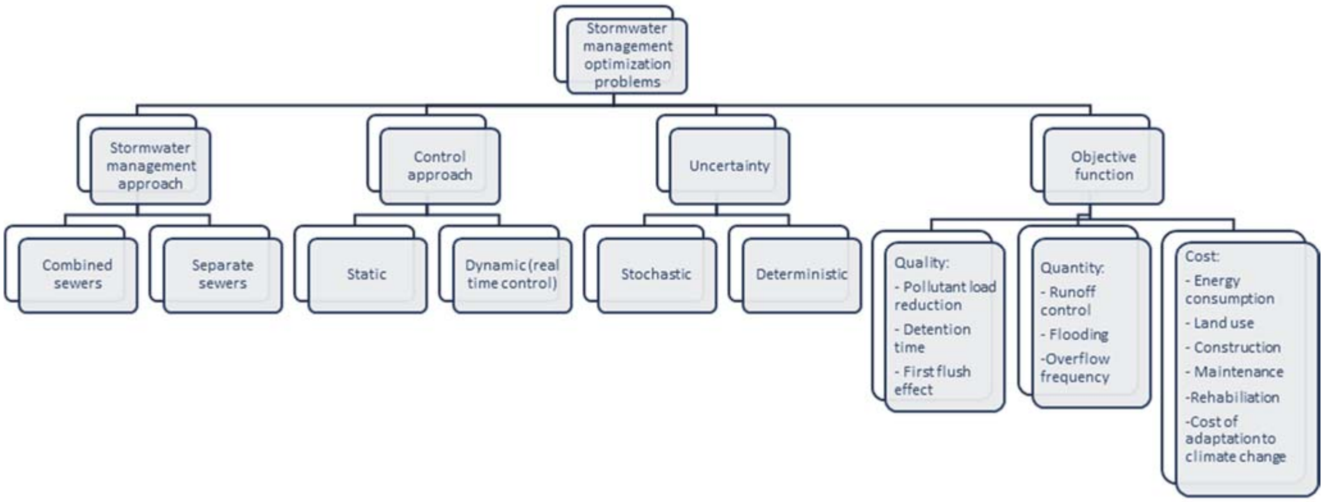

Figure 2-2- The optimization approach classification developed from the literature

2.5.4 Results

Table 3-2 provides a summary of stormwater management optimization studies and their modelling characteristics, according to the proposed classification (Figure 2-2). In this table, the studied literature is presented in detail, based on the characteristics of the systems and models. This allows highlighting the combinations that have been less considered in the literature.

According to Table 2-2, section 2.5.4.1 presents the literature for two different systems, namely the combined sewers and stormwater management systems. In section 2.5.4.2, we divided the literature in two categories based on two control approaches: static control and real-time control (RTC). As the uncertainty is an inseparable issue in environmental problems, section 2.5.4.3 presents the articles that pay attention to the uncertainties involved in their studied problem. In section 2.5.4.4, stormwater management optimization problems in the existing literature are investigated based on their objective function(s). The detailed explanation of each category brought in corresponding section.

2.5.4.1 Based on stormwater management approach

The combined sewer system refers to a large network of pipes that carries municipal wastewater, including both sanitary and industrial water, combined with the surface runoff from stormwater. While the separate sewer network is designed to collect the wastewater and stormwater in two separated networks. This helps prevent the overflow to natural water courses of a combination of surface runoff with residential and industrial wastewater. With the development of urban areas and growing population, separating stormwater from municipal wastewater became a matter and separate sewer systems were implemented in many recently constructed municipalities. However, in some parts of many older cities (like New York City, Toronto, Philadelphia and London), the urban drainage system is still combined as changing the whole infrastructure would be too costly and time-intensive. Generally speaking, it cannot be said that the separate sewers are necessarily more preferable than the combined sewers in all situations as these systems may result in an increase in pollutant loading to receiving environment, due to the increased discharge of untreated surface runoff (Mannina and Viviani, 2009). Different factors like rain characteristics, the pollutant concentration in the catchment and the sensitivity of the receiving water affect the choice of drainage network (De Toffol et al., 2007). Hence, there are still needs for solutions to employ the best approach and also to properly manage the already-constructed combined and separate sewer systems. Optimization algorithms fall within the most useful approaches in this regard.

a. Combined sewers

Optimization methods have been widely applied to combined sewer systems first, due to their capital-intensive nature and then, because they are known as the source of many urban river quality degradations, caused by combined sewer overflows (CSO) which occur when flows exceed the transport and/or the treatment capacity of the sewer system during heavy rain events. Using these methods helps researchers deal with many combined sewer related problems and also develop an optimal water resources management policy. Adams et al., (1972) were one of the firsts to formulate the wastewater sewer network as a mathematical nonlinear programming model, using a linear approximation for an optimal solution for the cost effectiveness problem through a computer software. Hydraulic and hydrologic considerations have also been taken into account in mathematical models, where some of the system component characteristics such as conduit size, junction dimensions, buried depth of pipes and storage capacity were optimized to meet constraints and accomplish designed objectives (Adams et al., 1972). In this regard, it has been found that a more efficient design of the urban drainage layout can lead to more significant savings than other alternatives. Li and Matthew, (1991) developed a nonlinear programming model decomposed in two smaller models, one for the placement of pumping stations and the second for manipulating the flow rates in the pipes. Also, the studies on location optimization of the different parts of the urban drainage system, like the online pumping stations (Dajani *et al.*

1972, Froise and Burges, 1978, Li and Matthew 1990), detention basins (Yeh and Labadie, 1997) and water quality sensors (Propato, 2006), refer to the importance of the issue and efficiency of the optimization algorithms in achieving the solution.

A further and equally important consideration is the general control of the drainage network using numerical formulations, which has always been a matter of interest to researchers. Cembrano et al., (2004) investigated a combined sewer network which is optimally controlled to prevent overflows and reduce the risk of flooding through developing an optimization model. To do so, an objective function was defined as the sum of the quadratic flow deviations from the sewers design flows, CSO volume to the sea and the volume stored in the reservoirs, prioritized with predefined coefficients and subject to several linear and non-linear equalities and inequalities to meet the optimal control of the network.

Despite the comprehensive literature on CSO control, because this issue is the most significant concern about the combined sewers, studies in this regard are still of increasing interests (Darsono and Labadie, 2007; Ocampo-Martinez et al., 2008; Regneri et al., 2010; Wang et al., 2007). Recently, Löwe et al., (2016) proposed a stochastic forecast-based optimization model for the real-time control of an urban drainage system to minimize the volume of CSO. In general, real-time control is one of the most conducive solutions to reduce the overflow volumes and frequencies in combined sewers (Duchesne et al., 2001), and has been widely discussed in the literature (Borsanyi et al., 2008; Gaborit et al., 2012; Pleau et al., 2005; Tobergte and Curtis, 2013; Vezzaro and Grum, 2014). Studies on real-time control of combined sewers will be presented in section 2.5.4.1.

Table 2-1-Summary of stormwater management optimization model characteristics found in the literature

Reference	Control objectives			Collection approach		Uncertainty		Control approach				
									Dynamic			
	Quality	Quantity	Cost	Combined	Stormwater	Uncertain	Deterministic	Static	Global	Local	Predictive	Reactive
(Gaborit *et al.* 2013)	×	×			×		×			×	×	
(Travis and Mays 2008)			×		×		×	×				
(Abraham *et al.* 1998)			×	×		×		×				
(Shamsudin *et al.* 2014)	×	×	×		×	×		×				
(Li and Matthew 1990)			×	×		×						
(Cembrano *et al.* 2004)	×	×		×			×		×		×	
(Fiorelli and Schutz 2009)		×		×			×		×		×	
(Mao *et al.* 2017)	×	×	×	×			×	×				
(Vanrolleghem *et al.* 2005)	×			×		×				×	×	
(Darsono and Labadie 2007)	×	×		×			×		×		×	
(Yeh and Labadie 1997)	×	×	×		×		×	×				
(Afshar 2010)			×		×		×	×				
(Zoltay *et al.* 2010)			×	×			×	×				
(Yazdi *et al.* 2014)		×	×	×		×		×				
(Vezzaro and Grum 2014)		×		×		×			×		×	
(Verdaguer *et al.* 2014)	×			×			×			×		×
(Tung 1988)		×	×		×		×	×				
(Rauch and Harremoes 1999)	×	×		×			×			×	×	
(Pleau *et al.* 2000)		×		×			×		×		×	
(Perez-Pedini *et al.* 2005)		×			×		×	×				

Reference	Control Objectives			Collection approach		Uncertainty		Control Approach				
									Dynamic			
	Quality	Quantity	Cost	Combined	Stormwater	Stochastic	Deterministic	Static	Global	Local	Predictive	Reactive
(Cano and Barkdoll 2016)			×		×		×	×				
(Chang *et al.* 2011)			×		×	×		×				
(Che and Mays 2015)		×			×		×			×	×	
(Duchesne *et al.* 2004)		×		×			×		×		×	
(Fu *et al.* 2008)	×		×	×			×			×		×
(Mobley and Culver 2014)		×			×		×	×				
(Baek *et al.* 2015b)		×		×			×	×				
(Jia *et al.* 2016)		×			×		×		×		×	
(Yu *et al.* 2017)		×	×	×		×		×				
(Joseph-Duran *et al.* 2014)		×		×			×		×		×	
(Löwe *et al.* 2016)		×		×		×				×	×	
(Marinaki and Papageorgiou 2003)		×		×			×			×	×	
(Giacomoni and Joseph 2017)		×	×		×		×	×				
(Baek *et al.* 2015a)		×			×		×	×				

b. Separate Sewer

Stormwater management systems are designed for collection of surface runoff during wet periods. Stormwater runoff can sometimes be directed to a stormwater basin for further controls. Stormwater basins, as one of the most used Best Management Practices (BMP), have been developed and implemented to ensure the control of rainwater in terms of flow rates and/or runoff volumes, and improve water quality by sedimentation. Several studies have addressed the optimization of stormwater control measures with different criteria, and used a variety of techniques, for example: the optimal design of the location and size of detention basins for the control of flood in urban areas using a Genetic Algorithm (GA) (Yeh and Labadie, 1997), runoff control in stormwater basin design, site by site, using dynamic programming (Behera *et al.* 1999), pollution load reduction by optimizing the detention time of a stormwater pond (Papa et al., 1999), and design of a detention basin outlet to minimize alteration in the natural flow regime through simulation-optimization methodology (Mobley and Culver, 2014). Also, the combination of multiple criteria could be considered like in Shamsudin et al., (2014), where the maximization of runoff control performance of a detention pond and the minimization of the cost are studied using an analytical probabilistic model and the Particle swarm optimization (PSO).

However considering the operation of a single basin rather than that of a whole network can be misleading. For example, a detention time balance in a single stormwater basin may cause a peak flow reduction in the related watershed but the final hydrograph in the receiving watercourse can be affected by flows from other upstream watersheds and cause critical conditions in the whole network. So, to obtain a global flow reduction plan, it is necessary to consider the whole network of pipes and detention ponds rather than studying them individually. Furthermore, only by having in mind stormwater basins as components of a network, the extreme rainfall events generating volumes exceeding each basin’s capacity, can be controllable. Thus, global optimization of detention basin networks from the perspective of flow, water quality and cost should definitely be beneficial.

2.5.4.2 Based on control approach

In a general definition, static optimization refers to “the process of minimizing or maximizing the cost/benefit ratio of some action for one instant in time only”, while dynamic optimization describes the process of finding the optimal value of one or some objective functions over a period of time (Gregory, 2002). In this study, by static control we mean a system which works without time consideration, i.e. that the set points stay constant in time. In contrast, a dynamic control is taken as real-time control (RTC) in which the control system performs on-line. In fact, a real-time control action continuously receives data as input, processes them and finally updates the outputs, or set points, in pre-specified time intervals which are mostly near real-time. Stormwater management can benefit from various RTC modeling techniques and their applications are of increasing interest. Unlike statically controlled stormwater management facilities which cannot adapt its operation to different storm events or changing land uses, RTC stormwater systems use system-level coordination to reduce flooding and minimize pollutant loading into receiving waters (Mullapudi et al., 2017). The two next sections provide an overview of the static and dynamic control approaches of the stormwater management problems in the literature.

a. Static

Most of the literature on stormwater management modelling relies on static control approaches showing that there is still a big potential to consider dynamic control and think out of the box to design more realistic and flexible systems. For example, instead of taking the maximum outflow of a detention basin as a constant value in order to reduce the pollution of water from both small and heavy rainfall events as in (Middleton and Barrett, 2008), a flexible outflow rate could be more efficient to satisfy the control of water quality (Gaborit et al. 2012).

Although there is no doubt that a dynamic system should perform more efficiently in most of the cases, sometimes, a statically operating procedure can avoid any extra expenditures and any additional energy consumptions or even increase the life expectancy of the involved equipment (Pleau et al., 2002). Moreover, in a static optimization strategy, the execution time of the program is not important since the optimization is realized only once, and off-line. This allows evaluating the possible solutions more productively increasing the probability of achieving a more optimal strategy, if the processes are nearly constant in time. However, in many environmental issues, the variation in time of the control variables and processes is critically important such that real-time consideration is desired.

b. Dynamic

The control of a system is said to be dynamic when a physical variable of the system is required to follow or track some pre-specified time function. In this study, more specifically, the focus is on RTC, i.e. the process where variables are measured in the system continuously and used to operate actuators (García et al., 2015) at the same rate of providing input data to the system, which mainly happens in very short time-steps. Recent advances in information technology and high-speed processors facilitate the implementation of RTC systems in various applications. Due to the continuously required control actions and the dynamic nature of stormwater management systems, the application of RTC on these systems can give proper results. RTC applications have been studied in different stormwater management systems to minimize CSOs (Duchesne et al., 2004; Marinaki and Papageorgiou, 2003; Pleau et al., 2001; Tobergte and Curtis, 2013; Vezzaro and Grum, 2014), to minimize the pollution load (Gaborit et al., 2012; Hoppe et al., 2011; Lacour and Schütze, 2011), to minimize the cost (Pleau et al., 2005), to prevent flooding (Niewiadomska-Szynkiewicz et al., 1996), and also to maximize the utilization of regulating devices like mobile gates, inflatable dams, variable speed pumps and variable crest weirs (Pleau et al., 2005).

Generally, RTC systems can be distinguished in regard to their control level or data type. In terms of levels of control, two levels have been studied, global and local, such that the global control level is responsible to provide the required set-points for the local controllers using the information gathered from all the system, while at the local level, all the set points are determined locally for each part of the system (Pleau et al., 2001; Vanrolleghem et al., 2005). On the other hand, RTC systems can be performed reactively or predictively. A reactive RTC system takes the control decisions based on the past and actual system data whereas a predictive system also uses predicted data as inputs to define the control actions (Duchesne *et al.* 2004, Vanrolleghem *et al.* 2005). In this regard, a global predictive RTC system was designed by Pleau *et al.* (2001) to reduce the frequency of CSOs using a non-linear programming package to produce flow set-points and optimize a multi criteria model constrained by the hydraulic and hydrologic linear equalities and inequalities for the Quebec City's sewer network. The application of global predictive RTC approach in this study resulted in a 60% reduction in overflow volumes compared to a static approach.

Optimization algorithms have been already applied to RTC of stormwater management problems in the literature, however, it is still an ongoing field. (Marinaki and Papageorgiou, 2003) developed a linear multi-variable feedback regulator to prevent overflows in a sewer network through a linear-quadratic design procedure. In their study, by maximizing the utilization of a reservoir's available storage space and draining it as soon as possible to provide the required volume for future rainfall events, the optimization problem aims at minimizing the combined network overflows.

Other optimization algorithms applied to solve stormwater management problems include the use of meta-heuristic programming models, like the bio-inspired mathematical algorithms (Afshar, 2010) that, due to their independency of the function derivatives, can be used to solve many complex, non-linear and multi-objective optimization problems. For example, finding the optimal flows between the detention basin and WWTP using GA to minimize the global cost function in RTC of an urban drainage system in Vezzaro and Grum (2014) or employing a nonlinear model predictive control (MPC) combined with a genetic algorithm to minimize transit pollution from an urban wastewater system (Rauch and Harremoës, 1999). A detailed description of several techniques and strategies, including optimization-based algorithms applied to urban drainage systems, can be found in García et al. (2015).

2.5.4.3 Based on uncertainty

Infeasible solutions or even those feasible solutions that mislead decision makers to take improper actions, may be the results of having uncertainties in system parameters and variables. However, the costly and time consuming nature of uncertainty analysis somehow hinder researchers to consider them in their investigations, but the tendency to design the models as close as possible to reality leads to significant advances in developing robust based models. In the stormwater management field, like every other fields, there are uncertainties in model parameters, input data, calibration data or in the model structure (Dotto et al., 2012). The next two sections will expand on stormwater management deterministic and stochastic optimization models found in the literature.

a. Deterministic models

Several optimization models have been reported in the literature in which all the model components are considered to be deterministic (Abraham et al., 1998; Afshar, 2010; H. Baek et al., 2015; Cembrano et al., 2004; Erbe et al., 2002; Fiorelli and Schutz, 2009; Gaborit et al., 2012; Tung, 1988). These studies mainly aim at introducing a new approach (Joseph-Duran et al., 2014), developing a new mathematical model (Montaseri et al., 2015) or proposing a corrigendum to an already existing solution (Afshar 2010). For example, Baek et al., (2015) investigated a new meta-heuristic particle swarm optimization approach for a multiple storage sewer network to control CSOs. To do so, a mathematical formulation of the simplified system is modeled to finally optimize the location and storage size of multiple storage tanks. In this study, the main focus is on developing two additional approaches to promote particle diversification: a diversity-guided three-phase velocity update rule and restricted social searching method, in which, however, there are many uncertainties involved, the reasonable strategy is to consider all the model components deterministic to avoid any complexity in the model and provide a better description of the newly developed methodology. Generally, in presence of uncertainty, although in most of the cases stochastic models are more realistic, deterministic models are more convenient to use when the sources of uncertainty are negligible or when considering them leads to a high complexity, and consequently causes the digression from the main research subject.

b. Uncertainty-based models

Unlike deterministic models where all the outputs are the exact result of the cause and effect relationships between all the system's components, uncertainty-based models often have varying results for the same set of initial inputs, due to the random nature of their components or processes (Obropta and Kardos, 2007). Inaccuracy of measurement devices in providing the exact value of model variables such as flow rates, rainfall intensity, water pollution and water level, uncertainties regarding maximum flow rates, estimation of CSO discharges based on rainfall time series (Regneri, 2014), uncertainties caused by modeling mismatches and simplifications (Pleau et al., 2002), and prediction uncertainties (Löwe et al., 2016), like the rainfall depth and duration in Yazdi et al. (2014) or runoff predictions in Vezzaro and Grum (2014), are some of the sources of uncertainties highlighted in the urban stormwater modelling literature. For example, in build-up and wash-off runoff quality model, uncertainty would cause inevitable unreliability. Indeed, in this kind of model, "build-up" of water contaminants on impervious surfaces during dry periods results in "wash-off" of the pollutants in wet periods. As these processes in the real world are more complicated than those modeled (Bonhomme and Petrucci, 2017), it often comes with uncertainty (Obropta and Kardos, 2007). Clearly, the degree of uncertainty is a function of model characteristics. (Regneri, 2015) reports for instance, as the length of the forecast horizon increases the uncertainty of predicted data gets worse. Shrestha (2009) suggested that for achieving a reliable and more realistic model, it is necessary to: 1) recognize the sources of uncertainty; 2) express the detected uncertainty numerically; 3) assess its propagation through the model; and 4) propose solutions to mitigate their consequences. To this aim, several approaches have been employed to counteract the uncertainty effects on the stormwater management operations. Vezzaro and Grum (2014) presented a Dynamic Overflow Risk Assessment (DORA) strategy as a global control approach to estimate the uncertainty of urban runoff forecasts in a Model Predictive Control (MPC) of urban drainage network, and subsequently minimize CSO costs (which refer to overflows generated by water volumes already in the drainage network) within the entire catchment. Also, the Generalized Likelihood Uncertainty Estimation (GLUE), which is a Monte Carlo based approach introduced by (Beven and Binley, 1992), has been widely used in the quantity and quality modelling of urban stormwater (Dotto *et al.* 2012), as in Jia and Culver, (2006) where a robust optimization model is developed to incorporate the uncertainty of water quality predictions and to minimize pollutant load reduction using the GLUE approach.

Moreover, as a probability distribution function can be used for the uncertain hydrologic or hydraulic variables in many cases, the stochastic methods have received lots of attention in stormwater management studies. The probabilistic Huff method (Huff, 1990) was applied to determine the probability distribution of two uncertain rainfall variables, depth and duration, to utilize in stochastic multi-criteria optimization model of urban drainage system rehabilitation (Yazdi et al. 2014). In another work, the previously-introduced method, DORA, has been combined with a stochastic grey-box model to deal with the probabilistic nature of runoff forecasting to RTC of urban drainage system (Löwe et al. 2014). Recently, Yu et al., (2017) proposed a stochastic optimization model for urban drainage design in order to achieve a more robust optimal solution to the effects of urban hydrological model parameter uncertainty. The trade-off between the total investment on drainage network rehabilitation and flood control goals have been conducted to solve the problem using heuristic algorithms while employing techniques of urban hydrological simulation and climate-change model downscaling. The results showed a higher level of system reliability in stochastic model, compared to deterministic one.

Generally, the negative impacts of uncertainties on the productivity of the strategies that decision makers employ to cope with urban stormwater management issues, have given rise to many uncertainty techniques for the development of more reliable optimization models. Although these techniques have evolved gradually from very simple to more complex forms, detection of new sources of uncertainty has influenced the reliability of the developed models. Therefore, not only the invention of new heuristic would be beneficial, but also the decision-making based on stochastic programming can markedly contribute to a more realistic modeling of dynamic processes.

2.5.4.4 Based on objective function

Many different criteria can be minimized, or maximized, when studying a stormwater management optimization problem, generally called a cost function or objective function. Stormwater management objectives can be classified under three main headings - ensuring the quality of water, quantity considerations and cost minimization. The trade-off between these objectives can also be considered depending on the problem, which is called “multi-objective optimization”. In the following sections, the use of these objectives in the literature will be explained.

a. Water quality

One of the main consequences of urbanization is the degradation of surface water quality which can affect directly public health and ecosystems. Therefore, stormwater quality considerations have become one of the critical challenges that stormwater management was engaged with (Obropta and Kardos 2007). Besides, the growing impact of urban stormwater on the vulnerability of water resources raised the need for more accurate modeling of stormwater pollution (Beck, 2005). Throughout the years, researchers have been studying different aspects of water pollution in their mathematical models and trying to propose solutions to overcome the factors that negatively affect the quality of water. Pollutant load reduction, detention time optimization, first flush effect minimization, storage facility de-watering time optimization are some of the control objectives studied to achieve the desired water quality in terms of optimization applications. For instance, a nonlinear model predictive control has been employed in Rauch and Harremoes (1999) to provide a flexible formulation for real-time control of urban wastewater system to minimize transient pollution. Papa et al. (1999) proposed two parallel formulations in order to maximize the long-term performance of a dry detention pond to more effectively remove total suspended solids (TSS) by selecting the optimal stormwater management pond detention times. Although detention time maximization is one of the major factors in stormwater basin design to enhance TSS removal (Shammaa et al. 2002), sometimes it leads to more overflows due to heavy rainfall. By designing an adjustable gate opening, hence, a flexible structure can be provided in order to maximize the detention time to improve TSS removal while protecting the receiving water bodies from hydraulic shocks and minimizing the probability of overflows (Gaborit et al., 2012). The outlet control in stormwater ponds could be considered as a key factor in optimization of stormwater management systems to protect water quality while avoiding any overflows in the receiving body, such that in (Middleton and Barrett 2008, Gaborit *et al.* 2012, Mobley *et al.* 2013). A few other criteria have been studied in the literature to preserve water quality such as i) minimization of the first flush effect (Abrishamchi et al., 2010; H. Baek et al., 2015; Verdaguer et al., 2014), which contains a greater initial stage wash-out pollutants compared to the remainder of the storm event (Verdaguer et al. 2014), ii) sediment-trapping BMP placement optimization, in which the results from the linear and dynamic programming are compared with a new method using a GA optimization and a nonlinear distributed watershed model in Limbrunner et al., (2013), and iii) the optimization of stormwater filtration to accommodate Total Maximum Daily Loads (TMDL) as in Hipp et al., (2006).

b. Quantity

Since one of the key issues in stormwater management, is the control of water quantity, the specialties in this field have been trying to simulate realistically the urban stormwater behavior, in order to define the optimal control performance of an effective stormwater management system and to prevent the undesired consequences of urban runoff in different ways. Failure in controlling the quantity of stormwater, especially in urban areas, may result in irreparable damages to infrastructure, but also to the quality of water resources, like when the CSOs in an industrial area discharge over-polluted water to the nearby streams, rivers and other water bodies. Efforts to minimize CSOs have prompted researchers to consider the CSO control as the main objective of their optimization problem, either in terms of CSO frequency mitigation (Pleau et al., 2001; Saber-Freedman, 2016) or overflow volume reduction (Joseph-Duran et al., 2014; Vezzaro and Grum, 2014). In this regard, a number of optimization-based techniques have been developed to minimize undesired sewage discharges. Baek *et al.* (2015) presented a meta-heuristic particle swarm optimization-based design methodology of complex sewer networks to investigate the optimally distributed locations, sizes and numbers of multiple reservoirs for efficient CSO reduction.

There are some traditional flood control ponds, whose function is primarily to attenuate peak flow rates (Papa et al. 1999). Although these ponds can be replaced by more equipped stormwater basins, the minimization of flooding is still a subject of interest. Reservoir operation is one of the solutions that is studied widely in the literature to control flooding through various optimization methods: linear programming (Needham et al., 2000; Watkins et al., 1999), goal programming (Choudhury, 2010), non-linear programming (Unver and Mays, 1990), dynamic modeling (Che and Mays, 2015) and fuzzy optimization methods (Guan and Lin, 2016; Zamani Sabzi et al., 2016).

Other criteria that have been addressed in the stormwater management literature based on the quantity of stormwater include runoff quantity minimization (Papa *et al.* 1999, Cembrano *et al.* 2004, Gaborit *et al.* 2012), overflow frequency and volume minimization (Tung, 1988) and flow equalization (Schaad et al., 2008).

c. Cost

Alongside with the above-mentioned objectives, the costs involved in stormwater management, especially in urban areas, have always been an issue of concern. The existing literature provides an extensive list of cost objective functions to be considered in stormwater management problems. Costs of land use, construction and maintenance of stormwater management systems are the most traditional components of objective functions found in the literature (Travis and Mays, 2008; Tung, 1988; Vezzaro and Grum, 2014). These objectives can be considered as the main criteria in different control problems. For example, the storage-release systems, that aim at controlling stormwater quantity (runoff) and its quality through defining long-term performance measures, such as the overall fraction of runoff controlled and the fraction of pollutant removal from the storage facilities (Wang et al., 2007), can be described as an optimization model. The aim of this model can be minimization of construction cost of stormwater management ponds while ensuring both the water quality and runoff quantity, as studied in Behera et al. (1999). In addition, the total cost minimization has also been considered as the objective function in Sebti et al., (2013), where the cost-effectiveness of the urban drainage system rehabilitation is assessed by a proposed algorithm considering both structural and hydraulic performances.

Also, in several studies, cost minimization comes along with other objectives and forms a multi-criteria optimization problem. Tung, (1988), as one of the firsts, proposed a framework to establish the trade-off between the risk of overflow and the cost of storage and treatment capacities through designing a multi-objective detention basin optimization model. Recently, (Cano and Barkdoll, 2016) introduced the multi-objective, socio-economic, boundary-emanating, nearest distance (MOSEBEND) algorithm that allows the optimal selection and placement of a set of BMPs for various sub-watersheds. The cost objective function used here is assumed to be a cost-benefit ratio in which the cost is the opportunity costs of using the land for the BMP instead of its original use, while the benefit is defined as runoff reduction or, alternatively, the level of pollution reduction. Also in a recent study, the minimization of implementation cost comes along with the minimization of peak-flow, runoff volume and a new introduced stormwater metric alteration, in three optimization models in order to achieve near optimal locations of green roofs and permeable pavements as two types of stormwater Low Impact Development (LID) measures (Giacomoni and Joseph, 2017).

While the most significant costs in a stormwater management system are related to the initial investments and the maintenance, some other expenditures are involved that cannot be easily denied. For instance, following the general increasing awareness of the limited resources of energy and considering this issue in the political agenda, the energy saving strategies have also been brought up in some recent studies (Chang et al., 2011; Wang et al., 2013; Zoltay et al., 2010). In this regard, Chang et al., (2011) proposed a stochastic linear programming model to achieve a degree of energy savings and stormwater conservations considering the optimal design of green roofs as one of the BMPs. In their study, it is proved that the benefits of such systems due to the long-term saving of energy is considerable and can offset the initial capital and ongoing maintenance costs of the system. In general, the consumption of energy is one of the today's global concerns and almost all the research areas are somehow involved in finding energy saving strategies, and stormwater management is no exception.

2.5.5 Concluding remarks and further studies

Our review encompasses various optimization problems studied in the field of stormwater management. It provides a review of over eighty papers from the major referenced journals within the field. According to the data from the collected literature, approximately 70% of the articles were published in the last 10 years; and the overall trend of publication numbers in this area has been upward (Figure 2-3).

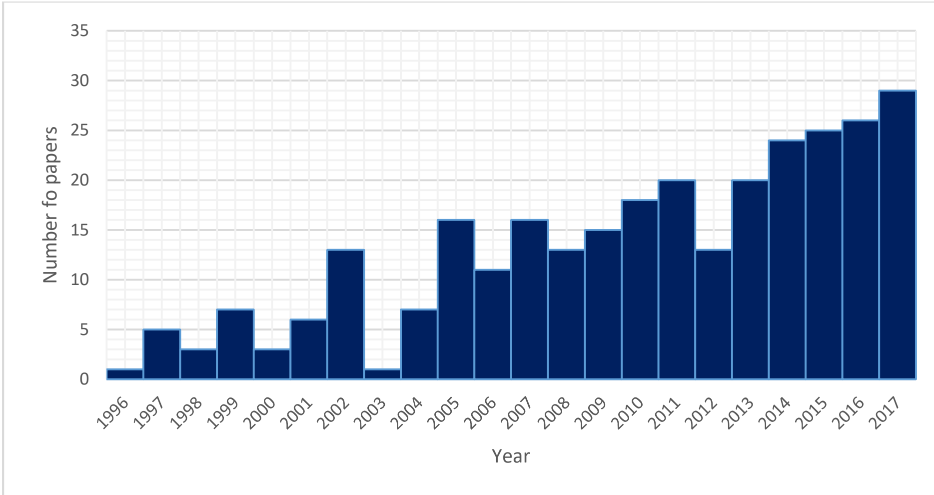

Figure 2-3-The accumulated number of papers published within the studied field from 1996 to 2017

Since the references were numerous, different factors have been proposed to facilitate the review of the literature (Figure 2-2). These factors include: i) the control approach (static or dynamic); ii) the stormwater management approach (combined and separate sewers); iii) the uncertainty consideration (deterministic or stochastic models); and finally iv) the objective functions (quantity, quality and cost). Table 2-1 presents the distribution of these perspectives in the literature. It shows that the related studies are numerous, but the efforts should be continued to complete the execution of the already proposed strategies, and to explore some unexpected challenges involved in established systems. For instance, in different parts of the world, there are many cities in which the urban drainage systems are controlled locally by simple RTC systems (Beeneken et al., 2013), while there exist only a few cities equipped with advanced global RTC systems as Quebec (Pleau et al. 2005), Vienna (Fuchs and Beeneken, 2005) and Dresden (Fuchs et al., 2004). There is still a huge potential for sustainable management of urban stormwater and its adaptability to climate change, and optimization methods are strong tools to achieve this aim. Therefore, utilizing the full potential of the optimization tools and applying new heuristic algorithms and programming methods to provide effective strategies, are desirable. Specifically, because it has been widely demonstrated that despite the growing invested capital, the actual technical systems perform ineffectively in critical situations due to the lack of 'a strong scientific or theoretical foundation' (Labadie, 2004).

2.5.6 Research gaps and directions for further studies

We defined some research gaps in the stormwater management studies based on the provided review, as follows: (1) perusal of the effects of the sources of uncertainty in the stormwater management systems which are controlled dynamically to deal with the unpredictable hydrologic processes; (2) a proper trade-off between all three quality, quantity and cost objective functions simultaneously in combined sewer investigations; (3) lack of evaluation of the feedback-loop between system design and its operation; (4) global predictive real-time control of stormwater management systems; and finally (5) designing reliable apparatuses that would perform based on accurate algorithms to optimize the performance of systems in order to respond to the future conditions, in terms of the rapid changing climate and land use. So, the following further studies are proposed.

Integration. Optimization challenges in stormwater management are not so different than the others. Integrating different segments of the system increases the complexity of the problem and the difficulty in achieving the solution. The necessity of using methods giving rapid and qualified solutions like metaheuristic optimization algorithms is inevitable. The analysis of the solutions in presence of uncertainty in data is the next step to a better integration of the available resources in designing decision support systems. Despite the application of deterministic models in the literature, stormwater management problems are engaged with different sources of uncertainties. The study of deterministic stormwater management models, in presence of these uncertain parameters does not always provide optimal results. Hence, it is necessary to integrate sources of uncertainty in the mathematical model and/or in the optimization problem. Another challenge is to enable decision makers to work and understand the way these methods work and how they can benefit from these models to result in satisfactory outcomes.

Design vs. operation. In design-level studies, the feedback with the operational-level decisions is rarely considered. Taking a specific design into consideration may not result in the same operational decisions and therefore joint optimization of these two levels seems necessary. The use of optimization techniques to realize global predictive RTC strategies on separate sewer systems is still an open research area, as a few related studies are based on rule-based approaches which are not always able to adapt to different types of problems with different sizes. While, by employing mathematical optimization techniques, it becomes possible to study a watershed at system-level scale not only for designing the system but to operate it considering different performance criteria at the same time. Using simulations along with optimization tools provides a comparative analysis for each design of the system in presence of operational performance and by using prediction data at different time scales. This helps decision makers to have stormwater management systems whose operations are adaptive to individual storms or even much further, to the impacts of climate change.

Acknowledgement

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2.6 Optimization using commercial software packages

Throughout the years, many commercial software packages have been developed to simulate single events and continuous rainfall-runoff quantity and quality modelling in sewer networks in urban areas. One of the most widely used in North America is the Stormwater Management Model known as SWMM, developed by the United States Environmental Protection Agency (EPA) (Rossman and Huber, 2016) and used as the base model for some commercial software packages. However, even if these commercial software have been widely employed to evaluate the optimization approaches proposed in the literature (Darsono and Labadie, 2007; Yazdi et al., 2014), in many cases, they need to be coupled with other commercial optimization packages to perform optimization. In the following, we describe four of these commercial tools, addressed in the literature, with the aim of optimizing some stormwater management problems.

2.6.1 System for Stormwater treatment and Analysis Integration

The *System for Stormwater treatment and Analysis Integration* (SUSTAIN) is a decision support system developed in 2003 by the EPA collaborating with Tetra Tech, to investigate different stormwater quantity and quality management strategies and also to evaluate the implementation of different BMP scenarios at multiple spatial scales, ranging from local to broad watershed applications, based on either a single storm event or a long-term continuous simulation. SUSTAIN operates based on the ArcGIS platform and encompasses six modules (Lee *et al.* 2012): a BMP sitting tool with which SUSTAIN is able to optimize the location, type and cost of different BMP/LIDs like in Mao et al., (2017), a watershed runoff and routing module, a BMP simulation module, a BMP cost analysis module, an optimization module and a post-processor. The optimization core of SUSTAIN is the optimization module which uses two metaheuristic optimization algorithms, scatter search and Non-dominated Sorting Genetic Algorithm-II (NSGA-II), to provide a solution for non-linear, multi-objective and complex optimization problems. Figure 2-4 illustrates how the optimization module works (Lee et al., 2012).

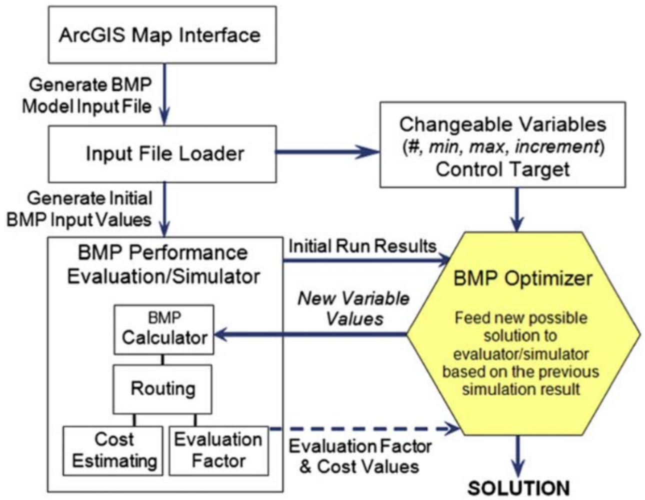

Figure 2-4-Organization of optimization module in SUSTAIN (from Lee et al. 2012)

2.6.2 Csoft

Csoft is a global predictive RTC simulation software designed by BPR-CSO commercial software development group in order to first, simulate the hydraulic behavior of the sewer network and then, optimize the performance of the sewer system (Colas 2004 ; Grondin et al., 2002). This software contains a simulation-optimization module which performs based on a mathematical optimization solver routine (Pleau and Pelletier 2000). The objective function of the optimization part could be defined to meet different system goals such as dewatering time minimization, flooding risk reduction, CSO control and flow equalization at the WWTP and the choice of the objective function depends on the circumstances under which the system performs, like wet weather, dry weather, critical events and system breakdown.

2.6.3 Storm Water Investment Strategy Evaluator

The Storm Water Investment Strategy Evaluator (StormWISE) is a tool to optimize the total investment of the implementation of new stormwater management systems, BMPs and LIDs, for strategic water quality preservation. The tool performs based on a multi-criteria constrained optimization model which is formulated with nonlinear benefit functions represented by the piecewise linear segments for an optimal sizing and placement of BMP/LID projects at drainage zones (McGarity, 2012).

2.6.4 Liu et al. (2016) decision support tool

Recently, a decision support tool was developed by Liu et al., (2016) for the optimal selection and placement of BMP/LID practices and to provide a trade-off between cost minimization and runoff and pollutant load reduction objectives. This optimization framework performs based on the collaboration of the L-THIA-LID 2.1 hydrologic/water quality simulation model, the optimization algorithms of AMALGAM (Vrugt and Robinson, 2007) and the multilevel spatial optimization (MLSOPT) to reduce the complexity of the optimization problem.

3 SECOND SCIENTIFIC PAPER: AN INTEGRATED OPTIMIZATION AND RULE-BASED APPROACH FOR PREDICTIVE REAL-TIME CONTROL OF URBAN STORMWATER MANAGEMENT SYSTEMS

French Title: Approche intégrée combinant l'd'optimisation et des règles de contrôle pour le contrôle prédictif en temps réel des systèmes de gestion des eaux pluviales en milieu urbain

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Contribution of the authors:

The authors confirm contributions to the paper as follows: All authors designed and developed the study conception during hours of discussions. Shadab Shishegar developed the integrated optimization rule-based algorithm, generated the results, and drafted and prepared the manuscript. Sophie Duchesne and Genevieve Pelletier provided the data and simulation model of the case study, supervised the project development and significantly helped in operational understanding of the stormwater management system. All authors reviewed the results and approved the final version of the manuscript.

Link between the previous paper and the following: The previous paper provided a comprehensive literature review on optimization techniques applied on stormwater management problems and extracted the research gaps in this domain among which the operational-level optimization of stormwater management systems was used as the main motivation of the second paper. Based on this research gap, the present paper proposed an optimization rule-based framework to optimize the operations of a stormwater management basin in real-time.

ABSTRACT

A smart decision-making framework for stormwater management systems is designed through predictive Real-Time Control (RTC) of the outlet gate of a stormwater basin. The proposed framework offers a cost-effective non-structural solution for dynamically controlling stormwater basins through manipulating the outlet gate and providing optimized outflow set-points. An integrated RTC optimization and rule-based approach is designed to mitigate the impact of the discharged runoff on the receiving watercourse, both in terms of quantity and quality. In this approach, the optimization part provides the optimized outflow set-points for the basin to minimize peak-flows during the wet periods, while the rule-based part controls the quality of the discharged water, through sedimentation, by increasing the detention time. Various rainfall data series are used as inputs for a case study stormwater basin to verify the performance of the proposed methodology. The efficiency of the stormwater basin in reducing peak-flows and improving the quality of outflow was estimated by comparing, respectively, the peak-flows and detention times of the integrated RTC strategy with those of a static approach. The results showed an improved quantity and quality control performance for the studied stormwater basin, in comparison to the static control approach, both in current climate conditions with a peak flow reduction from 73 to 95 % and detention times varying from 16 to 30 h, and in future climate conditions with an averagely reduction of 76 % in peak-flows and an average detention time of 19 h.

Keywords: Real-Time Control, Optimization, Water quality, Control rule, Climate change.

3.1 Introduction

Urbanization and climate change (CC) both affect the natural hydrologic cycle in urbanized watersheds. Urbanization expands the impervious surfaces, which increases the amount of urban stormwater runoff in terms of volume and peak-flows. For example, historical data about the urbanization of a peri-urban area in Swindon, United Kingdom, showed that an increase of the impervious cover from 11% to 44% augmented the peak-flows resulting from runoff in downstream areas by over 400% (Miller et al., 2014). This increased amount of runoff not only discharges significant pollutant loads annually into streams (Brombach et al. 2005), but it is the primary cause of urban flooding, water body erosion, sharp peak-flows and hydraulic shocks on the receiving streams (Jacopin et al., 2001; Middleton and Barrett, 2008; Muschalla et al., 2014).

On the other hand, climate change causes significant changes in rainfall patterns (Guhathakurta et al., 2011). It has been shown that, in several regions of the world, the extreme rain events are becoming more frequent due to CC (Mailhot et al., 2007; Miao et al., 2019; Westra et al., 2013) and that these events will become even more frequent in the future according to the generated projections (Dale et al., 2015; Giorgi et al., 2019). One of the important consequences of this changing climate lies in quicker and more severe urban runoff which results in further flooding and high peak-flows to the hydraulic system of nearby watercourses (Semadeni-Davies et al., 2008). Sustainable stormwater management seeks the restoration of the natural hydrological cycle, of groundwater and of the aquatic systems in urban and rural areas. To this aim, stormwater management infrastructure needs to be installed to tackle with stormwater key concerns in the most cost-effective way, first to mitigate the impacts of urbanization on the natural hydrologic cycle and on water quality, then to adapt to the changing environmental conditions caused, among others, by climate change. However, the combined impact of urbanization and climate change nowadays leads to the deterioration of water quality and to changing stormwater flow patterns which sometimes makes the conventional systems inefficient and calls for enhanced operational control systems (Astaraie-Imani et al., 2012). Stormwater management infrastructure protects receiving water bodies by attenuating peak-flows, controlling the stormwater flow rates and also promoting the pollutant sedimentation to preserve water quality. However, when statically controlled, as is most often the case, the traditional stormwater management infrastructure does not operate optimally and can be, in some cases, not adaptable to changing conditions caused by climate change or urban development.

Recent technologies make stormwater management systems adaptable to upcoming situations. In these approaches, despite conventional controls, real-time hydrologic states and rainfall predictions can dictate to the system how to modulate the outflow rates of stormwater management infrastructure (Marsalek, 2005; Wong and Kerkez, 2018). Employing Real-Time Control (RTC) strategies for this infrastructure brings flexibility to the urban stormwater management systems. A dynamically managed system that considers predicted data, besides actual and historical data, is able to adapt itself to variations in environmental conditions.

Advances in technology and automatic systems have led to the development and implementation of “smart” stormwater systems, which perform computerized control to continuously modify themselves to adapt to changing inputs (Kerkez et al., 2016). In this regard, S*ustainability*, as one of the key elements of smart cities, can be realized by equipping stormwater management infrastructures with RTC strategies. Kerkez et al. (2016) suggest retrofitting stormwater infrastructures with sensors and digital control systems to tackle with varying meteorological conditions and runoff dynamics. In a recent study by Wong and Kerkez (2018), using internet-connected sensors on an urban watershed, a control algorithm was developed to manage the operation of valves and gates at the catchment scale. The authors showed that by controlling only 30% of all watershed sub-systems, it was possible to achieve an adaptive performance in terms of flood mitigation and flow reduction. In another study, Kerkez et al. (2016) proposed connectivity and intelligence as two key factors of *adaptive* control of stormwater management systems. In order to exploit the potential of these systems for sustainable and adaptive management of urban stormwater, optimization algorithms are introduced as strong tools in Shishegar et al. (2018). These algorithms have been employed in different stormwater studies like water pollutant reduction (Middleton and Barrett, 2008), optimal design of location and size of stormwater management systems (Yeh and Labadie, 1997), flood prevention (Verworn, 2005), detention basin design (Mobley et al., 2013), and many other problems. Although, most of the literature on stormwater management systems optimization relies on static control approaches, systems controlled by RTC optimization strategies is an area of growing interest. In earlier RTC optimization of water system studies, the application of Model Predictive Control (MPC) to prevent flooding in downstream areas was investigated, in which the use of optimization algorithms for dynamic control of urban drainage systems has been promoted (Niewiadomska-Szynkiewicz et al. 1996; De Keyser et al. 1988). In further stages, other objectives have been added such as minimization of combined sewer overflows (Duchesne et al., 2004), maximization of the pollutant load reduction (Hoppe et al., 2011) and also performance optimization of the regulating devices installed in water systems (Pleau et al., 2005). Although the application of optimization methods on stormwater studies seems vast, there is still a lack of a universally integrated system for stormwater management structures at the operational level that performs optimally under varying environmental conditions (e.g., urbanization, extreme storm events, runoff dynamics, etc.). Stormwater basins are among the stormwater management structures that can be controlled in real time to exploit their potential for adaptive and sustainable management of urban stormwater. The RTC optimization of stormwater basins from the operational level perspective is still an emerging area of interest and most of the existing literature on optimization of stormwater management systems have addressed these systems only from the design level perspective (Shishegar et al., 2018). A few research efforts have been directed towards the development of stormwater basins RTC strategies, but they are mostly rule-based methods, like the ones in Gaborit et al. (2012) or in Bilodeau et al. (2019), where several control rules have been developed for real-time control of the outflow rate of stormwater basins. This has been realized by manipulating the outlet valve of dry detention ponds based on several automatic reactive RTC scenarios identified by customized thresholds. Although the corresponding results showed improved pollution load volume removal efficiency from 46% to 90% in Gaborit et al., (2016), the proposed scenarios are not necessarily optimal and are applicable only on the studied basin. In another study by Jacopin et al. (2001), some on/off regulations were designed to develop operational management practices for stormwater detention basins. These operational local reactive control rules depend on local hydraulic conditions to control flows during heavy storm events and pollutants sedimentation during smaller more frequent events. Generally, adding control rules to the outlet of stormwater basins brings the ability to adapt to weather conditions; however, integrating optimization techniques into the definition of control set points provides even more dynamic solutions to stormwater management problems that are applicable to different types and sizes of problems.

According to all of the above, rule-based methods have been studied for improving the performance of stormwater basins, and optimization methods have been applied only on a limited number of stormwater management problems such as best management practices placement, flooding control and cost minimization. The combination of these two approaches (ruled-based and optimization) has not been fully studied in stormwater basins control. Hence the objectives of this study are to:

- Propose a predictive RTC control strategy for stormwater basins outflows aiming at minimizing peak-flows and maximizing detention time, in order to improve water quality;
- Evaluate the performance of the proposed RTC strategy on a case study stormwater basin;
- Assess the outcomes of integrating quality control rules to the quantity control optimization model for the studied stormwater system;
- Test the impacts of climate change on the RTC strategy's performance; and
- Carry out a comparative analysis to evaluate the results obtained with the dynamic integrated RTC approach versus those of a more traditional static approach.

The main novelty of this study is to consider predictive RTC of stormwater basins for optimizing both quality and quantity control performance, using observed and predicted precipitation data. This allows to not only manage the actual rain event but also to get prepared for the upcoming ones. In addition, the performance of the proposed hybrid optimization rule-based approach will be examined in presence of climate change to provide an adaptive measure as an alternative to the construction of new infrastructure.

3.2 Methodology

An integrated predictive RTC optimization-rule-based model was developed to optimize the performance of a smart stormwater management system in terms of water quantity and quality. In this regard, a RTC framework was designed to better implement the proposed approach illustrated in Figure 3-1. This framework includes three different blocks, which are the Simulation block, the Optimization block and the Rule-based control block, and a final step for the final generation of optimal outflows and performance evaluation.

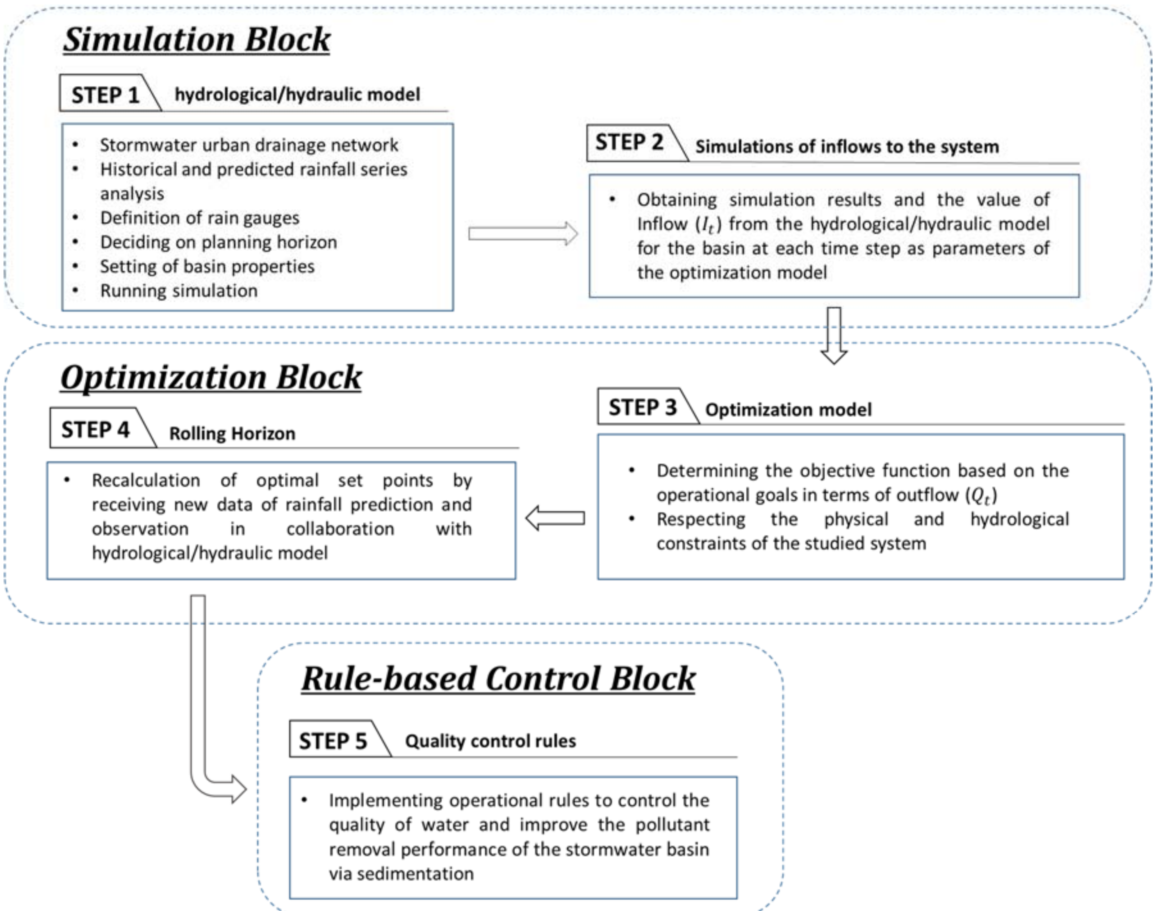

Figure 3-1-Steps to develop the integrated predictive RTC optimization-Rule-based framework

The first block consists of two steps to compute the inflows to the basin as a function of observed and predicted rainfall data with a simulation hydrological/hydraulic model. For the work presented in this paper, the Stormwater Management Model - SWMM (Rossman and Huber, 2016), implemented in PCSWMM 7.0, was used as the hydrological/hydraulic model. This type of model dynamically simulates stormwater runoff and flows in stormwater sewer networks from the specified rainfall series. It requires: i) observed and/or predicted rainfall data; and ii) characteristics of the studied watersheds and network components like slopes, area, imperviousness, etc. Therefore, in the first step of the Simulation block, the historical and predicted rainfall series are defined as input for the identified rain gauges across the network. Having all the data set, the hydrological/hydraulic simulation model is run during the second step, to compute the inflow hydrographs of the basin over the considered control horizon (the length of time that decision maker plans ahead) in the Rolling Horizon approach (see section 3.2.4). This hydrograph is then used as an input parameter (Figure 3-2) for the optimization model in the Optimization block.

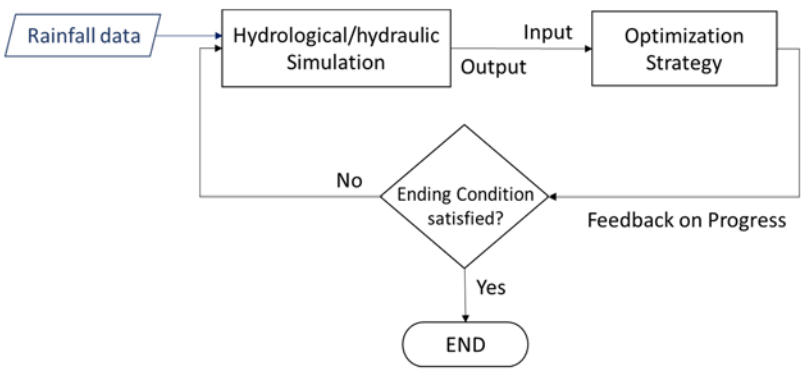

Figure 3-2-Simulation-optimization collaboration

The Optimization block starts with running the designed optimization algorithm for the RTC of the stormwater system outflows in step 3. To do so, the objective function minimizes the outflows from the basin to the receiving watercourse during the control horizon with respect to several physical and hydrological constraints such as the basins capacity constraint, the mass balance constraint, the maximum allowable outflow constraints and some others that all are formulated below. During wet periods (as long as there is an inflow), the optimization model is active to generate outflow set-points for the system. As a result, the flows discharged to the river are determined while running the integrated RTC strategies which is engaged, in this step (4), in a rolling horizon loop. This loop is responsible for creating a dynamic scheduling for the future outflows based on the predicted and actual received data and in collaboration with the simulation model. Whereas during dry periods, quality control rules that are formulated in the Rule-based control block are activated. These rules perform in such a way that the settling process of the retained water is satisfied by maximising the detention time in the basin up to a target value while ensuring that the available volume in the basin is sufficient for the next upcoming storm event without any basin overflow. Given the predictive nature of the RTC strategies, the optimization algorithm combined with the quality (detention) control rules define the outflow planning based on both the observed and predicted states of the system; indeed, the decisions made about the outfall gate opening (Figure 3-3) take into account not only the actual inflow to the basin but, also, data from the future runoff dynamics, based on short-term weather forecasts.

The quantity control optimization model for the predictive real-time control of stormwater basin outflows is developed in the following as a constrained linear programming problem. In this model, the outflow of the basin is the model decision variable. The water volume in the basin is another variable of the problem whose possible values are all dependent to the outflow decision variable values. Afterward, four different rules are developed based on the upcoming predicted rain event and the available storage volume in the basin.

3.2.1 Modeling principles

The stormwater system studied in this research is a detention pond (dry stormwater basin) whose structure is shown in Figure 3-3. A detention pond is a stormwater facility constructed in an open area impounded by an embankment. At the outlet of the pond, a structure can control the outflow rates to the receiving stream. In the case studied here, the control structure is a sluice gate which can be manipulated by a motor via an actuator. When the gate is partially or fully closed, the inflows I_t entering through the inlet pipe are attenuated at the outlet, thus reducing peak-flows and promoting sedimentation of suspended solids (SS), which provides more moderate and cleaner outflows Q_t to the river. Indeed, the temporary storage V_t of stormwater runoff is trapped in the basin and released slowly to the downstream area based on the control policy defined for the basin (Figure 3-3).

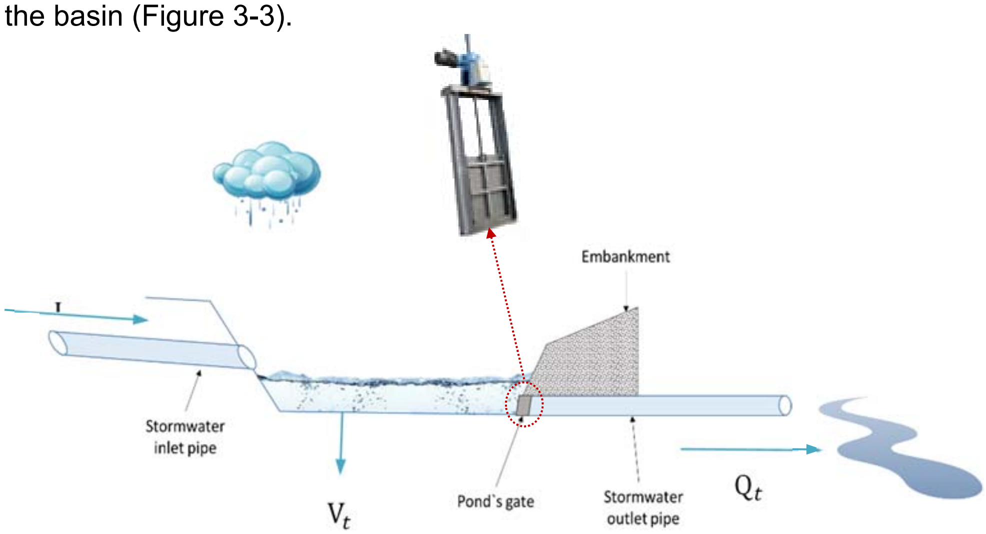

Figure 3-3- A detention pond during wet periods

In this study, the assumption is that the stormwater pond performs in such a way that:

- The water is detained as long as possible (maximum 40 h) in the basin to allow sedimentation while avoiding overflow.
- The emptying process of the basin can be started during, at the end or even before the beginning of the storm event to make available the required storage volume for the next upcoming rainfall event while avoiding high outflows to the river.
- Open-close sequences of the outlet gate are avoided to prevent the extra energy consumption and equipment depreciation.
- The pond is drained as gently as possible to prevent any sharp peak flow to the downstream river.
- A maximum allowable outflow from the basin is respected, as defined by local regulations to mimic pre-development flows (e.g. 50 L/s.ha).

3.2.2 Optimization model formulation

When there is inflow to the basin (wet periods), the outflows are determined by solving the following optimization problem where the objective function is:

Objective function

$$\mathrm{Min}\left\{\sum_{t}(Q_t + \xi * pp_t + \phi * qq_t)\right\} \qquad \forall t = 0,1,\ldots,n \qquad \text{Equation 1}$$

Where:

Q_t= outflow (decision variable) from the basin at time step t (m^3/s)

pp_t= positive variation of the set-point (continuous variable)

qq_t= negative variation of the set-point (continuous variable)

ξ = weight associated to the positive variation pp_t

ϕ = weight associated with the negative variation qq_t

n= number of time steps in the control horizon.

And there are seven constraints that have to be satisfied as listed below:

Capacity constraint:

$$\sum_{t}(I_t - Q_t)\,\Delta t + V_0 \leq V_{max} \qquad \text{Equation 2}$$

Where:

I_t= inflow to the basin at time step t (m^3/s)

V_{max}= maximum volume capacity of the basin (m^3)

Δt = difference of t between two time steps (s).

V_0= the initial volume of water in the basin (m^3)

Mass balance constraint: Equation 3

$$Q_t \Delta t + 2V_t = I_t \Delta t + I_{t-1} \Delta t + 2V_{t-1} - Q_{t-1} \Delta t \quad \forall t = 1, \dots, n$$

Volume positivity constraint: Equation 4

$$V_t \geq 0 \quad \forall t = 0,1, \dots, n$$

Maximum allowable outflow constraint: Equation 5

$$0 \leq Q_t \leq Q_{max} \quad \forall t = 0,1, \dots, n$$

Where:

Q_{max}= maximum allowable outflow from the basin (m^3/s).

Flow variation constraints: Equation 6

$$Q_t - Q_{t-1} = pp_t - qq_t \qquad \forall t = 0,1, \dots, n$$

Equation 7

$$pp_t \geq 0 \qquad \forall t = 0,1, \dots, n$$

Equation 8

$$qq_t \geq 0 \qquad \forall t = 0,1, \dots, n$$

With respect to Equation 1, the main objective of the optimization problem is to minimize the total outflow discharged to the receiving stream during the control horizon. Also, as it is desired to move the system regulators as less as possible, the fluctuations of the outflow over the time horizon have to be minimized too. The sum of pp_t and qq_t is minimized to this aim. Equation 2 ensures that the volume of the retained water does not exceed the maximum volume of the basin. The value of V_0 here, is updated at each time-step based on the generated set-points of the previous control horizon[1]. Equation 3 is the mass balance constraint. Equation 4 is the positivity

[1] This sentence is not included in the published scientific paper.

constraint of V_t dependent variable. Since municipal regulations often take into account a maximum allowable stream flow to the rivers, Equation 5 represents this maximum outflow along with positivity constraint of Q_t decision variable. Equation 6 represents the variation penalty constraints applied to the outflow set points to prevent the extra movement of the outlet gate. This formulation incudes the positive and negative variations of the outflow which have both strictly positive values, as shown in equations 7 and 8.

3.2.3 Quality Control Rules

Four generic rules are developed for controlling the settling process in the stormwater basin. The advantage of these control rules lies in their generality, which makes them applicable to different cases with different climate conditions and rainfall series. Unlike the existing strategies in the literature which mostly resulted from trial-and-error to come up with a threshold for the designed regulations (Bilodeau et al., 2019; Gaborit et al., 2012), the proposed strategy in this study provides some generic formulations that consider the required storage volume for the upcoming runoff inflows resulting from future rainfall events through an integrated collaboration with the optimization algorithm presented above. A minimum desired detention time of 20 h was selected based on the results presented in Carpenter et al., (2014), who showed that the Suspended Solids (SS) concentration decreased significantly in urban runoff water in the first 20 h of detention. On the other hand, after 40 h of detaining water in the basin, almost no more settling process is realized, as reported again in Carpenter et al., (2014). Accordingly, it is suggested to gently release the trapped runoff into the receiving watercourse after this time (40 h) to restore the system's maximum storage capacity (Gaborit et al., 2012). However, as the first objective in this study is to generate low rate outflows, it is sometimes desirable to detain water less than 40 h in order to provide enough time for water to discharge when some storage volume is required for the next upcoming rainfall event. Having all these in mind, the desired detention time is combined with the emptying time of the basin and the characteristics of the next predicted rainfall event(s) to specify the emptying rule. Then the selected rule provides the outflow from the basin as a result of manipulating the opening of the outlet gate. Equations 9 to 13 present the proposed rules.

- $\text{if } t_{\text{next rain}} \leq t_e \rightarrow \ Q_t = Q_{\max}$ Equation 9
- $\text{if } t_e < t_{\text{next rain}} \leq t_e + 20\text{h} \rightarrow \ Q_t = Q_{\max} * \frac{t_e}{t_{\text{next rain}} - t_f}$ Equation 10
- $\text{if } t_e + 20\text{h} < t_{\text{next rain}} < 40\text{h} + t_e^{\max} \rightarrow \ Q_t = Q_{\max} * \frac{t_e + 20\text{h}}{t_{\text{next rain}} - t_f}$ Equation 11

- if $t_{next\,rain} \geq 40h + t_e^{max} \rightarrow$

Equation 12

$$\begin{cases} Q_t = 0 & \forall\, t < 40h \\ Q_t = Q_{max} * \frac{t_e}{t_e^{max}} & \forall\, t \in (40h, 40h + t_e^{max}) \end{cases}$$

With:

Equation 13

$$t_e = \frac{V_{req}}{Q_{max}}$$

Where:

t_e= emptying time of the basin until availability of the storage volume V_{req} at maximum outflow Q_{max} (s)

$t_{next\,rain}$= time until the next predicted storm event starts (s)

t_f= time step when the previous rainfall event finished (s)

t_e^{max}= emptying time of the whole basin at maximum outflow Q_{max} (s)

V_{req}= required storage volume for the next coming rainfall event to avoid any overflow in the basin (m^3).

It should be noted that in case of a dry period longer than $40h + t_e^{max}$ after the last rain event, the water is retained 40 h in the basin (Equation 12) to realize the settling process and then released at a gentle outflow rate that allows keeping quiescent conditions in the basin during t_e^{max}. This limits the emptying of the basin to a certain amount of time that fulfills significant reduction of SS concentration (≈90%) and also avoids any mosquito breeding, as justified in Gaborit et al. (2012) and Carpenter et al. (2014).

3.2.4 Real-time Control: Rolling Horizon

Inspired by the Rolling Horizon decision-making approach for model predictive control technology (Sethi and Sorger, 1991), a rolling horizon strategy is embedded to the optimization model to realize the RTC and execute the optimization-simulation periodically. This approach provides a dynamic scheduling based on the planning for few time steps ahead, and then moving forward the time horizon at each step, after receiving feedbacks from the system following the implementation of the previously determined set points. The approach simulates the problem in a way that when real data become available, the model updates the information and accordingly re-plans for the next remaining time periods. Example of implementing this rolling horizon approach in the field of stormwater management can be found in Duchesne et al., (2003).

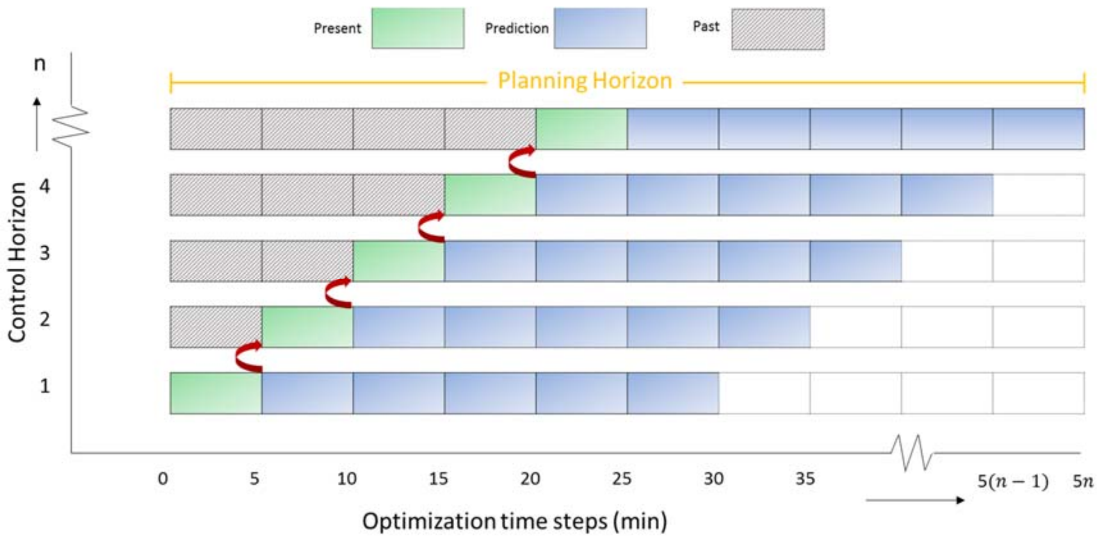

Figure 3-4-Concepts associated to Rolling horizon: Control horizon, Time steps and Planning horizon

The control horizon selected for the case study presented in this paper is 30 min, in which the periods are divided in n = 6 optimization time steps of 5 min each. As new rainfall data arrives, the planning is then rolled over and the model's predictions and decisions are updated. This concept is shown schematically in Figure 3-4. Using this strategy, the real-time scheduling of basin's outflow is implemented while considering dynamic meteorological conditions and dynamic runoff volumes.

3.2.5 Case Study

The studied case is a detention basin collecting stormwater from a watershed located in a Canadian city. This watershed is close to a river on its east side with its outlet to a small ditch which discharges finally to this river. Based on a master plan published by COGESAF (2010), several water-related issues across the watershed have been identified among which the degraded quality of water and several flood episodes, which affect the population of downstream areas. Furthermore, according to Ouranos (2015), this region will be affected by climate change through having more precipitation by 2050, more runoff flows, as well as earlier and less predictable floods. In addition, in summer, higher temperatures, lower water levels and sudden severe storms are more probable in the future than now. This makes this area an interesting case study benchmark for the proposed predictive RTC strategy, where the hypothesis is that employing the proposed integrated RTC approach provides minimized elevated peak-flows in the stream and enhanced pollutant sedimentation performance for the studied stormwater management system. The studied stormwater detention basin is located in an urban area of the watershed that includes medium density residential and some commercial and institutional lots (Table 3-1 and Figure 3-5). The SWMM hydraulic model of the studied sector was provided by the City's municipality. This model includes the stormwater sewer network of the studied catchment with 104 sub-basins and a total area of 162 hectares, 204 pipe sections totaling more than 13 km, pipe diameters ranging from 300 mm to 1800 mm, and an overall impermeability of 37%.

Table 3-1-Characteristics of the studied basin

Name	Studied watershed
Outlet	A natural ditch connected to the nearby river
Watershed area	162 ha
Basin volume	61,495 m^3
Maximum allowable outflow	2.43 m^3/s (based on 50 L/s.ha as maximum allowable outflow)
Maximum water height	6 m
Hydraulic characteristics	Detention basin without permanent body of water
Entrance pipes	• Length: 400 m, Cross-section: Circular, Diameter: 1.8 m • Length: 400 m, Cross-section: Circular, Diameter: 1.2 m
Exit orifice	Circular with 1.2 m height

The detention basin has a capacity of 61,495 m^3, which allows the collection of runoff resulting from a 100-year return period rainfall event. Although the basin has a large capacity, its outlet is not dynamically controlled so water rarely accumulates into it.

Figure 3-5 presents the SWMM model of the case study watershed. There are several problems reported in this drainage network, including an overload of the main collector to the detention pond and some parts of the pipes with low or zero slopes, which cause additional local surcharges. The network, previously designed for a 10-year service level, no longer meets this level of service due to urban development. Here are the assumptions of the problem for the case study presented in this paper:

- The control horizon is finite with a value of 30 min, while the planning horizon is infinite.
- The physical characteristics of the basin are finite and known.
- No evaporation is taken into account.
- There is no infiltration in the basin.
- The inflow to the basin is known (obtained from the hydrological/hydraulic simulation model).
- Zero volume of water in the basin at the start of the plan.
- There is no inflow during dry periods. The basin receives inflows during wet periods, only.
- Perfect prediction data is used when running the integrated RTC algorithm.

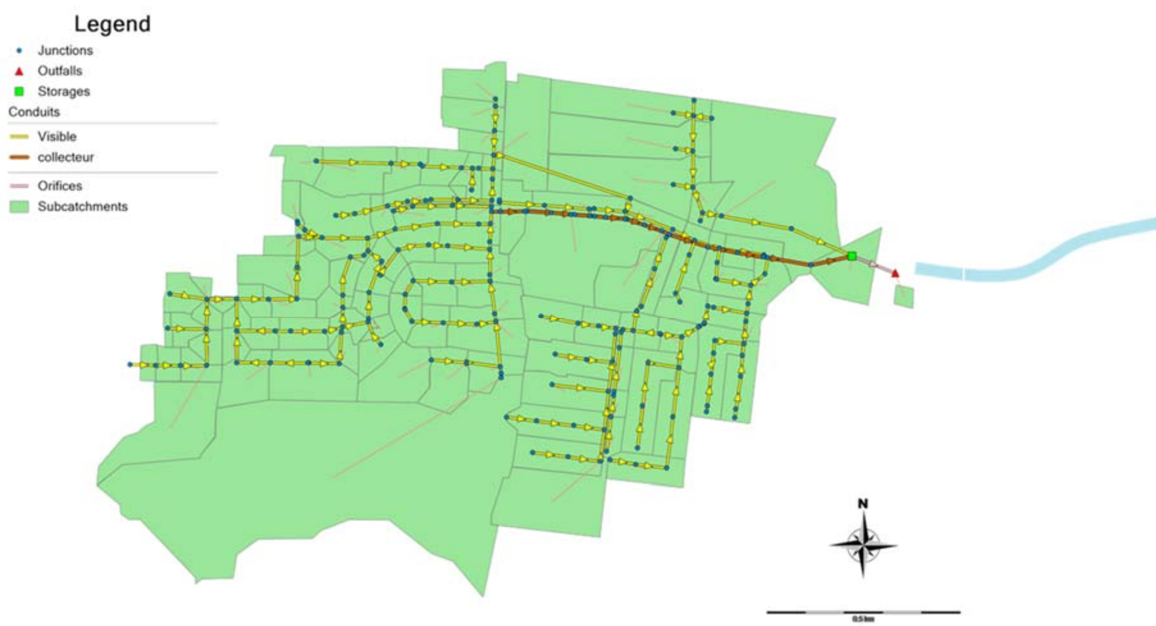

Figure 3-5-Geographic view of the studied drainage network, as simulated using PCSWMM v.7.0

3.2.6 Rain Series Characteristics

The recorded 5-minute rainfall series observed at a rain gauge located 80 km from the studied watershed is used. Meteorological characteristics of this region are close to those of the studied case. For this station, rainfall data are available from May to November for years 2002 and 2005 to 2013. From this series, rain events have been created based on two criteria, for the purpose of characterizing rainfall series (Table 3-3): a minimum of 1.2 mm/h of rain and a 6-h inter-event duration.

The average amount of rainfall recorded by Environment Canada for this station between 2000 and 2017, for the period of May 1 to November 30, is 759.56 mm. Tables 3-2 and 3-3 represent the rainfall characteristics of the 2007 and 2013 rainfall series for a 6-hour inter-event duration. Those two years were chosen because they represent respectively an average and a very rainy year. Validating the methodology employing the higher available rain volume data series (2013) provides a challenging situation for the studied system and allows to test the performance of the proposed strategy under critical meteorological conditions. In addition, climate change implication in the next 30 years (until 2050) is considered by adding 15% to the actual rainfall series as proposed by Ouranos (2015).

The hyetographs of rainfall series related to years 2007 and 2013 are illustrated in Figures 3-6 and 3-7, respectively.

Table 3-2-The monthly and total rainfall height of the simulated years 2007 and 2013 in comparison to the total rainfall total height of 2000-2017 at the considered station (taken from: http://climate.weather.gc.ca/historical_data/search_historic_data_e.html)

Total Rain (mm)									
Year	May	Jun	Jul.	Aug.	Sep.	Oct.	Nov.	Total	Avg. 2000-2017
2013	180.8	154.5	70.0	166.9	145.8	100.2	85.7	903.9	759.56
2007	90.3	97.0	93.8	123.6	137.4	133.2	106.7	782	

Table 3-3-Characteristics of 2007 and 2013 rainfall series with an inter-event duration of 6 hours

Characteristic	2013	2007
Number of events	74	64
Average water height/event (mm)	8.94	8.23
Average intensity/event (mm/h)	1.84	2.71
Average maximum intensity over 10 min (mm/h)	12.08	9.95
Average minimum intensity over 10 min (mm/h)	0.63	0.56
Average duration (h)	6.23	5.76

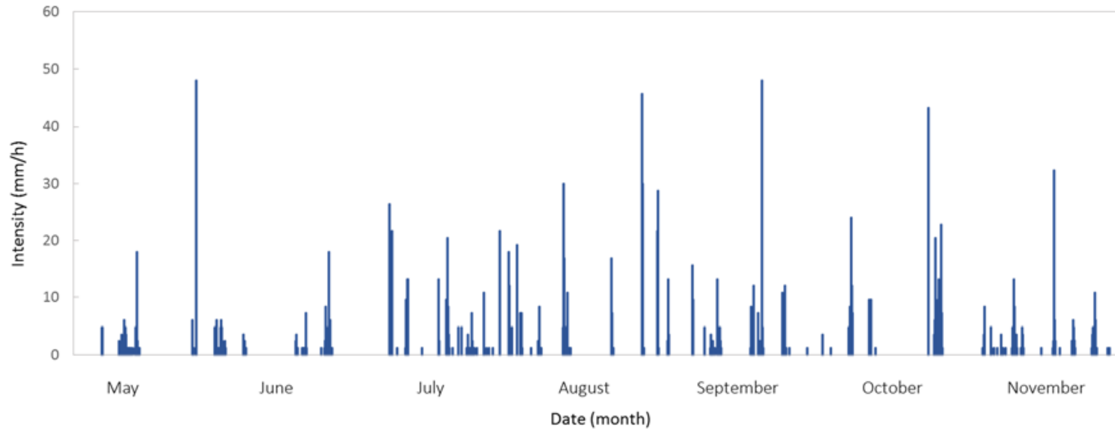

Figure 3-6-2007 Rainfall series of the considered station at 5-minute time steps

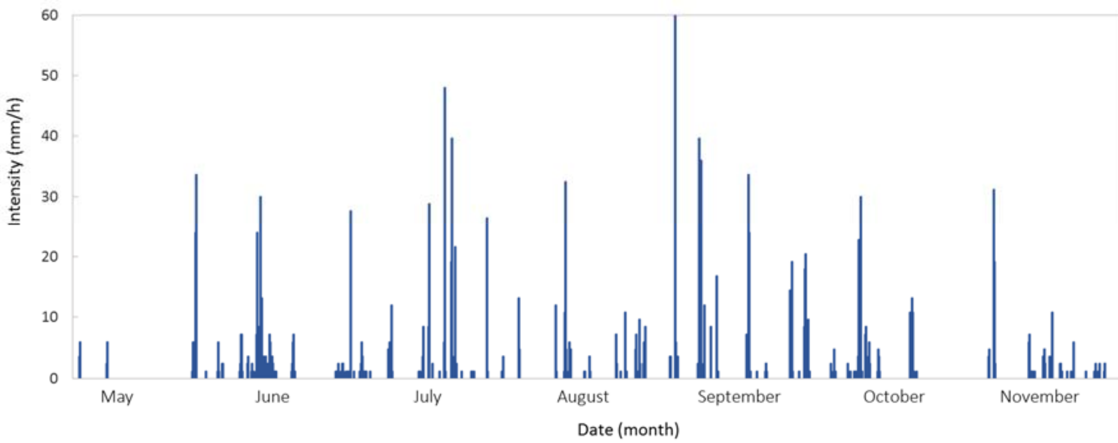

Figure 3-7-2013 Rainfall series of the considered station at 5-minute time steps

3.2.7 Performance criteria

Different performance criteria are considered to quantify the integrated RTC strategy benefits in terms of peak discharge mitigation, water quality improvement, overflow prevention, improved flow attenuation and outflow variation minimization, which are illustrated in Table 3-4.

In order to assess the applicability of the proposed model in practice, four different scenarios are presented; scenario 1: a normal year (2007) with the studied basin, scenario 2: a rainy year (2013) with the studied basin, scenario 3: a smaller basin with a volume capacity of 20,498 m^3 (1/3 of the studied basin) in a rainy year (2013), and finally scenario 4: the increased 2013 rainfall series to reproduce the effect of the expected climate change, with the studied basin.

Table 3-4- RTC advantages and the related quantitative performance measures

Advantage	Quantitative performance measure
• Peak discharge mitigation	Peak flow reduction efficiency of integrated RTC strategies compared to those of the static control: ρ $$\rho = \frac{Q_{t,max_{static\ strategy}} - Q_{t,max_{integrated\ RTC\ strategy}}}{Q_{t,max_{static\ strategy}}} \times 100$$
• Quality improvement	Detention time*: t^d
• Overflow prevention	Percentage of used volume capacity of the basin: V^{ovf} $$V^{ovf} = \frac{V_t}{V_{max}} \times 100$$
• Improved flow attenuation	Standard deviation of attenuated flows: $\bar{F}^{sd}$ $$F_t = \frac{I_t - Q_t}{I_t} \times 100$$ $$\bar{F}^{sd} = \sqrt{\frac{\sum(F_t - \bar{F})^2}{N}}$$ Where: F_t: Attenuated volume percentage N: Number of time steps in the wet period
• Outflow variation minimization	The average outflow variations percentage and number of variations: ($\overline{Q^{var}}$, N^{var}) $$Q_t^{var} = \frac{\lvert Q_t - Q_{t+1} \rvert}{Q_t} \times 100$$ $$\overline{Q^{var}} = \sum Q_t^{var} / N$$ Where: Q_t^{var}: The variation of outflow at time t (t is in wet period)

*The detention time t^d is calculated as the difference between the inflow and outflow center-of-mass times.

It should be noted that all these criteria are formulated for one single event to further evaluate the performance of the whole studied period by calculating their standard deviation. Also, these formulations and the presented integrated mathematical model are coded in MATLAB environment and runs using a Desktop PC Intel Ci7.

3.3 Results and Discussions

In this section, the validity of the proposed integrated RTC optimization – rule-based approach is discussed. Several storm events are extracted from the one-year rainfall series to analyze the performance of the studied system in different meteorological conditions and considering climate change.

Figure 3-8 represents the outflow schedule resulting from the integrated RTC strategy for the four defined scenarios and Table 3-5 presents a summary of the performance criteria values. As shown in Figure 5-8, in all scenarios, the stormwater basin experiences a delayed, distributed and steady outflow; however, the results of scenarios 3 and 4 (with a smaller basin and in presence of climate change, respectively) show higher outflow rates. The results related to scenario 3 show that the integrated RTC strategy is affected by the volume capacity of the basin and the selected rainfall series. Nevertheless, the dynamic strategy schedules the outflows in such a way that it retains runoff to allow SS sedimentation while attenuating outflows, although in higher rates than in other scenarios. An average 16 h detention time is reported (Table 3-5) for the 2013 series under scenario 3 that comes with an average 73 % reduction in peak-flows in comparison to the static approach, which provides a significant improvement in both quality and quantity points of view. Similarly, under scenario 4 and under climate change, the proposed dynamic approach provides an overall 76 % reduction in peak flow rates over the traditional static approach. Even though the integrated RTC strategy generates lower flow attenuation performance criteria (higher outflow rates) for scenarios 3 and 4 in comparison to scenarios 1 and 2 (Figure 5-8 and Table 5-5), it provides a 64 % reduction in overall flow rates compared to the static approach.

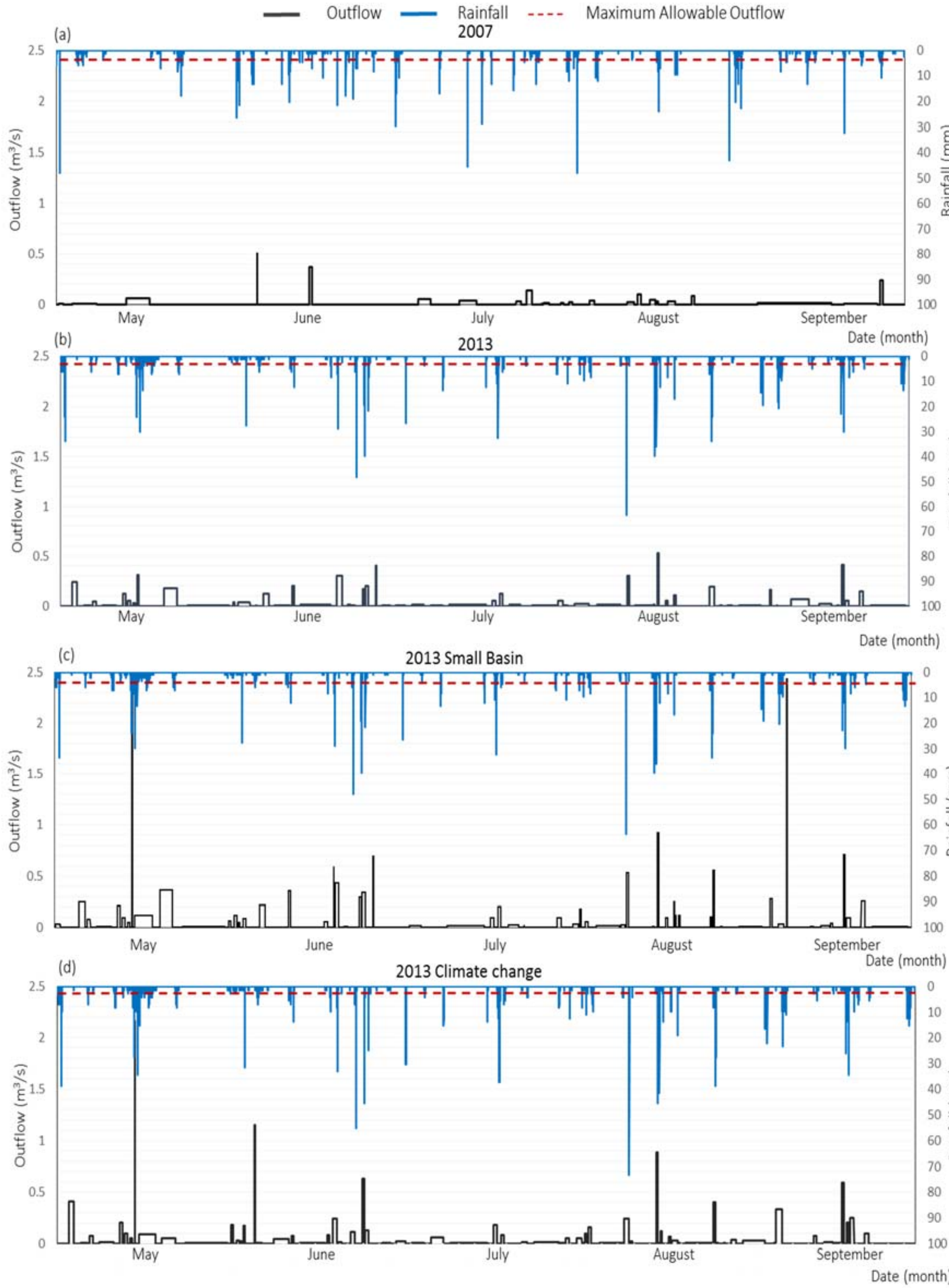

Figure 3-8-Generated outflow schedule by Integrated RTC strategy for a) scenario 1, b) scenario 2, c) scenario 3, and d) scenario 4

Table 3-5 indicates that under different scenarios representing different basin characteristics and different meteorological conditions, employing integrated RTC strategy results in a significant improvement in controlling peak flow rate of stormwater discharge. In average, 48 % of the volume capacity of the basin is filled under climate change, due to the higher volume of runoff entering the basin. This value is 51 % in scenario 3, where the capacity of the basin is low, while for the less challenging scenarios 1 and 2, 12 % and 10 % of the volume basin, respectively, are used in average. Also, quality control criteria has been realized at an average of 30 h, 23 h, 16 h and 19 h under scenarios 1-4, respectively. It means that under optimization strategy, the system tends to keep water in the available storage, while quality control regulations make the system generate delayed outflows to realize optimal detaining of water.

Table 3-5-performance criteria for four studied scenarios

Performance Criteria	Ind.	2007	2013	2013 Small Basin	2013 Climate Change
Peak discharge mitigation	ρ	95.1	92.4	73.2	75.7
Quality control (hour)	t^{d}	30.1	23.4	16.2	19.4
Overflow control	V^{ovf}	11.7	10.2	51.7	48.2
Flow attenuation	$\bar{F}^{sd}$	92.8	81.9	67.2	63.7
Outflow variations	$\overline{Q^{var}}$	0.31	0.39	0.41	0.43

3.3.1 Examples of Scenarios 1-3: Actual meteorological conditions

3.3.1.1 Scenario 1: 2007 Rainfall Series as an Average Year

Figure 3-9 shows the performance of the integrated RTC strategy under the rain event occurring on 26-28 September 2007, versus the traditional static approach.

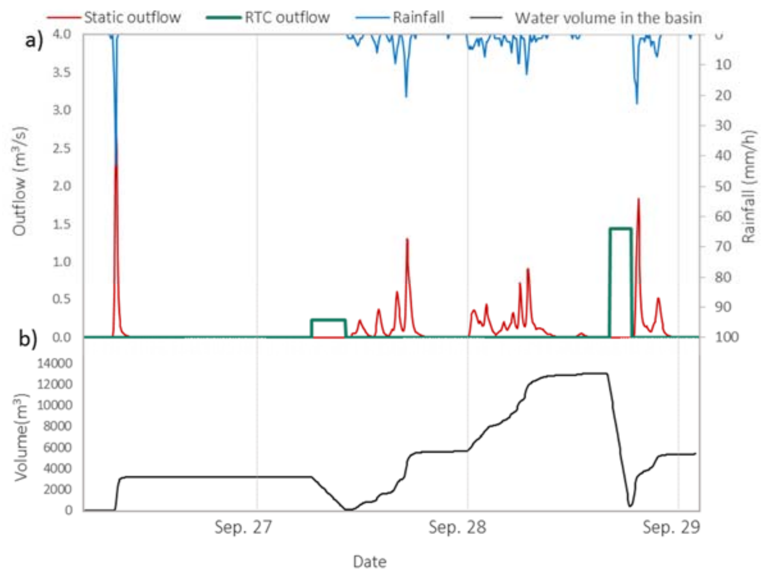

Figure 3-9- a) The controlled and uncontrolled basin outflow hydrographs, b) the basin volume in the controlled case during the storm event of 26-29 September 2007 under scenario 1

This period (Figure 3-9) starts with a high rain intensity where outflows from the basin to the receiving water course are high with the static approach, while in the controlled approach, the received runoff is kept into the basin to allow the settling process. In this situation, as there are two consecutive rain events predicted for the next 24 h, the trapped water is released at a steady rate from 4:15 on September 27, to prevent any possible overflow. Accordingly, the basin is emptied and then the outlet gate is closed at 7:55 on September 27, to detain newly arrived inflows; the water volume in the basin continues to rise as far as prediction data, storage capacity and control rules allow. In all situations, to avoid abrupt moves of the outlet gate, the generated outflow set points are steady, with minimal fluctuations.

As another example of the performance of the basin when controlled by the RTC approach, Figure 5-10 demonstrates the storm events of September 11-17 2007. Unlike the static control method, which generates the outflow based upon the received runoff without any adaptation, the RTC outflow is scheduled in such a way that it always considers the forecasted precipitation; an ability that helps the system to perform based on an optimized operational planning.

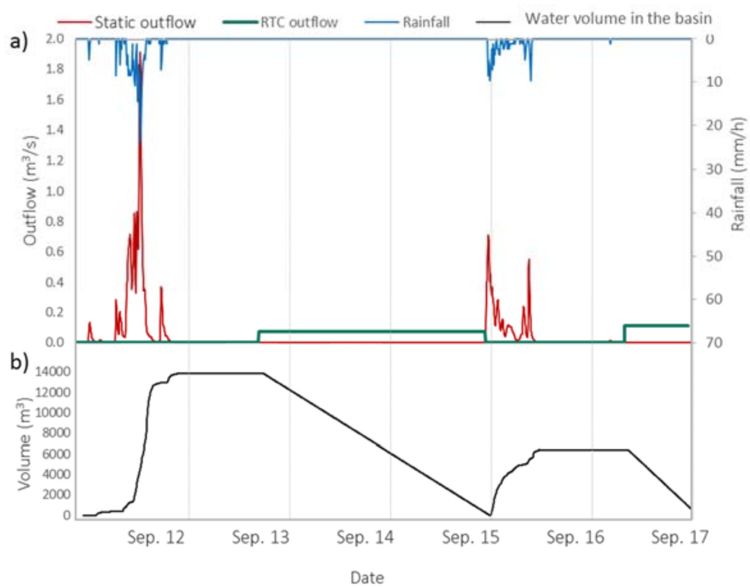

Figure 3-10- a) The controlled and uncontrolled basin outflow hydrographs, b) the basin volume in the controlled case during the storm event of 12-17 September 2007 under scenario 1

3.3.1.2 Scenario 2: 2013 Rainfall Series as a Rainy Year

Figure 3-11 represents the hydrographs of the stormwater basin outflow when controlled using the integrated RTC strategy versus the static approach during four storm events recorded in May 2013. As it is shown, unlike the static approach, the RTC strategy detains water in the basin for 20 h after the first rain event, to realize sedimentation and then release flows at a steady rate to get prepared for the next upcoming event. During the second event, which occurred on 21 May beginning at 7:05, the received runoff is trapped in the basin. However, the RTC strategy decides to open the outlet gate before 20 h of detention at a low steady rate (0.08 m^3/s ≈ 0.49 L/s.ha). Although in this case, the detention time is lower that the ideal 20 h, it is possible that the 0.08 m^3/s outflow rate would allow sedimentation by keeping quiescent conditions in the basin.

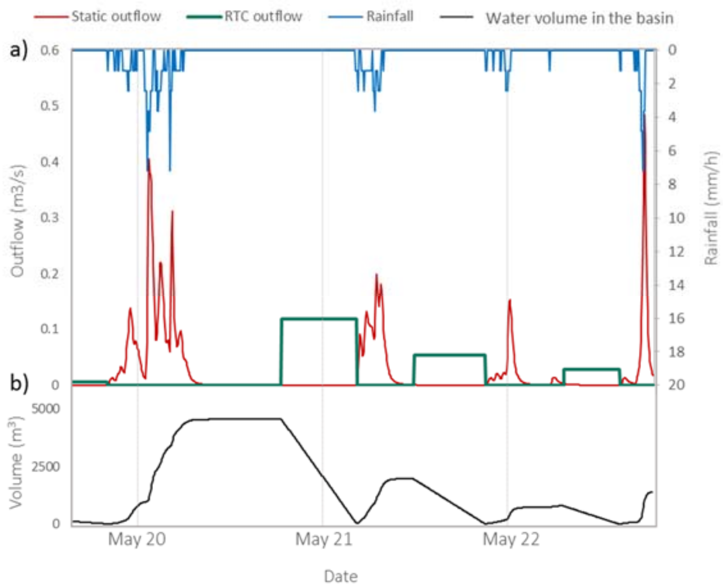

Figure 3-11- a) The controlled and uncontrolled basin outflow hydrographs, b) the basin volume in the controlled case during the storm event of 20-22 May 2013 under scenario 2

Figure 3-12 illustrates the basin's hydrographs during a 5-day period in September 2013. Sharp outflows are imposed to the body of water with the static control as a consequence of runoff inflows. Employing the integrated RTC strategy results in attenuated and uniform flows at the outfall whilst detaining water in the basin. During the rain event of September 12 beginning at 19:35, the optimization model decides to release water to the river slowly, as high inflows are predicted for the next hours. Henceforth, right after the further rain event on September 13, all received runoff volume is detained (water volume in the basin is 7500 m^3 at this time) to allow sedimentation and after almost 24 h, the outlet opening is set to allow a delayed discharge.

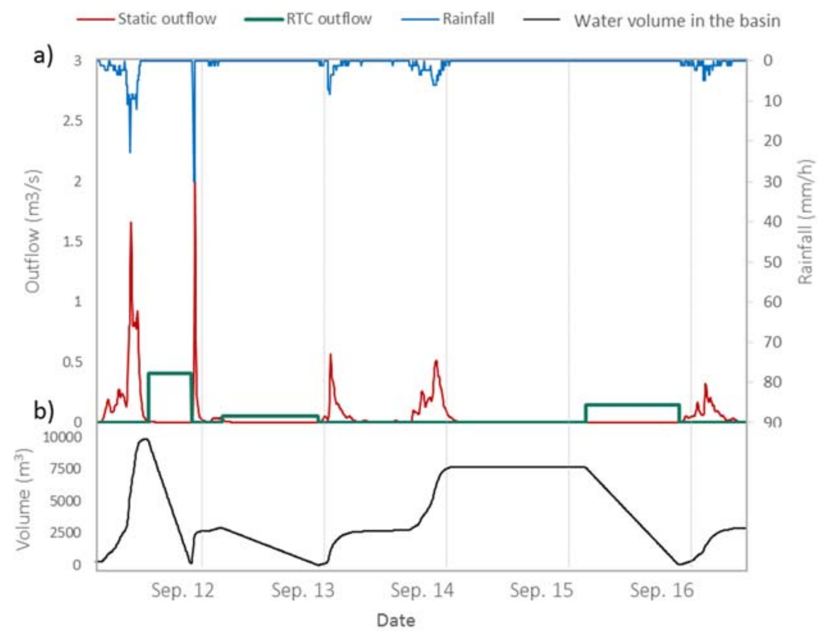

Figure 3-12-a) The controlled and uncontrolled basin outflow hydrographs b) the basin volume in the controlled case during the storm event of 12-16 September 2013 under scenario 2

3.3.1.3 Scenario 3: Low Volume Basin with 2013 Rainfall Series

To pose an additional challenge to the controlled system, a smaller stormwater basin with a volume capacity of 20,498 m^3 has been taken into account. In such a situation, sometimes the optimization model is not able to generate zero value outflows in order to keep the required available storage for the future incoming runoff flows. As shown in Figure 3-13, although the gate is partially open from May 24 to 26, the trapped water reaches its maximum volume in the basin. This demonstrates the predictive performance of the RTC framework since it is able to anticipate the required volume of storage in near future (here, 24 h). Accordingly, a 20 h detention time is obtained while providing gentle outflow of 0.36 m^3/s (which corresponds to 2.22 L/s.ha) at the outfall from 13:05 May 27 to 12:15 May 28.

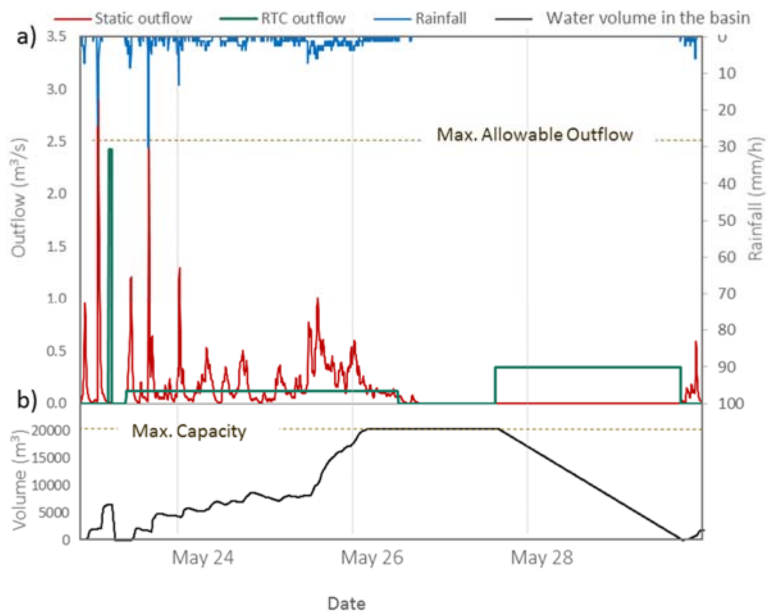

Figure 3-13-a) The controlled and uncontrolled basin outflow hydrographs, b) the basin volume in the controlled case during the storm event of 24-28 May 2013 under scenario 3

3.3.2 Scenario 4: Climate change

Figure 3-14 shows the hydrographs of the studied stormwater basin with the modified (+15%) May 20-30 2013 data series. In this case, as the system receives high runoff inflows on May 23, the optimization model decides to open the outlet gate at a low percentage in wet period (May 23-26) to prevent overflow of the basin. While during the original rain event (without CC), the water is detained for a certain amount of time to allow the settling process. It means that, in critical situations, the integrated RTC strategy prioritizes the quantity control measures (avoiding overflow) over the quality control ones (retaining water). Looking at the water volume variation (Figure 14), it can be seen that the storage capacity of the basin reaches its maximum. In this case, although detaining water in the basin could result in improving the quality of discharged water, it could also result in system overflow and even elevated peak-flows to the receiving stream. Hence, the designed algorithm performs in a way that, besides providing peak flow reduction, it generates optimized detention times except when there is a risk of capacity exceedance. The efficiency of the system in mitigating the peak-flows for the illustrated period in Figure 3-14, is calculated as 78%.

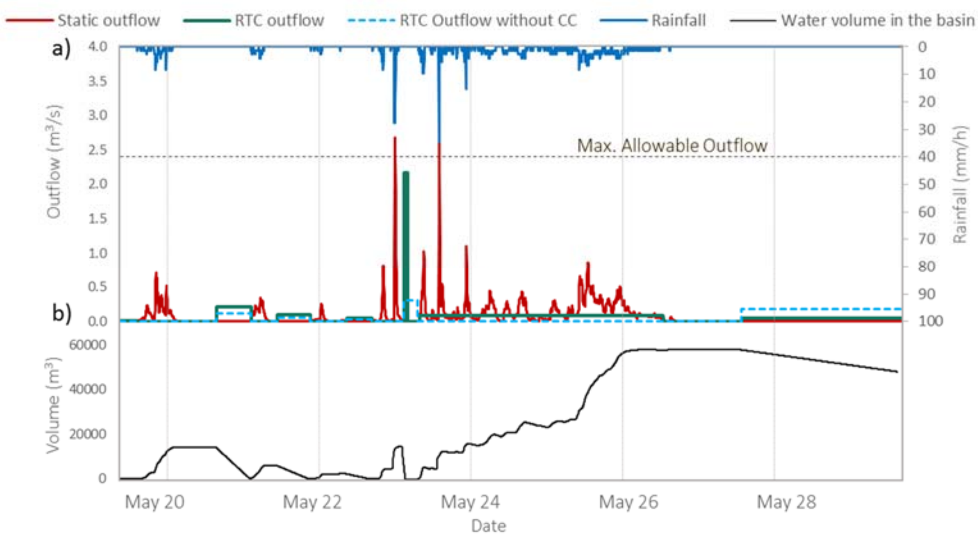

Figure 3-14- a) The controlled and uncontrolled basin outflow hydrographs, b) the basin volume in the controlled case during the storm event of 20-28 May 2013 under scenario 4

3.4 Conclusion

This study proposed an integrated predictive RTC optimization-rule-based approach for adaptive and sustainable management of urban stormwater. The main threefold contributions that differentiate this study from previous relevant work are summarized as below:

- A predictive RTC optimization model is developed to minimize the peak-flows imposed to the receiving watercourse in the downstream area via generating the outflow set points at predefined time steps. This optimization model is implemented periodically on a rolling horizon basis.

- Four generalized quality control rules are designed considering the next upcoming storm event and the volume of trapped water in the basin. Unlike the existing control rules in the related state-of-the-art, these rules are applicable to all stormwater detention basins.

- The decision-level combination of quantity control optimization model and quality control rules provides an integrated approach for RTC of stormwater basin in a dynamic environment whose state is varying from wet to dry (or dry to wet) period continuously.

The designed integrated RTC strategy has the potential for optimizing the performance of stormwater management systems facing challenges like urbanization and climate change. The dynamic scheduling of the outflows at the outlet of the studied separate sewer network of a city in Canada highlights the importance of employing smart approaches on traditional systems, in order to enable them to perform in an adaptive and predictive way. This predictive nature of the presented RTC approach allows optimizing the outflow rates, while generating desired possible detention times for the stormwater management system, to improve water quality, and preventing overflow of the basin.

According to the results, the hydraulic stress on receiving water body was controlled by reducing peak-flows up to 95 %, although lower values have been reported in more challenging situations like with a lower volume basin or with increased rainfall intensities due to climate change. Noteworthy is that in all situations the peak flow reduction was at least 73 % while preventing any overflow. Moreover, the average detention time of the basin was realized under normal to challenging situations for different scenarios from 16 h to 30 h, in comparison to the static approach, where in practice there is not any detention time. Although these two factors were the most important performance criteria when optimizing the problem, along with overflow prevention, other benefits were identified and quantified when analyzing the final scheduled flows at the outlet of the basin, namely flow attenuation and reduced outflow variations. This provides strong implications for municipal decision makers to computerize the traditional stormwater management systems and exploit their full potential when facing varying environmental conditions.

The key results of this study lead us to the following conclusions:

- Smart control algorithms are enabling stormwater management systems to significantly improve the quality and quantity control performance.
- In presence of climate change, the environmental risk can be managed by employing dynamic adaptation measures as an economic and efficient solution.
- Transforming sharp fluctuated flows to steady, distributed, delayed and attenuated outflows is the key indication of the optimized performance of integrated RTC strategy.
- The safety of stormwater basin can be preserved with the proposed algorithm even in case of a low volume capacity basin with the aid of alternative control measures that equilibrate quality and quantity objectives.

There are several research directions that can be further continued based on this study. Even though considering control measures at the local scale resulted in optimal performance for that stormwater system, it does not guarantee the optimal performance when considering downstream areas globally. Accordingly, the actual framework can be extended to the watershed scale in order to provide a global adaptive measure for the stormwater management systems. In this case, the complexity of the problem is inevitable, for which developing meta-heuristic algorithms and incorporating artificial intelligence approaches are recommended. Additionally, in a few time periods, the volume stored in the basin reached its maximum capacity. This may put the basin at risk of overflow; a fact that can be better managed by considering longer-term prediction data and/or by defining flexible priority coefficients for the quality and quantity objectives. Finally, it is important to consider the uncertainties engaged into the problem in order to produce more reliable solutions. Here, meteorological forecasting error is one of the main sources of uncertainties for which stochastic analysis can provide the best optimal solution. Also, a robust plan can be taken into account as an efficient approach in even the worst case scenarios. One should notice that this robustness in the solution may come with excessive costs. In all cases, a reliable, adaptive and sustainable management solution for urban stormwater systems is desirable.

3.5 Notations

$\bar{\mathrm{F}}^{\mathrm{sd}}$= Standard deviation of attenuated flows

$\mathrm{F_t}$= Attenuated volume percentage

$\mathrm{I_t}$= Inflow to the basin at time step t (m^3/s)

N= Number of time steps in the wet period

$\mathrm{N^{var}}$= Number of variations of outflow from one time step to another time step

n= Number of time steps in the control horizon

$\mathrm{pp_t}$= Positive variation of the set-point (continuous variable)

$\mathrm{qq_t}$= Negative variation of the set-point (continuous variable)

$\mathrm{Q_t}$= Outflow (decision variable) from the basin at time step t (m^3/s)

$\mathrm{Q_{max}}$= Maximum allowable outflow from the basin (m^3/s)

$\mathrm{Q_{t,max_{static\ strategy}}}$= Peak flow at the outlet of the basin controlled by static strategy at time t

$\mathrm{Q_{t,max_{integrated\ RTC\ strategy}}}$= Peak flow at the outlet of the basin controlled by integrated RTC strategy at time t

$\overline{\mathrm{Q^{var}}}$= The average outflow variations percentage

T= Planning time horizon

$\mathrm{t_e}$= Emptying time of the basin until availability of the required storage volume $\mathrm{V_{req}}$ at maximum outflow $\mathrm{Q_{max}}$ (s)

$t_{\text{next rain}}$= Remaining time until the next predicted storm event starts or time until the next predicted storm event starts[2] (s)

t^d= Detention time (s)

t_f= Time step when the previous rainfall event finished (s)

V_t= Volume of water in the basin at time step t (m^3)

V_{max}= Maximum volume capacity of the basin (m^3)

V_{req}= Required storage volume for the next coming rainfall event to avoid any overflow in the basin (m^3)

V^{ovf}= Percentage of filled volume capacity of the basin

ξ = Weight associated to the positive variation pp_t

ϕ = Weight associated with the negative variation qq_t

ρ = Peak flow reduction efficiency of integrated RTC strategy compared to those of the static control

3.6 Supplementary materials

The mass balance equation, given the incompressibility of water is given by:

$$\frac{dV}{dt} = I - Q \qquad \textbf{Equation 14}$$

Where I is the inflow rate, Q is the outflow rate, V is the storage volume, and t is time.

For the finite time period Δt, Equation 14 can be written in finite difference form in terms of average inflow and average outflow and rearranged as:

$$\frac{\Delta V}{\Delta t} = \bar{I} - \bar{Q} \qquad \textbf{Equation 15}$$

$$2 * (V_t - V_{t-1}) = [(I_t + I_{t-1}) - (Q_t + Q_{t-1})]\,\Delta t \qquad \textbf{Equation 16}$$

[2] This sentence is added in thesis report and does not appear in the published scientific paper.

This equation represents the mass balance where the storage difference $V_t - V_{t-1}$ equals to the difference between the average upstream runoff flow $(I_t + I_{t-1})/2$ and the average downstream flow $(Q_t + Q_{t-1})/2$ during time period Δt.

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4 THIRD SCIENTIFIC PAPER: A SMART PREDICTIVE FRAMEWORK FOR SYSTEM-LEVEL STORMWATER MANAGEMENT OPTIMIZATION

French Title: Un cadre prédictif intelligent pour l'optimisation de la gestion des eaux pluviales à l'échelle du système

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Contribution of the authors:

The authors confirm contributions to the paper as follows: Sophie Duchesne and Shadab Shishegar designed and developed the study conception during hours of discussions. Shadab Shishegar extended the integrated optimization rule-based algorithm to the global level, generated the results, and drafted and prepared the manuscript. Sophie Duchesne and Genevieve Pelletier provided the data and simulation model of the case study, supervised the project development and significantly helped in operational understanding of the stormwater management system. Reza Ghorbani contributed to the extension of control optimization and rules to the global scale, and also helped significantly in definition and visualization of the smart control system. All authors reviewed the results and approved the final version of the manuscript.

Link between the previous paper and the following: The previous paper provided a local scale integrated optimization and rule-based approach for real-time control of a single stormwater management basin. The present paper extended the previous algorithms at global scale to optimize the operations of all stormwater management basins in real-time. In addition, the performance of the global algorithm is investigated in presence of prediction uncertainty and the resiliency of the system is examined in unpredicted situations.

ABSTRACT

Stormwater management in urban areas faces many global challenges like climate change and urbanization. However, municipalities are highly dependent on human decisions at system-level to achieve catchment scale stormwater management goals. This study presents a global real-time control approach for sustainable and adaptive management of stormwater. A network of inter-connected devices are assumed to dynamically generate the required set-points for the system actuators at the remote control center where global optimization algorithms calculate real-time operational decision-making target values. These target values activate the local controllers to manipulate the spatially distributed detention basin's outlets that enables a smart catchment scale optimal control. A real world watershed with four outlets to a nearby watercourse is chosen to test the applicability and efficiency of the proposed dynamic control approach. Results show that the proposed autonomous control approach has the ability to enhance the global performance of the stormwater management system in terms of quality and quantity to balance the network flow dynamics and environmental demands, while reducing the potential for erosion of receiving water bodies. Climate change is specifically discussed as a challenge for the designed control framework. Although, the performance criteria are shown to be affected by the increased rainfall intensities compared to actual rainfall scenarios, the proposed methodology still improves the peak flow reduction and detention time of water, at global scale, up to 54% and 14 hours respectively under climate change conditions.

Keywords: Detention basin, Global control, Water quality, Real-Time control, Peak flow

4.1 Introduction

Sustainable urban development relies on the design of advanced urban planning systems among which stormwater management infrastructures can play an important role in facing the challenges posed by urbanization and climate change (CC). For example, historical data about urbanization of a peri-urban area in Swindon, United Kingdom, showed that an increase of impervious cover from 11% to 44% increased peak-flows resulting from runoff in downstream areas by over 400% (Miller et al., 2014). Besides, extreme climatic events and growing population have increased the need to upgrade stormwater management systems; it is now essential for urban stormwater management systems to operate dynamically and adaptively. Despite advances in technology, global digitally-enabled environmental systems have rarely been investigated. Employing smart systems and advanced Internet of Things (IoT) techniques, municipalities are now able to retrofit traditional stormwater infrastructures with sensors, actuated control valves and dynamic gates to allow an adaptive performance for controlling urban stormwater runoff against the changing environment (Kerkez et al., 2016). This allows transferring the conventional infrastructures that are controlled statically (with a single or a series of actions whose settings are constant in time) to dynamic and adaptive infrastructures. This has led to the definition of smart stormwater systems that aggregate observed and predicted data over the watershed for real-time monitoring and control of urban stormwater. Figure 4-1 illustrates the mechanism of a globally-controlled smart stormwater management infrastructure. Various field-deployed sensors collect the observation data of water quantity and quality over the network to finally store them into the cloud database. In addition, meteorological forecasting data, historical precipitation data and also data on actual weather conditions will be transferred to the cloud where all data is maintained, backed-up and analyzed remotely for further distribution over the network when needed. A remote control center looks over the network to generate decision-making target values for the local actuators. This performs as the core of the system and every decision made imposes a global impact on the whole system. Integrating IoT devices into such a system provides an embedded technology that enables proper communication, sensing and interaction between the stormwater system assets to achieve some common goals (Zhang, 2019). All these operations should be managed using a system-level control strategy that incorporates system flow dynamics and environmental demands for sustainable management of urban stormwater infrastructures. Although literature on the control of stormwater generally considers some simple rules to identify what actions need to be taken at the outlet of a drainage network to mitigate the impacts of urbanization on the natural streams (e.g. Gaborit et al., 2012), employing optimization algorithms proved to bring an enhanced performance for quantity and quality control of stormwater management systems. In a recently published study by Shishegar et al. (2019), a smart predictive decision-making framework is presented for real-time control of stormwater management basin in such a way that an optimization algorithm is integrated with some control rules to enable optimal quality and quantity control performance for the detention basin. Although this approach showed a significant improvement in the peak-flow reduction and detention time of the basin, it serves the stormwater system at local-level, and the impact of erroneous rainfall predictions on the real performance of this approach was not evaluated.

Optimized performance of a single basin does not necessarily result in an optimal performance at system-level, it would therefore be beneficial to study the operations of stormwater management systems as a component of a greater whole (Shishegar et al., 2018). In addition, erosion, as one of the direct impacts of urbanization on the natural hydrological regime, can be an important source of phosphorus in watersheds (Wong and Kerkez, 2016) and proper stormwater management strategies are required to reduce erosion (Ministry of the Environment, 2003). However, without considering a system-level control, stormwater management practices may lead to adverse impacts such as erosion of waterbodies (Hawley and Vietz, 2016). Hence, controlling the velocity of *global* discharges to limit erosion is a necessity. There are only a few studies that have investigated the global performance of urban drainage systems as a whole (Cembrano et al., 2004; Darsono and Labadie, 2007; Duchesne et al., 2003; Pleau et al., 2005), most of which consider combined sewer systems. There is a lack of practical solutions to enhance the system-wide performance of built stormwater management infrastructures; a solution that provides the system with the ability to perform dynamically and predictively against the varying environmental conditions and helps define an optimal control strategy that satisfies changing socio-environmental needs. As for the impact of uncertainties linked to rainfall predictions on the performance of real-time stormwater control systems, they have only been taken into account, to the authors knowledge, by Vezzaro and Grum (2014) and yet for the control of combined sewer systems. Yet, analyzing the performance of RTC strategies in presence of uncertainties can provide a more realistic and reliable decision-making while allowing an effective study of the resiliency of stormwater management systems as the ability to “bounce back” from a failure to the normal condition (Hosseini et al., 2016).

Figure 4-1-Smart Stormwater Management at System-Level

The aim of this study is to develop a smart framework for global control and optimization of urban stormwater via long and short-term flow planning. Such framework should be capable of reducing the peak-flows at the outlet of a stormwater management network while improving the detention time of the received runoff in all system detention basins over the watershed.

More specifically, the objectives of this paper are:

- To propose a global predictive dynamic control (GPDC) approach to enhance the quality and quantity control performance of a stormwater management system in real-time at the catchment scale.
- To discuss the global resiliency of the system in critical situations such as more intense rainfall events imposed by climate change.
- To identify challenges of the proposed global approach by evaluating the comparative performance of a real catchment case study under dynamic and static approaches.
- To analyze the erosion reduction ability of the proposed system-level approach compared to the static approach.
- To evaluate the impacts of uncertainties linked to rainfall predictions on the performance of the proposed control approach.

4.2 Methodology

A global predictive dynamic control optimization approach (GPDC) is developed that involves establishing the optimal operation of stormwater system regulators during rainfall periods and then incorporating some water quality control rules to detain runoff in the basin during dry periods. This approach is the expansion of the local integrated rule-based and optimization approach proposed in Shishegar et al. (2019), where local controllers generate the operational set-point for each single stormwater basin locally without considering the global system state. In the present study, the strength of optimization techniques allows establishing a global mathematical model based on the local one, to coordinate the discharges amongst spatially distributed detention basins across an urban watershed using real-time observed and forecasted precipitation data. The proposed methodology is first tested on a case study drainage area in Canada using a 2013 rainfall series observed from a rain gauge near the studied case from May to November, that includes 74 rainfall events. Secondly a modified rainfall series mimicking the expected climate in 2050 is used to evaluate the performance of the proposed control approach in presence of climate change. For this purpose, 15% are added to the volume of the selected rainfall series volume as recommended in Ouranos (2015). First, the employed prediction data in both scenarios (2013 year and climate change) are supposed to be perfect. The impacts that errors on rainfall predictions can have on the performance of the approach are afterwards investigated.

4.2.1 Integrated rule-based and optimization approach

The global predictive RTC approach, GPDC, is based on the integration of several control rules into an optimization model, which aims at minimizing peak-flows to the receiving water body under several constraints while maximizing the detention time up to a predefined limit. This optimization model, described in section 4.2.1.1 below, is run in sequence with the control rules described in section 4.2.1.2 over predefined time intervals, in such a way that the dynamic optimization algorithm is active as long as the inflow to all basins is not zero. Once the dry period starts, the quality control rules become active to decide on the detention time of water in each basin. All planning intervals (control horizons) are part of a rolling horizon framework that allows the system parameters to be continuously updated based on the newly received data (Ziarnetzky et al., 2018). A simulation model is used in all steps of the optimization framework to assess the future performance of the system as a function of predicted rainfall events by incorporating all hydrologic/hydraulic characteristics of the catchment. The time in a rolling horizon context is defined in discrete periods of equal length, which are called time steps. Outflow scheduling from each basin is then computed at each time step by running the simulation and optimization models successively at over the control horizons. The control horizon is the period over which the dynamic outflow scheduling is planned with respect to several physical and hydrological limitations. Figure 4-2 illustrates the planning process using the rolling horizon approach. This process is supposed to be continued over a long period of time, namely the planning horizon, which can be either finite or infinite depending on the studied problem nature.

For all investigations in this study, a 6-hour inter-event time is considered, as recommended in Giroux and Simoneau (2008) for Quebec province, to separate the 2013 rainfall series into rainfall events and compute the performance criteria. Additionally, a 2-hour control horizon is considered to run the integrated rule-based and optimization algorithms including 24 time-steps of 5 minutes. Also, the prediction horizon is up to 48 hours with an infinite planning horizon that allows the designed algorithms to operate as long as required.

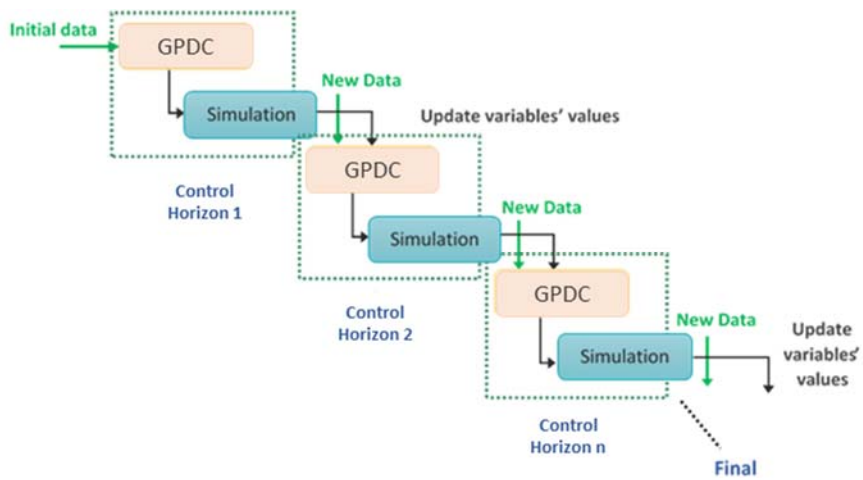

Figure 4-2-Planning by the Rolling Horizon approach and the Simulation-GPDC process

Figure 4-3 represents a stormwater network representation where the stormwater basins are considered as end-of-network storage structures connected to a smart controller with the ability to dynamically manipulate outflow rates while communicating with other controllers embedded over the network to balance the flow dynamics. This provides the stormwater system with the capabilities to not only measure, monitor and sense catchment parameters, but also to optimize the dynamic operations of these systems in an adaptive and predictive approach.

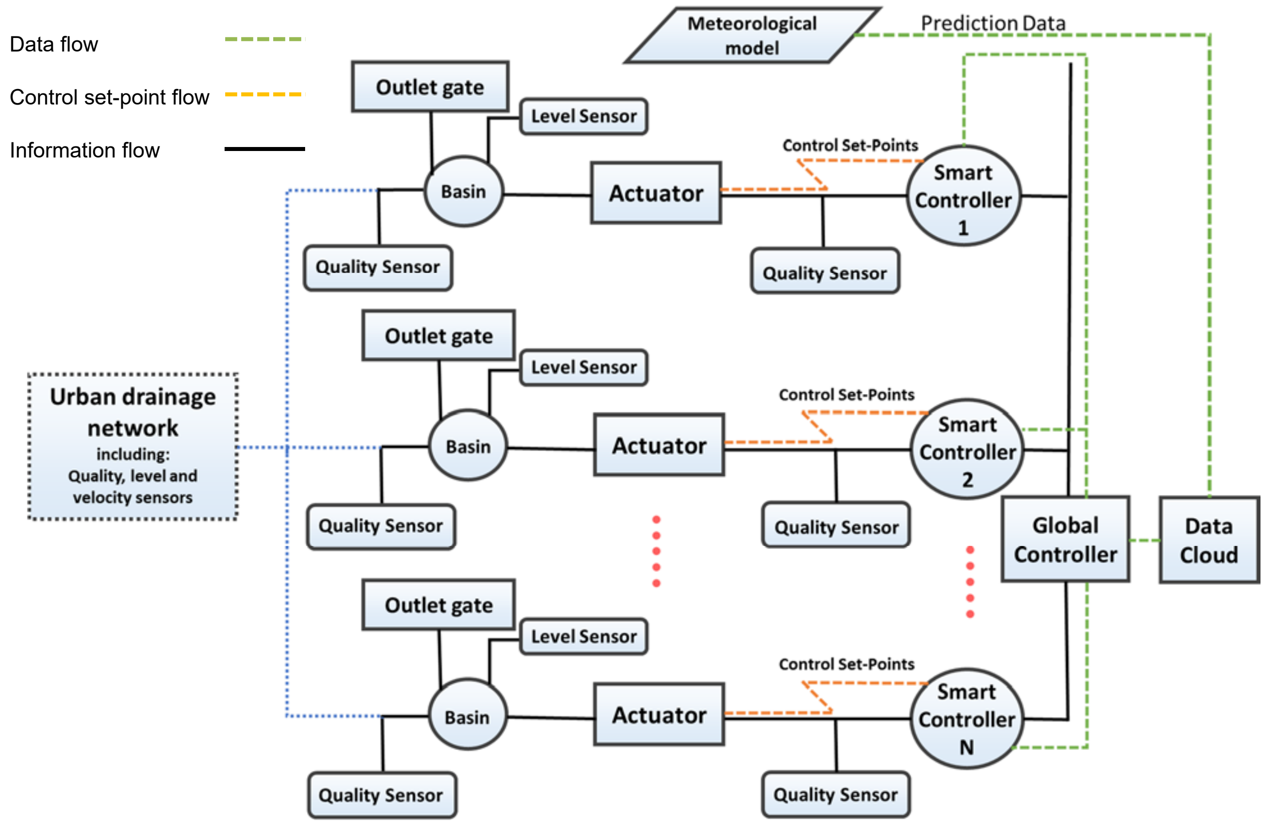

Figure 4-3-Schematic representation of a stormwater management system and its associated assets

The N-basin network shown in Figure 4-3 concurrently directs urban runoff into the receiving watercourse via its detention basins. For this purpose, forecasting data must be available to support prediction-based decisions on stormwater detention basins, simulate the upcoming inflows and plan for the next rainfall events, while satisfying the settling process via quality control rules. All these decisions are made following the planning generated by the optimization model, which accordingly affects the interrelations between the basins even during the dry periods. This facilitates the stormwater system control so that its components operate jointly, while considering the overall state of the system. The quantity and quality control mathematical formulations will be explained in the next sections.

4.2.1.1 Dynamic Predictive Quantity Control Optimization Problem (PQ-COP) for interactions between the stormwater basins

A mathematical model is formulated, PQ-COP, to optimize the interrelationship operations of various stormwater basins. This optimization model aims at minimizing the total peak flow discharged from the stormwater management system to the receiving river and can be formulated as the following linear programming minimum cost function problem:

$$Min\left\{\sum_i \sum_t (\mathrm{Q}_{i,t} + \xi * pp_{i,t} + \phi * qq_{i,t})\right\}$$ Equation 1

Subject to:

$$\sum_t (I_{i,t} - \mathrm{Q}_{i,t})\,\Delta\, t + V_{i,0} \le V_{i,max} \quad \forall i = 1,2,\ldots,N$$ Equation 2

$$Q_{i,t}\Delta t + 2V_{i,t} = I_{i,t}\Delta t + I_{i,t-1}\Delta t + 2V_{i,t-1} - Q_{i,t-1}\Delta t \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 3

$$\mathrm{V}_{i,t} \ge 0 \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 4

$$0 \le Q_{i,t} \le Q_{i,max} \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 5

$$Q_{i,t} - Q_{i,t-1} = pp_{i,t} - qq_{i,t} \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 6

$$pp_{i,t} \ge 0 \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 7

$$qq_{i,t} \ge 0 \quad \forall t = 0,1,\ldots,L\ \&\ \forall i = 1,2,\ldots,N$$ Equation 8

Where:

$Q_{i,t}$= outflow (decision variable) from basin i at time step t (m^3/s);
$pp_{i,t}$= negative variation of the set-point (continuous variable) associated to basin i;
$qq_{i,t}$= positive variation of the set-point (continuous variable) associated to the basin i;
ξ= weight associated to the positive variation $pp_{i,t}$;
ϕ = weight associated with the negative variation $qq_{i,t}$;
L= number of time steps in the control horizon;
$I_{i,t}$= inflow to basin i at time step t (m^3/s);
$V_{i,t}$= volume of water in the basin i at time step t (m^3);
$V_{i,max}$= maximum volume capacity of basin i (m^3);
Δt = difference of t between two time steps (s);
$V_{i,0}$= initial volume of water in basin i (m^3);
$Q_{i,max}$= maximum allowable outflow from basin i (m^3/s); and
N= number of controlled basins in the drainage network.

The linear decision-making model incorporates the simulated inflows to each storage basin to further generate the final optimal set-points related to the outflows from each basin. When applied in real-time, the inflows, $I_{i,t}$, are computed from rainfall predictions using a hydrological/hydraulic model. The objective function is formulated in such a way that it provides minimum total outflow rates to the receiving stream during the control horizon. It should be noted that the operation of parallel basins can be optimized using this mathematical formulation and for taking into account the flow sharing between the basins in series, further modelling adjustment is needed.

4.2.1.2 Dynamic Predictive Quality Control Rules (DP-QCR) formulation

The pseudo-code of the proposed dynamic global predictive-quality control rules (DP-QCR) is presented below. These rules have been extended to a watershed with multiple stormwater basin systems from the quality control rules developed in Shishegar et al. (2019) for one single basin network. Here, at each time-step, based on the predicted precipitation data, the outflows from each basin are computed to decide on a proper detention time with respect to the defined constraints where:

$V_{i,req}$: required storage volume for the next coming rainfall event to avoid any overflow from basin i (m^3);

$t_{i,e} = \frac{V_{i,req}}{Q_{i,max}}$ = emptying time of basin i until availability of the required storage volume $V_{i,req}$ at maximum outflow $Q_{i,max}$ (s);

$t_{next\ rain}$ = time until the next predicted storm event starts (s);

t_f = time when the previous rainfall event finished (s);

t_i = emptying time of basin i at rate $Q_{i,t}$ which is $\frac{V_{i,available}}{Q_{i,t}}$;

$t_{i,e}^{max}$ = emptying time of basin i until $V_i = 0$ at maximum outflow rate $Q_{i,max}$ (s); and

$V_{i,available}$ = available storage capacity in basin i (m^3).

The DP-QCR pseudo-code is as below:

Set the parameters of DP-QCR

for i=1:N

  set $t_{i,e} = \frac{V_{i,req}}{Q_{i,max}}$

    if $t_{next\ rain} < t_{i,e} + t$ then

        $Q_{i,t} = Q_{i,max}$

    if $t_{i,e} + t < t_{next\ rain} < t_{i,e} + t + 20h$ then

$$Q_{i,t} = Q_{i,max} * \frac{t_{i,e}}{t_{next\ rain} - t_f}$$

if $t_{i,e} + 20h + t < t_{next\ rain} < t_{i,e}^{max} + 40h + t$ then

$$Q_{i,t} = Q_{i,max} * \frac{t_{i,e} + 20h}{t_{next\ rain} - t_f}$$

if $t_{next\ rain} \geq t_{i,e}^{max} + 40h + t$ then

if $0h \leq t_{i,e} \leq 40\text{h}$ then

$$Q_{i,t} = 0$$

if $40h < t_{i,e} < t_{i,e}^{max} + 40h$ then

$$Q_{i,t} = Q_{i,max} * \frac{t_{i,e} + 20h}{t_{i,e}^{max}}$$

if $t_{next\ rain} - t_i > t_{i+1,e}$ then

$$t = t + t_i$$

set i=i+1

After checking the last designed rule, this pseudo-code will be repeated for the next stormwater basin (N times in total) in order to set a proper detention time, by looking at $\boldsymbol{t_{next\ rain}}$, $\boldsymbol{V}_{i,req}$ and the emptying time of the basin ($\boldsymbol{t_{i+1,e}}$). This allows the discharging process from the basins to be set either sequentially starting from the basin in need for higher percentage of capacity for the upcoming rainfall or simultaneously, depending upon the $t_{next\ rain} - t_i > t_{i+1,e}$ condition.

4.2.2 Erosion analysis

In this study, in order to evaluate the reduction of potential erosion, the Manning equation is applied to evaluate the velocity of storm flow discharges into the water bodies when the global predictive dynamic control strategy is employed. This approach that has been widely used in water engineering studies, is reported as an accurate formulation for water velocity analysis in operational hydraulics (Brutsaert, 2005).

4.2.3 Impact of errors on rainfall predictions

As mentioned before, perfect prediction data are first used to investigate the performance of the proposed control approach. Then, the impact of uncertainties linked to rainfall predictions on the performance of the proposed control approach is investigated. For this evaluation, prediction precipitation data from the High Resolution Deterministic Prediction System (HRDPS) version 5.0 (Environment Canada, 2020) were used. This model is a set of nested forecast grids that generate 48-hour predictions of atmospheric elements, including precipitation, at 1-hour time step 4 times per day (Kehler et al., 2016). Analysis of prediction data obtained by this model shows that the quality of generated data in terms of accuracy of prediction varies during the day (Perez-Bello, 202. Sensitivity of the model to the uncertain input data can vary based upon these accuracy variations.

The impact of using imperfect prediction data as the input parameter for the proposed dynamic control approach is assessed over a one-month period (July 2017). For this assessment, as illustrated in Figure 4-4, the parameters values (water volume in the basins and observed inflows to the basins) are updated based on the observed data of the current system state at the end of each control horizon, while the planning for the next time-steps is performed based on the prediction data from HRDPS. It is worth mentioning that this evaluation could not be performed with the 2013 rainfall series, since the HRDPS predictions were available only from May 2017 onwards.

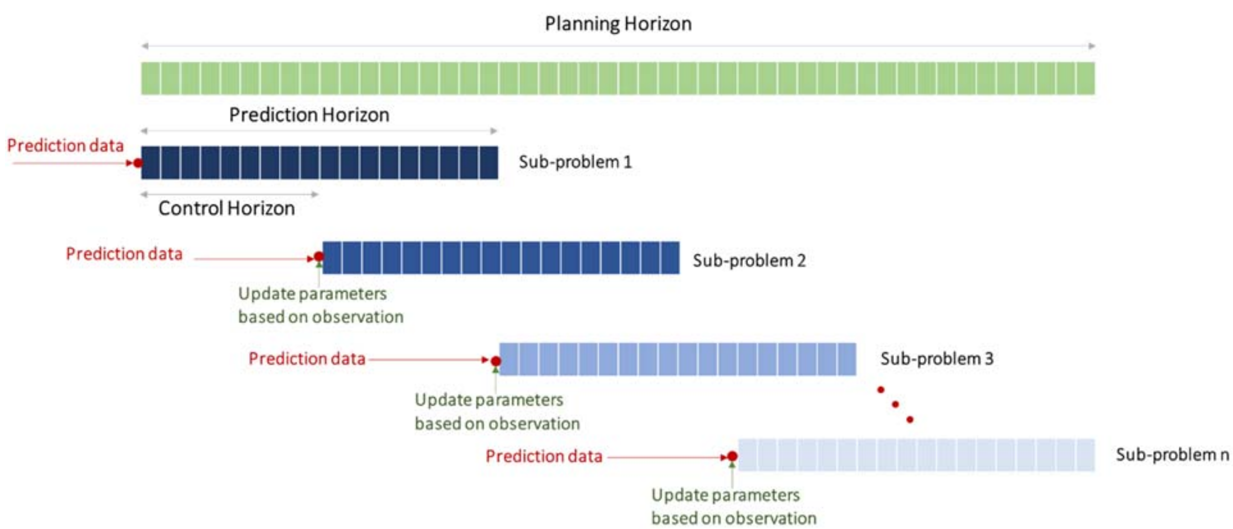

Figure 4-4- Assessment of the performance of the control approach when imperfect prediction data are used

4.2.4 Case study

The studied case is a Canadian drainage network located in a mid-size municipality in the province of Quebec, established on the banks of a river whose watershed covers an area of nearly 3400 km^2. This river is the main source of drinking water for the municipality, making the quality of its water crucially important, especially against the polluted urban runoff that annually discharges into this stream. The studied catchment is over 311 hectares, with erosion problems (mostly due to sharp peak-flows) that increase the volume of sediments in the stormwater runoff which also carries relatively high levels of phosphorus, nitrogen and nitrites-nitrates due to industrial activities in the region (Giroux and Simoneau, 2008). In addition, the sector is an urbanized and developed region that includes occupancy predominantly residential, with light businesses and some industrial, commercial and institutional lands, resulting in an average imperviousness of 55%. The hydraulic/hydrologic SWMM model (Rossman and Huber, 2016) of the drainage network has been provided by the municipality, which is the owner and manager of the sewer network. However, the network is currently a combined sewer network that is planned to be separated in the upcoming years. For the case study presented herein, in order to represent the behavior of the future stormwater network, all wastewater flows in the simulation model are valued as zero, to convert the combined sewer into a separate storm sewer model. Figure 4-5 schematically illustrates the studied sector, which consists of 470 sub-catchments, 526 nodes and 544 links. This sector is located in a denser part of the municipality and includes four outlets to the river (from left to right on Figure 4-5, A, B, C and D). Since the real drainage network is not separated yet, detention basins are not currently integrated in the network. For our case study, a detention basin was virtually added at each of the four outlets. These basins were designed using a 1-hr SEA (Service Atmosphérique Environnement Canada) design storm of 100-year return period, a maximum outlet discharge of 50 L/s/ha (based on municipal regulations) and a maximum height of 1.5 m, as detailed in the Supplementary Material section. The resulting characteristics of the four basins are summarized in Table 4-1.

Table 4-1-Characteristics of the drainage area and of the stormwater basins for the four studied outlets

Outlet	Drainage area (ha)	Maximum outflow rate	Orifice diameter (m)	Volume (m^3)
A	86.52	4.33 m^3/s	1.95	30430
B	80.53	4.03m^3/s	2.10	25670
C	115.67	5.78 m^3/s	1.80	18570
D	115.68	5.78 m^3/s	1.95	22160

Figure 4-5- Simulation model of the studied sector using SWMM

4.2.5 Performance Criteria

In order to quantitatively evaluate the performance of the developed global control model, some performance indicators are extended based on the local RTC strategy performance criteria introduced in Shishegar et al. (2019) as presented below:

Peak discharge mitigation indicator that represents the peak flow reduction of the proposed dynamic control in comparison to the static control approach.

$$\rho_{i,r} = \frac{Q_{i,r,max_{\text{static strategy}}} - Q_{i,r,max_{\text{GPDC strategy}}}}{Q_{i,r,max_{\text{static strategy}}}} \times 100 \qquad \text{Equation 9}$$

Where:

$Q_{i,r,max_{\text{static strategy}}}$ = peak flow generated by the static strategy for basin i during rainfall event r.

$Q_{i,r,max_{\text{GPDC strategy}}}$ = peak flow generated by the GPDC strategy for basin i during rainfall event r.

I. Quality control enhanced performance, that can be assessed through the detention time assigned by the dynamic model to each basin t_i^d.

II. Overflow prevention indicator formulated based on the percentage of volume capacity used within each basin $V_{t,i}^{ovf}$

$$V_{t,i}^{ovf} = \frac{\mathrm{V}_{i,t}}{\mathrm{V}_{i,max}} \times 100 \qquad \text{Equation 10}$$

III. Outflow variation minimization that is formulated based on the average outflow variation percentage and the number of variations ($\overline{Q_i^{var}}$ and N_i^{var})

$$Q_{i,t}^{var} = \frac{\left|Q_{i,t_{\text{GPDC strategy}}} - Q_{i,t+1_{\text{GPDC strategy}}}\right|}{Q_{i,t_{\text{GPDC strategy}}}} \times 100 \qquad \text{Equation 11}$$

Where:

$Q_{i,t}^{var}$: The variation of outflow at time t (t is in wet period)

It is worthy to note that the static control approach means that the outlet gate for each basin remains at a fixed position.

4.3 Results and Discussion

4.3.1 Peak-flows and detention times

The overall results of the performance of the GPDC strategy for the entire studied watershed are provided in Table 4-2, assuming perfect predicted rainfall data, for the 2013 rainfall series and for the climate change scenario (2013 series increased by 15%). These results show that the mean peak-flows from each basin are reduced by at least 75% and 57% for each scenario, respectively. Also, employing the dynamic control strategy caused a total mean peak discharge mitigation, over the static control strategy, of 59% for the 2013 rainfall series and 54% in presence of climate change. On the other hand, detention times demonstrate an improvement in the quality control performance of the proposed approach, with at least 17 h and 14 h mean detention times for all the 2013 rainfall events under actual and climate change scenarios, respectively. In addition, for the overflow control criteria, it can be noticed that despite realizing an enhance quality and peak discharge control performance, the risk of overflow is managed properly by not allowing the water volume to surpass the volume capacity of the basins. The highest average capacity used in both scenarios is related to the smallest basin, C, with 16% and 18% mean capacity usage under the actual and climate change scenarios, respectively.

Table 4-2-Performance criteria calculations for two scenarios and four studied stormwater basins over a year

Performance criteria (Mean ± Standard Deviation)	2013 (actual) scenario assuming perfect predicted rainfall data				
	A	B	C	D	Total
Peak discharge mitigation (%)	87 ± 47	77 ± 39	75 ± 40	78 ± 43	59 ± 38
Quality control (h)	26 ± 13	24 ± 14	17 ± 11	18 ± 13	
Overflow control (%)	8 ± 9	12 ± 11	16 ± 12	11 ± 9	
Mean flow variations	0.37	0.39	0.40	0.37	
Performance criteria (Mean ± Standard Deviation)	**Climate change scenario assuming perfect predicted rainfall data**				
	A	**B**	**C**	**D**	**Total**
Peak discharge mitigation (%)	68 ± 40	61 ± 39	58 ± 37	57 ± 40	54 ± 37
Quality control (h)	20 ± 11	18 ± 12	14 ± 9	14 ± 11	
Overflow control (%)	9 ± 9	11 ± 11	18 ± 15	13 ± 10	
Mean flow variations	0.38	0.43	0.42	0.39	

While the visual representation of the generated outflow schedule by the dynamic and static control approaches for the entire year of 2013 is difficult to illustrate, a clearer hydrograph can be provided for individual rainfall events. In this regard, the outflow schedules at the four studied outlets planned under the global predictive and static control approaches are shown in Figures 4-6 and 4-7 for the periods between June 10 and June 14 (actual scenario) and May 24 and 26 (climate change scenario), respectively.

As illustrated in Figure 4-6, the outlet gates are partially opened in sequence and not simultaneously to allow reducing the total peak discharge to the river. This contributes to the operation of the whole system where, by looking at the predicted meteorological conditions, the water flow variabilities are controlled efficiently at system-level. Besides, the generated schedule allows the settling process to improve the quality of released water by planning 10 h, 8 h, 14 h and 7 h of detention times for basins B, D, A and C respectively, while reducing the total peak flow rate by 68%.

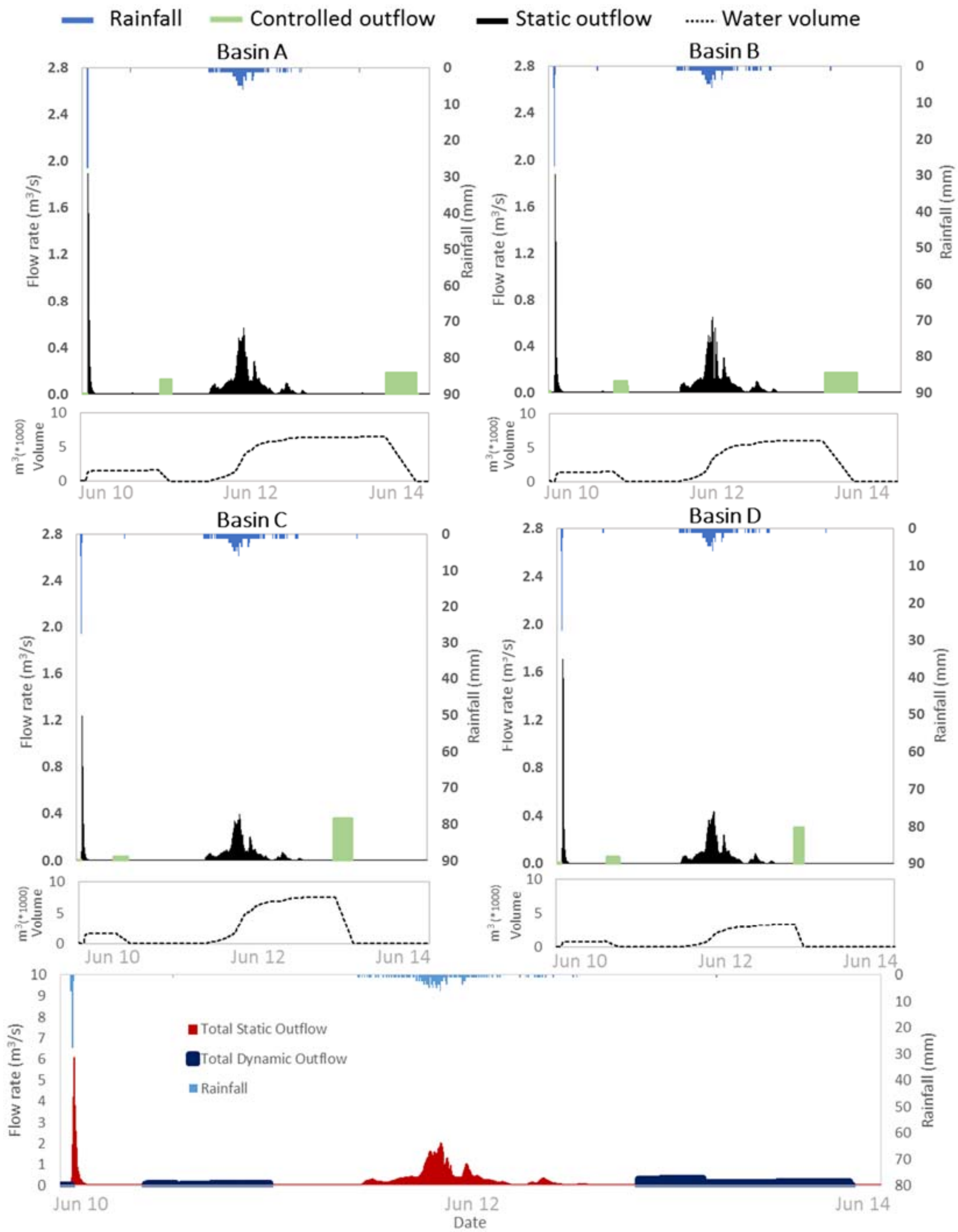

Figure 4-6- Outflow schedule under the 2013 rainfall series for the four studied outlets during a 4-day period (June 10 to June 14)

Figure 4-7 illustrates the results under the climate change scenario for a 3-day period after a critical and long storm event. As shown, the optimization aimed to reduce total outflows as much as possible to avoid any sharp peak flow in the river. This caused the water volume in the stormwater basins to reach a high level (the maximum level for the basin C) at the end of this rainfall event. Here, the GPDC framework assigns a relatively high outflow rate adjusted for each outlet, to minimize the overflow risk due to upcoming inflow to the basins. Hence, in such challenging circumstances, not only the safety of detention basins can be preserved, but the quality requirements of the runoff outflows can also be met.

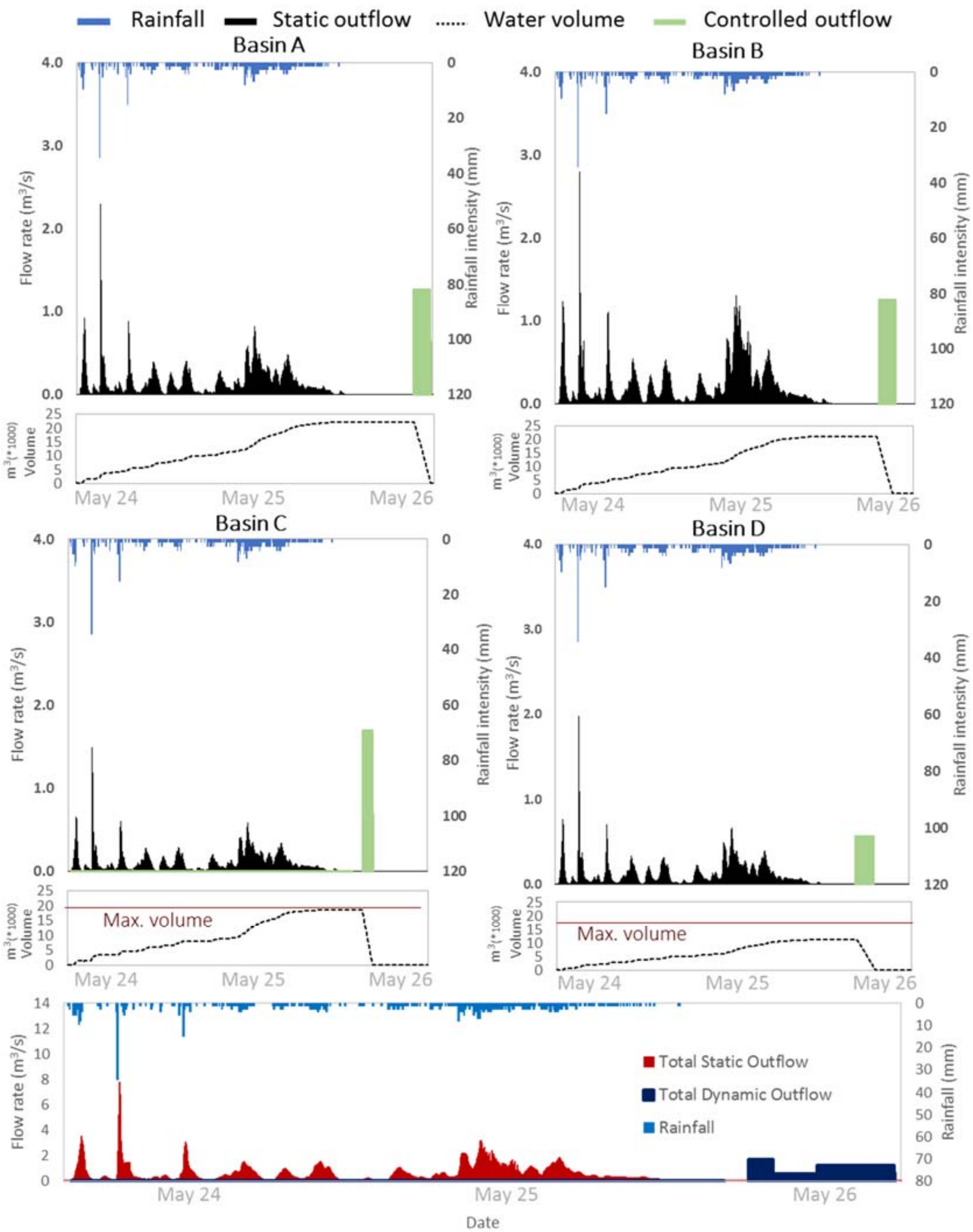

Figure 4-7-Outflow schedule under climate change scenario for the four studied outlets during a 3-day period (May 24 to May 26)

4.4 Erosion analysis

Table 4-3 shows the quantitative results obtained for both the static and dynamic control approaches. As expected, outflow velocities from the dynamic control approach are lower than those of the static control approach. Among the four studied outlets, B discharges the water slower than the others, probably due to the gentler slope of its outlet pipe (0.005 m/m). Conversely, C outlet produced more speedy outflows in comparison to the other studied outlets. Besides, the outlet pipes of the basins C and A have steep slopes to the nearby stream (the slope of C is almost 10 times larger than B) which contributes to the high outlet velocities.

Table 4-3-Studied outlets characteristics and velocity calculations

Outlet	Slope	Velocity (Mean ± Standard Deviation)		Mean velocity reduction
		Static	Dynamic	
A	0.04242	0.32 ± 0.19	0.15 ± 0.15	54%
B	0.00564	0.21 ± 0.13	0.10 ± 0.09	51%
C	0.05185	0.49 ± 0.31	0.33 ± 0.30	33%
D	0.02645	0.49 ± 0.29	0.30 ± 0.27	39%
Total				**47%**

The above-mentioned percentage reductions accounts for the efficiency of the proposed dynamic control approach in reducing the potential erosion imposed on the receiving waterbody.

Figure 4-8 shows 5-minute flow velocities at the B outlet for a 3-week period under climate change. The outlet velocity is the main parameter impacting erosive potential. It can be seen on Figure 7-8 that the dynamic control approach considerably reduces the velocity at the outlet and, consequently, the potential erosion of nearby streambanks.

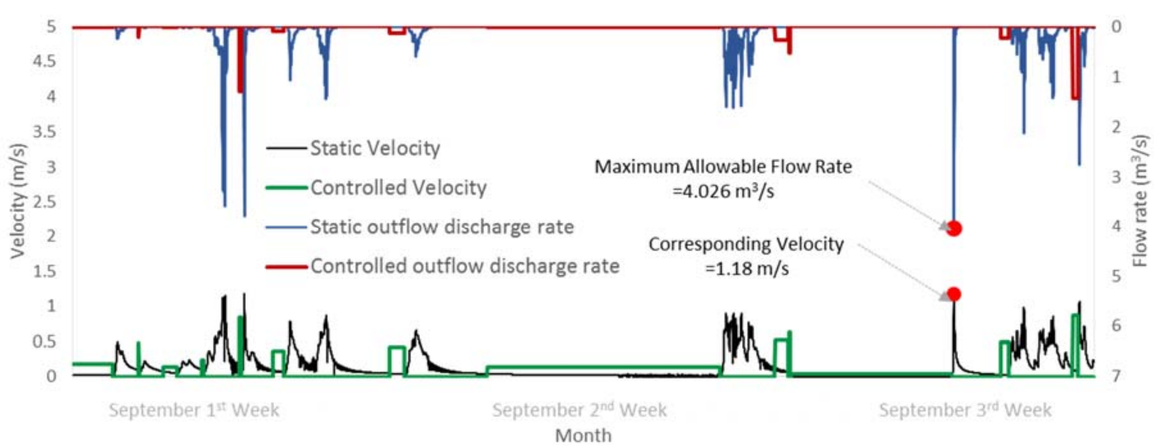

Figure 4-8-Flow velocity associated with the outflow rates produced by static and dynamic control strategies at B outlet under climate change scenario during a 3-week period

4.5 Impact of errors on rainfall predictions

Table 4-4 shows the calculated performance criteria as well as the number of overflows at each basin, computed when considering or not the errors on rainfall predictions. These results show that using the HRDPS prediction data as input to compute the control settings increases the risk of overflow and local flooding. Noteworthy, the higher peak discharge mitigation performance values shown in Table 4 in some cases, when errors in rainfall predictions are taken into account (like for basins A, C and D), does not necessarily mean that the model performed better. Rather, this could be due to not generating a proper response against an upcoming rainfall event and keeping the outlet closed, while it would have been a better strategy to open it to avoid any overflow. For example, in the case shown in Figure 4-9, although a zero outflow generated after a 20-mm rainfall event resulted in a higher value of the peak discharge mitigation performance criterion, it is followed by an overflow from the B basin.

Table 4-4-Quantitative comparison of the performance of the GPDC model when considering or not the errors on rainfall prediction data for July 2017

Performance criteria (Mean)	Perfect rainfall predictions					With errors on rainfall predictions				
	B	D	A	C	Total	B	D	A	C	Total
Mean peak discharge mitigation (%)	64	58	69	53	60	62	61	69	54	54
Mean quality control (h)	20	17	21	15	-	17	17	19	13	-
Mean overflow control (%)	12	15	12	16	-	15	19	14	22	-
Mean flow variations	0.32	0.29	0.32	0.36	-	0.29	0.26	0.29	0.32	-
No. of overflows	0	0	0	0	0	1	1	1	1	-

As an example, Figure 4-9 illustrates a critical situation where the prediction model is not properly able to forecast a 20-mm rainfall event may result in undesirable outcomes. Although the proposed dynamic model is designed in such a way that it receives the new data at each time step, the best currently available prediction models, like HRDPS, provide forecasting data significantly less frequently (at each 6 hours in the case of HRDPS). In this situation, given the variability of the weather condition, there is a possibility of not providing enough volume capacity for an upcoming extreme event because of not forecasting it well. Retarded discharge of stored water may result in basin overflow. As shown in Figure 4-9, an unpredicted rainfall event occurred while the basin was not prepared for the runoff caused by this rainfall episode. In this case, the integrated model decides to keep the water in the basin without being aware of the 20-mm coming rainfall. This causes an overflow from the basin, which is reported to the model in the next time step, when it generates the outflow set-points that allow discharging the water into the nearest stream. This shows that, although the rainfall predictions are not precise enough in this example to avoid any overflow, the dynamic performance of the GPDC framework enables a fast and reliable recovery of basin overflow caused by inaccurate prediction data.

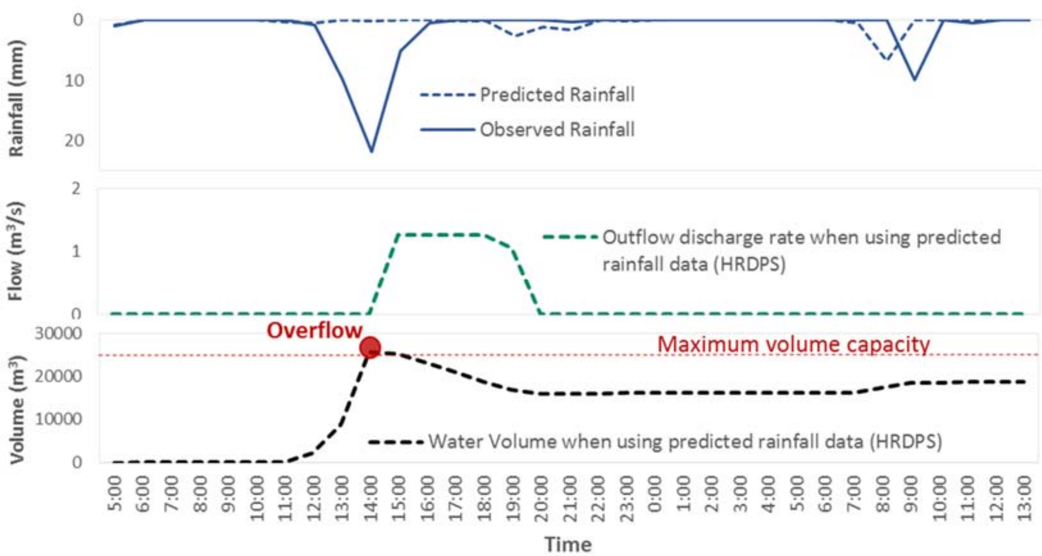

Figure 4-9- GPDC strategy performance when considering the errors in rainfall prediction data (a 20-mm rainfall event is not foreseen)

To sum up, these results demonstrate the importance of taking into account the uncertainty linked to input parameters and data when assessing the performance of a control approach. Although the performance of the GPDC strategy depends on the quality of the prediction data, it has the ability to recover when faced with unpredicted events and provide the system with a resilient decision-making process. Thus, future studies should focus on the system resiliency and features that could be added to the stormwater management infrastructures and/or control approach to act as a back-up in case of intense unpredicted events. However, it is suggested to address the resiliency measures based on multiple functionalities of the system as the focus on the enhanced resiliency of one system functionality may result in degradation of other functionality resilience (Shin et al., 2018). Another solution can be the robust optimization approach where the “best policy” is found by considering a variety of uncertain scenarios (Jia and Culver, 2006). However, satisfaction of the worst-case scenario as the fundamental concept of a robust approach may impose excess cost on the specific objective function of the studied problem (like extra designed capacity for the basin that may never be used). Yet, a stochastic approach can consider different overflow probabilities to provide a reliable solution facing with rainfall uncertainties (Yazdi et al., 2014).

4.6 Summary and Conclusion

A system-level predictive real-time control optimization and rule-based algorithm was introduced in this study as an adaptation measure to modernize traditional stormwater management systems considering new emerging global challenges. This algorithm performs as the core for a smart stormwater management system enabling the system components (like detention basins) to act inter-connectedly in order to balance the flow dynamics based on the meteorological variations. Both quality and quantity of water were considered in designing the dynamic control algorithms that provides an overall improved performance for the studied catchment. This provides a multi-disciplinary framework that attenuates the total peak flow to the stream, enhance the quality of water through sedimentation and reduce the erosion of receiving streambanks.

Results showed that the global quality and quantity performance of the system improved considerably when applying the proposed approach, with a 59% mean reduction in total peak-flows and a 21h mean increase in average detention time, as compared to static control, when considering the observed rainfall series of year 2013. It was also shown that, with a modified rainfall series taking climate change into account, average peak outflow velocity using the dynamic control approach is reduced by 47% in comparison to the static control approach. Hence, the proposed global dynamic control approach provides an efficient tool for decision makers to prevent disruptive impacts of urban runoff on natural streams.

Integrating data-driven dynamic models in smart stormwater infrastructures can thus enable multiple system components to be adapted to environmental variabilities through process optimization and automation, and bring improved operational efficiency, better level of service and greater accountability for these systems. In presence of global challenges like climate change, urbanization and growing populations where the significant stress on urban infrastructures is undeniable, deployment of technology-based urban stormwater management infrastructure that is more environmentally friendly and resilient seems to be a necessity to improve social and environmental well-being. However, this inherent ability comes with some uncertainties when operating based on weather forecasting data. Results presented herein showed that, although the errors in predicted input parameters may cause miss-operation of the system, the dynamic nature of the predictive model helps the system to rapidly recover from failures like overflows. Hence the proposed methodology, in its actual form, can be used by decision makers to transform conventional infrastructures into smart and modern urban systems that performs dynamically against varying environmental conditions. However, as a further research direction, robust, stochastic and resilient-based approaches should be developed and tested, to provide more reliable solutions for the system. Since the frequency and intensity of extreme storm events is increasing due to climate change, integration of such approaches to distributed real-time control framework becomes even more essential in highly developed urban areas where there are tens, or even, hundreds of stormwater basins. By providing accurate spatio-temporal parameters of the system to the control mechanism in order to optimally shape the outflow hydrographs of these basins, we can preserve waterbodies from probable ecological damages, avoid excess sediment mobilization and finally provide an adaptive performance facing with emerging global challenges.

Acknowledgement

The authors would like to thank the Canadian municipality that provided the hydrologic and hydraulic data of its municipal drainage network; Alexis Perez-Bello for his efforts in generating precipitation forecasting data using HRDPS; and Veronique Guay for the sizing calculations of the stormwater basins. This work was funded through the Fonds de recherche du Québec - Nature et technologies (FRQNT) under a Doctoral research program for foreign students and Team research project grant no. 2016-PR-190817.

4.7 SUPPLEMENTARY MATERIALS

Stormwater Basin Sizing Method

Currently, there is no detention basin at the four outlets of the studied case since the sewer network is still combined. A volume-based methodology was applied for sizing the four detention basins. For this purpose, an initial width for the detention basin and a diameter for the outlet orifice is set to further iterate the hydraulic/hydrologic simulation model and find the smallest combination of the outlet diameter and the basin width while respecting the two following design criteria: a) the maximum storage depth (1.5 m), and b) the maximum allowable outflow rate which is defined by the municipal regulations (50 L/s/ha). It should be noted that the designed basins have a truncated rectangular pyramid shape with a 4:1 length/width ratio. While a detention basin with a high length/width ratio is more effective in removing pollutants (Meyer, 1985), a report by Missouri Office of Administration (2008) shows that a 4:1 ratio is appropriate to capture fine sediments. Thus, this study considers a length-to-width ratio of 4:1 and slopes of horizontal to vertical ratio of 3:1. Furthermore, MDDEP and MAMROT (2014) recommends a variable height between 1 and 2 m for a detention basin. For this application, 1.5 m is considered as the maximum height of the stormwater basins.

A 1-hr SEA design storm of 100-year return period was used for the sizing of the basins. Using the data from the studied rain gage IDF curve (Agrométéo Québec, 2020), located in the same region as the case study, this leads to a total of 59.6 mm of rainfall distributed as illustrated in Figure S.1. The SEA rainfall distribution model has been originally developed based on real storm mass curves of southern Quebec and proved to be suitable for urban runoff calculations in this region (MDDEP and MAMROT, 2011).

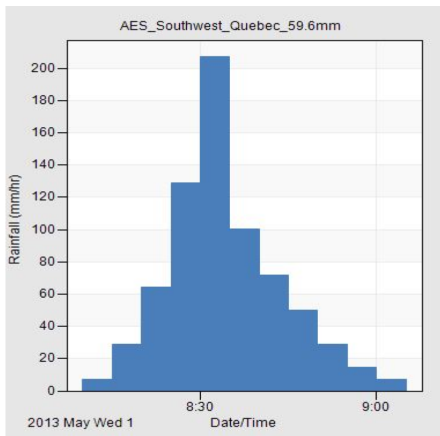

Figure S.1- SEA design storm used for sizing the four basins

Once all the preliminary calculations were done, the simulation model was adjusted through an iterative process until the required criteria (maximum height in the basin and maximum allowable flow at the outlet) were met with the smallest outlet orifice diameter and the smallest width possible for each basin. The resulting combination of the outlet diameter and the basin width with the calculated sizing for each basin is presented in Table 7-2.

5 FOURTH SCIENTIFIC PAPER: RAINFALL-RUNOFF MODELLING USING OCTONION-VALUED NEURAL NETWORKS

French Title: Prévision du ruissellement à l'aide de réseaux neuronaux à valeur octonionale

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Contribution of the authors:

The authors confirm contributions to the paper as follows: Reza Ghorbani and Shadab Shishegar designed and developed the study conception during hours of discussions. Shadab Shishegar designed and developed the octonion-valued neural network algorithm for the rainfall-runoff application modelling with great support of Reza Ghorbani. Also, she generated the results, drafted and prepared the manuscript. Sophie Duchesne and Genevieve Pelletier provided the data and simulation model of the case study, supervised the project development and significantly helped in understanding of the rainfall-runoff process. All authors reviewed the results and approved the final version of the manuscript.

Link between the previous paper and the following: The previous paper provided a global scale integrated optimization and rule-based approach for real-time control of all stormwater management basins over the watershed where the SWMM model was used to provide the inflow to the basins as the input parameter. The present paper developed a multi-dimensional neural network to estimate the flow rates at the inlet of the basins which can be used a fast tool to update system parameters in real-time control of stormwater management systems.

A B S T R A C T

Rainfall-runoff modeling is at the core of any hydrological forecasting system. High spatio-temporal variability of precipitation patterns, complexity of the underlying physical processes, and large quantity of parameters to characterize a watershed make the prediction of runoff rates quite difficult and, at times, a challenging task. In this study, a hyper-complex Artificial Neural Network (ANN) in the form of an Octonion-Valued Neural Network (OVNN), is proposed to estimate runoff rates using 8-dimensional inputs, outputs, weights and biases that are defined based on Octonion numbers. The multi-dimensionality of OVNN allows for accurate modelling of complex processes while: (1) reducing the input-output dimensions by eight; and (2) expanding the traditional backpropagation algorithm by adding seven other dimensions. These features lead to a simplified, yet more accurate, solution approach than traditional ANN algorithms. Evaluation of the proposed methodology is performed using a rainfall time series from a rain gauge near a Canadian City characterized by four stormwater sewer outlets. Results of the AI-generated runoff rates illustrate the capacity of the OVNN algorithm to produce more computationally efficient runoff rates when compared to those obtained using a physically-based model. In addition, comparison of training the rainfall-runoff data using the proposed OVNN versus a real-valued neural network shows less space-complexity (1*3*1 vs. 8*10*8, respectively) and more accurate results (0.1% vs. 0.95% of mean absolute error, respectively) from the OVNN that accounts for the efficiency of these algorithms in real-time control applications.

Keywords: Machine learning, Prediction, Stormwater management, Hydrology, Multi-dimensional, Hyper complex network

5.1 Introduction

The paradigm shift from using physically-based simulation to Artificial Intelligence (AI) in hydrological processes allows accurate modelling of complex systems without prior understanding of physical laws governing the process (Kalteh, 2008). Artificial Neural Network (ANN) algorithms are among AI forecasting methods that have been widely employed in various hydrological fields particularly in the context of Climate Change (CC) (Daliakopoulos and Tsanis, 2016) including rainfall-runoff modelling (Kan et al., 2015; Tayyab, 2019), flood prediction (Berkhahn et al., 2019) and long-term rainfall forecasting (Mekanik et al., 2013). All these hydrological phenomena are highly non-linear, time-varying and spatially distributed (Rajurkar et al., 2009), and their simulation process requires detailed data on physical infrastructure, precipitation time series and hydrological characteristics of the studied watershed that causes high complexities in the modelling process. Rainfall-runoff simulation can be realized by either data-driven or physically-based models (Kan et al., 2015). Hernonin et al. (2013) report, in their state-of-the-art, that physically-based simulation models are not fast enough for real-time forecasting. However, the historical statistics and simple data-driven models have the ability to perform fast and reliably (Hernonin et al., 2013). Application of ANN as a data-driven model to estimate streamflow out of a rainfall data series was successfully employed during the last decades and it has been growing fast (Daliakopoulos and Tsanis, 2016). Even the popularity of ANN amongst hydrologists has been reported by American Society of Certified Engineering Technicians (ASCET) (Tayyab, 2019).

The related literature shows that several procedures and architectures of ANN were proposed to deal with rainfall-runoff modelling. In (Aytek et al., 2008), the performance of two ANN techniques, Feed Forward Back Propagation (FFBP) and Generalized Regression Neural Network (GRNN), were evaluated using historical hydro-meteorological data for the estimation of runoff in the Juniata River Basin (USA). In another study by (Mittal et al., 2012), a dual ANN was proposed to improve the performance of the flow prediction model in extreme events and compared to a Feed-Forward ANN (FF-ANN), which is widely present in the rainfall-runoff modelling literature. The developed dual ANN in that study outperformed the popular FF-ANN technique in prediction of high flows and it was suggested to be used under extreme events. Three other neural networks have been studied in (Chen et al., 2014) where Copula-entropy theory was employed to skip the marginal and joint probability calculation in the ANN algorithm. Multi-layer FF-ANN, radial basis function networks and GRNN were chosen to evaluate the stream flow prediction performance of the system (Chen et al., 2014). Recent real domain ANN models have been developed to higher dimensional domains based on which several hyper-complex techniques have been proposed. Among all these hyper-complex ANNs, Octonion-Valued Neural Networks (OVNNs) are proved to be one of the most promising approaches to model high-dimensional nonlinear processes (Saad Saoud and Ghorbani, 2019). OVNNs consist of 8-dimensional inputs, outputs, weights and biases that are defined based on the Octonion numbers introduced by Conway and Smith (2003). In spite of Clifford algebras, the Octonion algebras are neither associative nor commutative i.e. $i_k i_l \neq i_l i_k \; \forall \, k \neq l$ and $i_k \left(i_l i_m \right) \neq \left(i_k i_l \right) i_m \; \forall \, k \neq l \neq m$.

This study is motivated by the need to model the complex process of rainfall transformation to runoff in real-time. As recommended in Shishegar et al. (2019), this complexity is inevitable specially in watershed-level investigations where the spatio-temporal variability of precipitation patterns is high, the associated physical processes are difficult to study and there are numerous parameters involved in the representation of the watershed. On the other hand, the OVNN algorithms are proved to be capable of providing efficient forecasting outputs for multi-dimensional complex problems relying on their two main features: 1) the ability to reduce the input-output dimensions by eight times; while 2) expanding the traditional backpropagation algorithm by adding seven other dimensions (Saad Saoud and Ghorbani, 2019). Hence, in this study, an OVNN algorithm is developed as an alternative to simulation models for runoff predictions in urban areas. To the best of our knowledge, the OVNN has not yet been employed in the literature for the estimation of runoff volumes of precipitation time series. Considering the real-time forecasting required in designing many *modern* urban stormwater management systems as a component of a greater whole named *smart city*, the problem solving speed is an important factor here.

In order to address the above problems, the scientific objectives of this study can be presented as follows:

- To propose an octonion-valued neural network algorithm to estimate the runoff rates at the outlets of a stormwater management network;
- To evaluate the performance of the proposed algorithms over the traditional rainfall-runoff simulation approach in terms of not only the quality of prediction, but the computing time;
- To assess the outcomes of the multi-dimensional neural network for a real-case urban stormwater system; and
- To carry out a comparative analysis between the real-valued neural network and OVNN performances.

5.1.1 Experimental Area

The study area is a Canadian City located at the central Quebec. The catchment area has a surface of 311 ha of which 64% is residential, 14% is industrial, 9% is commercial and 13% is institutional, with an average impermeability of 62%. The rainfall-runoff simulation model of the sewer network of this catchment has already been developed and is used here for the comparative analysis of the proposed OVNN algorithm. PCSWMM software Version 7.0 was used for the rainfall/runoff simulation of the studied sector. This software performs based on the Stormwater Management Model - SWMM (Rossman and Huber, 2016), that dynamically simulates stormwater runoff and flows in sewer networks from the specified rainfall series. In order to convert the current combined drainage network to a separated (stormwater) sewer network, all the wastewater flow values were given a zero value. This allows studying the runoff volumes generated from the rainfall series which is here considered as the inputs of the proposed algorithm. Four storage units, designed at the outlet of the separate sewer network, are the points where the runoff rates will be estimated. A more detailed explanation of the input parameter structure is given in section 5.3.2.

5.1.2 Precipitation Data

An operating rain gauge located 80 km from the studied watershed measures the rainfall data by a tipping bucket and provides the observation record at a 5-minute time step. This recorded data is then validated by performing a comparative analysis with the recorded rainfall series by Environment Canada at the same station. In this study, the rainfall time-series of the year 2013 from May to November, has been selected for the analysis of generated runoff. Generally, due to the meteorological characteristics of the Quebec Province region with long and snowy winters, the rainfall analysis is performed for the months May to November. The data recorded for this period of the year 2013 shows a relatively higher average amount of rainfall (903 mm) compared to those recorded in average between 2000 and 2017 for the same period (759 mm). The reason to select this rainfall series for the investigations of this paper, is to enable assessing the performance of the proposed OVNN algorithm under challenging conditions. Evidently, the more the proposed algorithm is trained based on critical data, the better its performance would be facing rainy periods. The rainfall characterization analysis is carried out based on two criteria: the inter-event duration of 6 hours and the minimum rainfall intensity of 1.2 mm/h. Table 5-1 shows the monthly and total rainfall height of the year 2013 in comparison to the average values (2000-2017), along with the characteristics of this 2013 rainfall time series that provides a better understanding of the precipitation data used for ANN training. Also, the hyetograph of the 2013 rainfall series is illustrated in Figure 5-1.

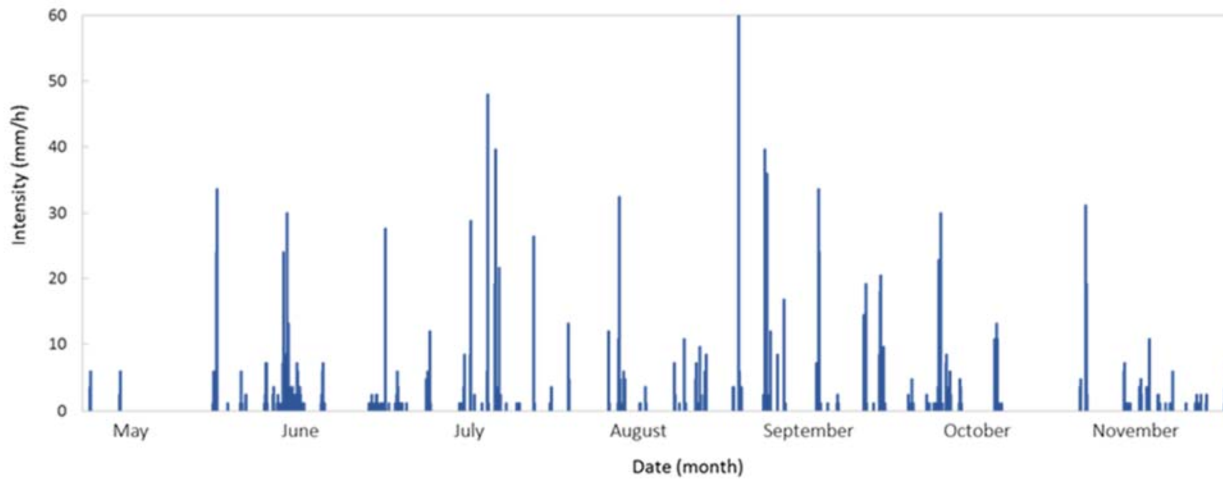

Figure 5-1- Time series plot of 2013 rainfall data for the period May to November.

Table 5-1- Characteristics of 2013 rainfall series with an inter-event duration of 6 h and comparison to the total rainfall height of 2000-2017 at the considered station (Environment Canada 2019)

2013 Rainfall Characteristics									
Month	May	Jun	Jul.	Aug.	Sep.	Oct.	Nov.	Total	Avg. 2000-2017
Total rain depth (mm)	180.8	154.5	70.0	166.9	145.8	100.2	85.7	903.9	759.5
Number of events									74
Average water height/event (mm)									8.94
Average intensity/event (mm/h)									1.84
Average maximum intensity over 10 min (mm/h)									12.08
Average minimum intensity over 10 min (mm/h)									0.63
Average duration (h)									6.23

5.2 Methodology

5.2.1 Octonion Valued Neural Network (OVNN)

This section develops the octonion valued neural network for training the rainfall and runoff data series in the form of octonion numbers given like:

$$o \overset{def}{=} x_1 + i_1 x_2 + i_2 x_3 + i_3 x_4 + i_4 x_5 + i_5 x_6 + i_6 x_7 + i_7 x_8 \tag{1}$$

Where: x_i, $i \in \{1,2,\ldots,8\}$ are the real parts and

$x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8 \in \mathbb{R}$

and i_j, $j \in \{1,2,\ldots,7\}$ are the imaginary parts and

$i_1^2 = i_2^2 = i_3^2 = i_4^2 = i_5^2 = i_6^2 = i_7^2 = -1$

The latter includes three layers (Figure 5-2): an input layer with n octonion inputs, one hidden layer with m neurons, and one output layer with s neurons. These layers are related, respectively, to weights w_{nm}^{1} and w_{ms}^{2}. The hidden and output layers have biases represented by w_{0m}^{1} and w_{0s}^{2}, respectively. All network settings, inputs and outputs are considered octonion.

The j^{th} OVNN output can be calculated using the following equation:

$$\hat{y}_j\left(k+1\right) = f^{2}\left(\tilde{y}_j^{\mathrm{Re}}\right) + \sum_{r=1}^{7} i_r \; f^{2}\left(\tilde{y}_j^{\mathrm{Im}(i_r)}\right) \tag{2}$$

Where:

Re and $\mathrm{Im}\left(i_r\right)$ indices are the real and imaginary parts of i_1, i_2, i_3, i_4, i_5, i_6 and i_7, respectively.

f^{2} is the sigmoid non-linear function given by the following equation :

$$f^{2}\left(\cdot\right) = \frac{1}{1+e^{-(\cdot)}} \tag{3}$$

$$\tilde{y} = \sum_{l=1}^{m} w_l^2 h_l + w_0^2 \tag{4}$$

Where:

$l = 1, \; \ldots, \; m$

h_l is the l^{th} hidden neuron output, which is given by:

$$\begin{aligned} h_l = {} & f^{1}\left(\tilde{h}_l^{\mathrm{Re}}\right) + i_1 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_1)}\right) + i_2 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_2)}\right) \\ & + i_3 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_3)}\right) + i_4 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_4)}\right) + i_5 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_5)}\right) \\ & + i_6 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_6)}\right) + i_7 \; f^{1}\left(\tilde{h}_l^{\mathrm{Im}(i_7)}\right) \end{aligned} \tag{5}$$

Where:

$$\tilde{h}_l = w_{nl}^{1} u_n + w_{0l}^{1} \tag{6}$$

u_n is the octonion valued vector of n octonion elements.

Noteworthy is that ReLU and sigmoid are the most employed non-linear activation functions in the literature for the hidden and output layers, both of which have the lower bound of zero. The sigmoid function transfers all the data to the bounded range between zero and 1, while ReLU keeps the upper bound of the data and converts all the negative values to zero. This feature of ReLU may be problematic as it decreases the ability of the ANN to train negative values by ignoring them. However, in rainfall-runoff modeling where there is no negative data, the ReLU activation function can be used. In addition, ReLU is far more computationally efficient with a faster training process than the sigmoid function due to neurons with rectified functions that perform well to overcome saturation during the learning process as reported in Mboga et al., (2017). The non-linear ReLU function is employed in the hidden layer which is given by the equation below:

$$f^1(x) = \max(0, x) \tag{7}$$

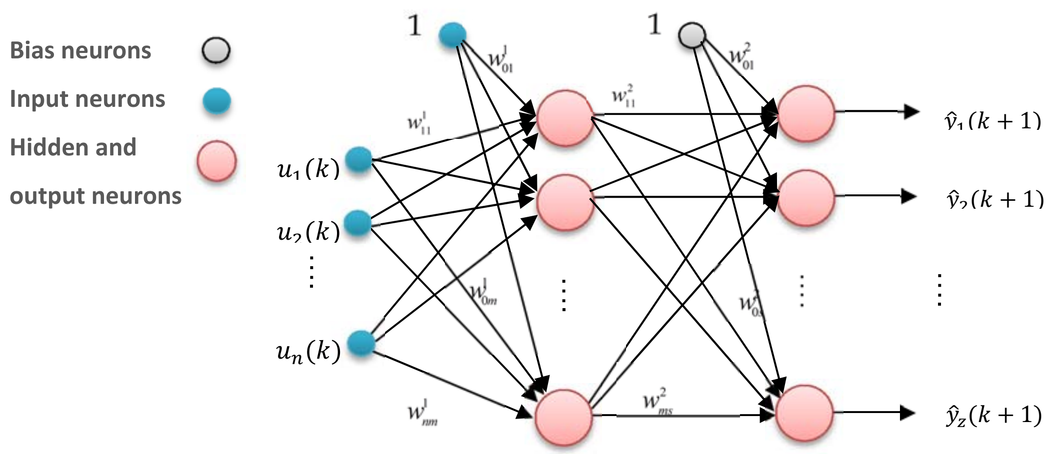

Figure 5-2-Octonion valued neural network architecture and the associated parameters

To optimize the network parameters, the octonion valued backpropagation is used. The objective is to optimize the parameters of the network in such a way that the total sum squared error in the output layer is minimized, which can be expressed as:

$$E = \frac{1}{2}e^C e = \frac{1}{2}\sum_d e_d e_d^* = \frac{1}{2}\sum_d E_d \tag{8}$$

$$E_d = e_d e_d^* = \left|e_d\right|^2 \tag{9}$$

Where:

The superscript '*' represents the conjugate operator;

C is the Cayley operator (Cayley, 1846);

d is the number of samples; and

e^* is the error's conjugate.

The error e between the desired output y and estimated output $\hat{y}$ is:

$$\begin{aligned} e &= y(k+1) - \hat{y}(k+1) \\ &= e^{\mathrm{Re}} + \sum_{r=1}^{7} i_r e^{\mathrm{Im}(i_r)} \end{aligned} \tag{10}$$

In order to determine the optimal network parameters including weights and bias, the real valued delta rule proposed in Saad Saoud and Ghorbani (2019) is extended as follows:

The bias w_{0s}^2 is:

$$\begin{aligned} w_{0s}^2 &= w_{0s}^{2\,\mathrm{Re}} + i_1 w_{0s}^{2\,\mathrm{Im}(i_1)} + i_2 w_{0s}^{2\,\mathrm{Im}(i_2)} + i_3 w_{0s}^{2\,\mathrm{Im}(i_3)} \\ &\quad + i_4 w_{0s}^{2\,\mathrm{Im}(i_4)} + i_5 w_{0s}^{2\,\mathrm{Im}(i_5)} + i_6 w_{0s}^{2\,\mathrm{Im}(i_6)} + i_7 w_{0s}^{2\,\mathrm{Im}(i_7)} \end{aligned} \tag{11}$$

We have:

$$\begin{aligned} \Delta w_{0s}^2 &\overset{def}{=} \Delta w_{0s}^{2\ \mathrm{Re}} + i_1 \Delta w_{0s}^{2\ \mathrm{Im}(i_1)} + i_2\ \Delta w_{0s}^{2\ \mathrm{Im}(i_2)} + i_3\ \Delta w_{0s}^{2\ \mathrm{Im}(i_3)} \\ &\quad + i_4\ \Delta w_{0s}^{2\ \mathrm{Im}(i_4)} + i_5\ \Delta w_{0s}^{2\ \mathrm{Im}(i_5)} + i_6\ \Delta w_{0sl}^{2\ \mathrm{Im}(i_6)} + i_7\ \Delta w_{0s}^{2\ \mathrm{Im}(i_7)} \\ &= \Delta w_{0s}^{2\ \mathrm{Re}} + \sum_{r=1}^{7} i_r \Delta w_{0s}^{2\ \mathrm{Im}(i_r)} \\ &= -\eta \left(\frac{\partial E}{\partial w_{0s}^{2\,\mathrm{Re}}} + \sum_{r=1}^{7} i_r \frac{\partial E}{\partial w_{0s}^{2\,\mathrm{Im}(i_r)}} \right) = -\eta \nabla_{w_{0s}^2} E \end{aligned}$$

$$\Rightarrow \nabla_{w_{0s}^2} E = \frac{\partial E}{\partial w_{0s}^{2\,\mathrm{Re}}} + \sum_{r=1}^{7} i_r \frac{\partial E}{\partial w_{0s}^{2\,\mathrm{Im}(i_r)}} \tag{12}$$

$$\begin{aligned} \nabla_{w_{0s}^2} E = -\Big\{ & e^{\mathrm{Re}} \left(1 - \hat{y}_s^{\mathrm{Re}}\right) \cdot \hat{y}_s^{\mathrm{Re}} \\ & + \sum_{r=1}^{7} i_r e_s^{\mathrm{Im}(i_r)} \left(1 - \hat{y}_s^{\mathrm{Im}(i_r)}\right) \cdot \hat{y}_s^{\mathrm{Im}(i_r)} \Big\} \end{aligned} \tag{13}$$

$$w_{0s}^2 \left(k+1\right) = w_{0s}^2 \left(k\right) - \eta \nabla_{w_{0s}^2} E \tag{14}$$

For the weights w_{ms}^2 :

$$w_{ms}^2 \left(k+1\right) = w_{ms}^2 \left(k\right) - \eta \nabla_{w_{ms}^2} E \tag{15}$$

where

$$w_{ms}^2 = w_{ms}^{2\,\mathrm{Re}} + \sum_{r=1}^{7} i_r w_{ms}^{2\,\mathrm{Im}(i_r)}$$

and

$$\nabla_{w_{ms}^2} E = \frac{\partial E}{\partial w_{ms}^{2\,\mathrm{Re}}} + \sum_{r=1}^{7} i_r \frac{\partial E}{\partial w_{ms}^{2\,\mathrm{Im}(i_r)}} \tag{16}$$

$$\nabla_{w_{ms}^2} E = -h_{ms}^* \cdot \left\{ e^{\mathrm{Re}} \left(1-\hat{y}^{\mathrm{Re}}\right) \cdot \hat{y}^{\mathrm{Re}} + \sum_{r=1}^{7} i_r e^{\mathrm{Im}(i_r)} \left(1-\hat{y}^{\mathrm{Im}(i_r)}\right) \cdot \hat{y}^{\mathrm{Im}(i_r)} \right\} \tag{17}$$

For bias w_{0m}^1 and weights w_{nm}^1, the same procedure is used where:

$$w_{0m}^1 = w_{0m}^{1\mathrm{Re}} + i_1 w_{0m}^{1\mathrm{Im}(i_1)} + i_2 w_{0m}^{1\mathrm{Im}(i_2)} + i_3 w_{0m}^{1\mathrm{Im}(i_3)} + i_4 w_{0m}^{1\mathrm{Im}(i_4)} + i_5 w_{0m}^{1\mathrm{Im}(i_5)} + i_6 w_{0m}^{1\mathrm{Im}(i_6)} + i_7 w_{0m}^{1\mathrm{Im}(i_7)} \tag{18}$$

$$w_{nm}^1 = w_{nm}^{1\mathrm{Re}} + i_1 w_{nm}^{1\mathrm{Im}(i_1)} + i_2 w_{nm}^{1\mathrm{Im}(i_2)} + i_3 w_{nm}^{1\mathrm{Im}(i_3)} + i_4 w_{nm}^{2\mathrm{Im}(i_4)} + i_5 w_{nm}^{1\mathrm{Im}(i_5)} + i_6 w_{nm}^{1\mathrm{Im}(i_6)} + i_7 w_{nm}^{1\mathrm{Im}(i_7)} \tag{19}$$

The modification approach is therefore given as follows:

$$\nabla_{w_{0m}^1} E = \frac{\partial E}{\partial w_{0m}^{1\mathrm{Re}}} + \sum_{r=1}^{7} i_r \frac{\partial E}{\partial w_{0m}^{1\mathrm{Im}(i_r)}} \tag{20}$$

$$\nabla_{w_{0m}^1} E = -\left\{ \left(1-h_m^{\mathrm{Re}}\right) \cdot h_m^{\mathrm{Re}} \cdot \nabla_{w_{0s}^2} E \cdot w_{ms}^{2*} \left(\nabla_{w_{0s}^2} E \cdot w_{ms}^{2*}\right)^{\mathrm{Re}} + \sum_{r=1}^{7} i_r \left(1-h_m^{\mathrm{Im}(i_r)}\right) \cdot h_m^{\mathrm{Im}(i_r)} \cdot \left(\nabla_{w_{0s}^2} E \cdot w_{ms}^{2*}\right)^{\mathrm{Im}(i_r)} \right\} \tag{21}$$

$$w_{0m}^1 (k+1) = w_{0m}^1 (k) - \eta \nabla_{w_{0m}^1} E \tag{22}$$

$$\nabla_{w_{nm}^1} E = \frac{\partial E}{\partial w_{nm}^{1\mathrm{Re}}} + \sum_{r=1}^{7} i_r \frac{\partial E}{\partial w_{nm}^{1\mathrm{Im}(i_r)}} \tag{23}$$

$$\nabla_{w_{nm}^1} E = -u_n^* \cdot \nabla_{w_{nm}^1} E \tag{24}$$

$$w_{nm}^1 (k+1) = w_{nm}^1 (k) - \eta \nabla_{w_{nm}^1} E \tag{25}$$

With η as the learning rate.

Note that the conjugate of an octonion number is:

$$o^* \overset{def}{=} x_1 - i_1 x_2 - i_2 x_3 - i_3 x_4 - i_4 x_5 - i_5 x_6 - i_6 x_7 - i_7 x_8 \tag{26}$$

5.2.2 Determination of Input Structure

Following the discussion provided in the « Experimental area » section, the input data can be selected by running the PCSWMM simulation model in order to generate the inflow rates associated with all four outlets of the studied drainage network.

The model is built based on the combinations of the recorded rainfall time series and simulated runoff inflows to the four outlets of the network. In total, 61,630 5-minutes records were recorded over the period of May-November 2013 for the studied area. This data set is divided into two subsets for training and testing, as shown in Table 5-2, where the parameter $data_{min}$ represents the minimum value, $data_{max}$ is the maximum value, S_{data} is the standard deviation, and $\overline{data}$ is the mean for each subset, separately. As for the proposed methodology, the first 85% of the data is employed for training of the OVNN with 15% of the remaining data for testing based on which all the performance criteria are calculated.

Table 5-2- Characteristics of training and testing data

	Training set	**Testing set**
$data_{min}$ (mm)	0	0
$data_{max}$ (mm)	73.14	35.88
S_{data} (mm)	1.455	1.008
$\overline{data}$ (mm)	0.1878	0.1554

As seen in Table 5-1, the most critical months in terms of rainfall height are May and August with reported total rainfall of 180 mm and 166 mm, respectively. However, the highest rainfall volumes over a month are recorded in August and June with 73 mm and 56 mm, respectively. Also, looking at the data recorded over other years, like the year 2007 for instance, some extreme events occurred in May, September and October with no reported extreme event in August and June. This shows that the occurrence of extreme events can be in any month and also highlights the importance of the input data used to train the model and how these data may sometimes be noisy, correlated or even with no relevance to the output parameters (Chen et al., 2014). In this study, the data is modified in such a way that it becomes feedable to the OVNN-forecaster. For this purpose, all the data are defined in the octonion domain as shown in Figure 5-3. This data preparation allows employing the eight rainfall height predicted over the next eight 5-minute time-steps (40 minutes in total) for prediction of upcoming runoff rates during a 40-minutes period.

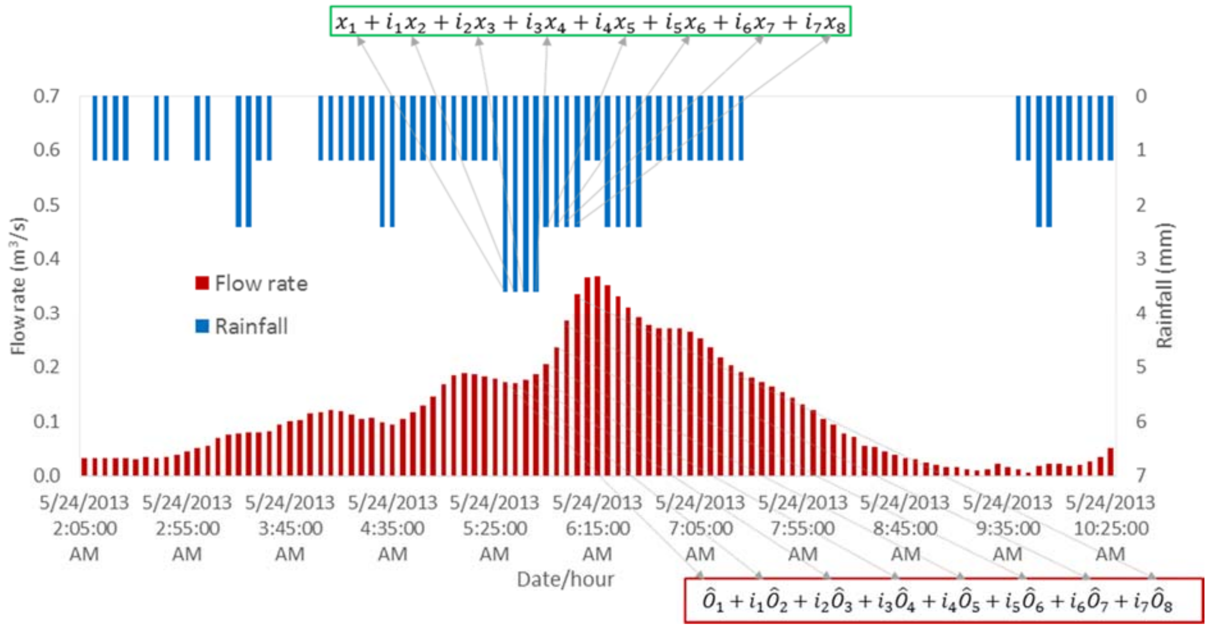

Figure 5-3-Input-output relationship in OVNN of rainfall-runoff modeling

As the last step of the methodology, the available data-set related to the year 2013 is trained using a developed real-valued neural network (RVNN) in order to evaluate the advantages of using the OVNN-forecaster. The designed RVNN algorithm consists of 8 input/output pairs with 61,630 samples, 75% of which is used for training with 25% for testing. Ten neurons over one hidden layer are considered that results in total 178 parameters in the network including weights and biases. Besides, coherent with the proposed OVNN, the ReLU activation function is responsible for non-linearity of the outputs from the neurons in RVNN. A comparative analysis of the runoff estimation performance of RVNN and OVNN will be carried out in section 5-3.

5.3 Results and Discussion

Figure 5-4 illustrates the hydrographs of the simulated (with the SWMM model) versus predicted (with the OVNN model) flow rates at the outlets of the studied watershed model. As can be seen from Figure 5-4, the OVNN model is able to reasonably estimate the flow rates out of the precipitation data of the year 2013. To provide a quantitative analysis of the OVNN-forecast accuracy, two performance criteria are considered; 1) the Normalized Root Mean Squared Error (nRMSE), and 2) the Mean Absolute Error (MAE). nRMSE is employed here to facilitate the comparison of model performance for different stormwater outlets that may have different flow rate scales. Also, MAE is a common metrics in neural network studies with the ability to measure the accuracy for continuous variables. Table 5-3 compares the value of these two performance criteria for each stormwater outlet separately. It can be seen that the runoff estimation by OVNN is carried out with small nRMSE and MAE, when compared to the SWMM model outputs, for all studied outlets with less than 0.2% and 4% calculated errors, respectively. Besides, training OVNN from scratch using 61,737 samples and with a space complexity of 1*3*1, takes an average time of 1 min and 47 seconds using a PC computer Core i7 16GB GPU, while the simulation using SWMM for the same period takes more than 26 minutes.

Table 5-3- OVNN performance criteria calculations for the four studied outlets

	nRMSE (%)	MAE (%)	Max. Simulation	Max. Estimation
Outlet 1	2.8722	0.0825	4.29 m^3/s	3.95 m^3/s
Outlet 2	3.4541	0.1193	6.47 m^3/s	6.81 m^3/s
Outlet 3	3.8336	0.1470	7.39 m^3/s	6.03 m^3/s
Outlet 4	2.3397	0.0547	7.01 m^3/s	6.76 m^3/s

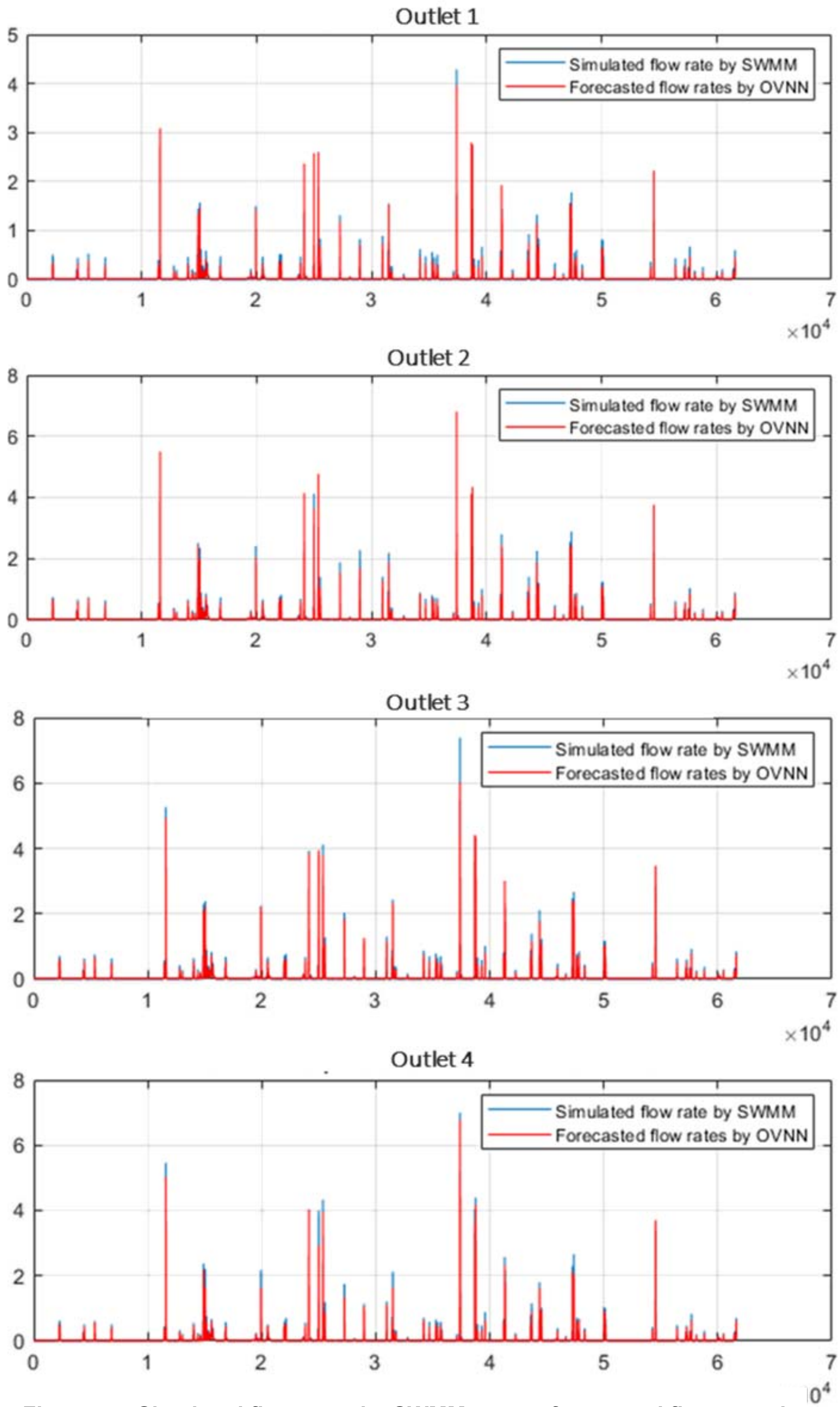

Figure 5-4-Simulated flow rates by SWMM versus forecasted flow rates by OVNN based on the data samples of the year 2013

Figure 5-5 shows the linear fit between the values simulated by the SWMM and OVNN models, for all studied outlets, to evaluate the performance of the OVNN forecaster. As a result of this univariate linear analysis, obtained using the least-squares fit polynomial method, the coefficient of correlation (R) along with the forecast intercepts are calculated to determine the goodness of fitness of the model forecaster as shown in Table 5-4.

Table 5-4- The regression analysis parameters calculated for the four studied outlets

	Coefficient of correlation (R)	Forecast intercept (b)
Outlet 1	0.8597	0.0103
Outlet 2	0.9553	0.0065
Outlet 3	0.8939	0.0118
Outlet 4	0.9451	0.0062

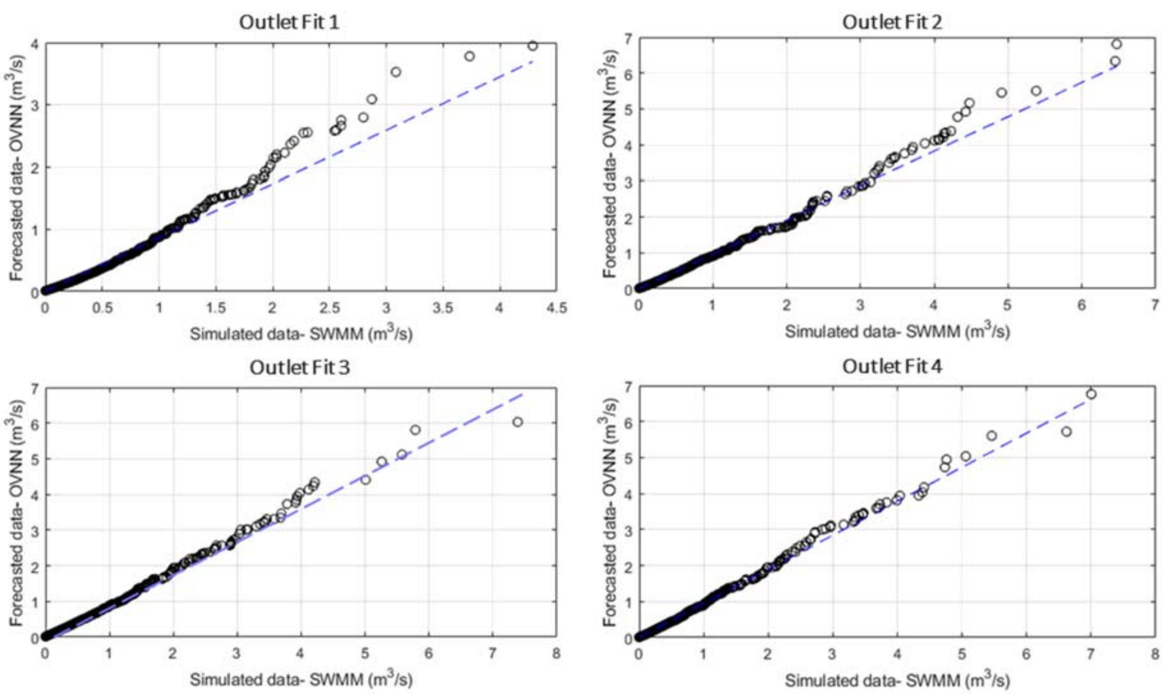

Figure 5-5- Univariate linear regression analysis of the simulated and estimated flow rates for the four studied stormwater outlets

As reported in Table 5-4, the high value of R (≅1) and low value of b (≅0) shows the ability of the proposed model in determining the runoff data however, for higher flow rates, more variations from the simulated values are shown. Here, since more than 96% of the sample data are related to flow rates less than 1.3 m^3/s, the regression line does not represent well the higher rates especially in outlets 1 and 2. This implies the importance of the qualified input data in the ability of the model forecaster to estimate properly the outputs. As aforementioned, since the model training based on more critical meteorological conditions is more beneficial, the rainiest year (the year 2013) was selected in this study to train the OVNN.

As a further analysis and in order to validate the advantages of the introduced OVNN, the data of the studied case was also trained using a real-valued neural network (RVNN). To this purpose, the RVNN algorithm was developed with varying number of iterations from 200 to 20000 to ensure the errors have already been reduced. The results from the performance criteria obtained using RVNN modelling approach are shown in Table 5-5.

Table 5-5- RVNN performance criteria calculation with considering 20000 and 200 iterations

Number of Iterations	20000		200	
Performance Criteria	**nRMSE (%)**	**MAE (%)**	**nRMSE (%)**	**MAE (%)**
Outlet 1	10.27	1.056	10.58	1.12
Outlet 2	9.82	0.966	10.72	1.15
Outlet 3	9.51	0.906	10.53	1.11
Outlet 4	9.25	0.857	9.99	0.99

In Table 5-6, the comparative analysis between the performances of the introduced OVNN with those of the real-valued neural network show that the developed RVNN performs slower in comparison to the OVNN while the accuracy of OVNN in estimation of runoff rates is much higher. The implementation of RVNN can achieve the same level of accuracy only by allocating more iterations, which causes a significant increase in running time. On the other hand, the total size of the input vector for the RVNN is 61,630, while the OVNN has an input vector with a total size of only 7,703. Furthermore, the space complexity of OVNN is significantly less than the RVNN with a size of 1*3*1 versus 8*10*8, respectively. Although the OVNN architecture can be extended to support longer term predictions, a neural network with more neurons in the output layer has to endure a relatively higher training and prediction time, which makes it inappropriate to use in real-time control applications.

Table 5-6- Comparison between the RVNN and QVNN models over the four studied outlets

Network	Iterations	Parameters	Neural Network Architecture	Average nRMSE (%)	Average MAE (%)	Time (sec.)
RVNN	20000	178	8x10x8	9.71	0.95	9372
OVNN	2000	10	1x3x1	3.12	0.1	127

5.4 Conclusion

Physically-based models have been employed for several years for rainfall-runoff modelling, however advances in technology along with the emergence of real-time control systems, created a need to employ faster tools to generate real-time forecasting data. Octonion-valued neural networks as a multi-dimensional network was introduced in this paper for representing complex problems like rainfall-runoff hydrological modeling. Through this study, precipitation time series data is used to model the flow rate data based on a developed octonion neural network algorithm where, the ReLU is employed as the activation function. Simulated flow rates using the physically-based simulation model were used to train of the proposed OVNN-forecaster and, furtherly, the performance of the proposed model in estimating runoff flow rates was compared with those obtained using a real-valued neural network. Results showed that using the OVNN model was beneficial in terms of run time and accuracy making it an efficient, fast and reliable tool for decision makers in real-time controllers that finally serve as a small, yet effective, component of a greater whole named *smart city*.

It was also shown that the model is less accurate for more intense rain events. Hence, it would be beneficial to train the model based on more critical meteorological conditions. In addition, a metacognitive component can be added to the OVNN-forecaster to enable self-regulation of the network parameters during the learning process. This capability provides an enhanced learning process by selecting more critical samples to train the model. In all cases, keeping the computational efficiency of the algorithm to achieve smaller running times yet more accurate predictions, should be taken as the highest priority.

6 THESIS CONCLUSION

This thesis proposed and investigated a system-level predictive real-time control framework to apply adaptive and sustainable management of urban stormwater systems. High-performance and smart methods that balance the network flow dynamics were developed to deal with the global challenges of urbanization, climate change and population growth. This study showed that the stormwater management objectives can be realized at watershed-level only through a dynamic collaboration of smaller stormwater management components and by incorporating meteorological forecasting data along with historical and observation precipitation data. This novel dynamic control framework involves hydraulically linked flow optimization routines across a two-layer network of stormwater management: local and global scales. A real-time optimization model joined with several quality control rules were developed to meet the requirements of municipal regulations with different performance criteria. This proposed distributed integrated approach accommodates runoff dynamics into the watershed network that is connected to a cloud-based data of system parameters, environmental states and generated set-points to enable transferring from a static-state network to an adaptive, distributed and dynamic network. As the first phase, a quantity control optimization algorithm was developed at the local scale, for one single basin, to generate optimized outflow schedule in wet periods taking the hydraulic/hydrologic constraints into account. Here, the objective function was to minimize the peak discharge at the outlet of the basin to mitigate the hydraulic shocks on the receiving streams and attenuate the flow hydrograph. Then four quality control rules were designed aiming at maximizing the detention time in the basin to realize sedimentation during dry periods. As the next phase, this integrated quality and quantity control approach was extended to the global scale in order to serve the stormwater management system at the watershed-level. At this level, the control is on interactions between different local sections in terms of flow planning to realize a balance between the available network capacity and outflow rates. This assumes that a system-wide planning has been already done on the system for sizing of the detention facilities. The optimal stormwater flow at this level updates the flow variables to better utilize the distributed system capacity in which the calculation of runoff is carried out by the SWMM model (Rossman and Huber, 2016). The results showed a 59 % mean reduction in total peak flow imposed on the nearby river as well as a 21 h mean increase in the detention time in the network of basins as compared to a static control approach. Besides, the study of the performance of the proposed dynamic strategy in presence of climate change resulted in a 54 % attenuation in the peak flow rates as compared to a static control approach, accounting for the efficiency of the global predictive RTC approach in more critical meteorological conditions. In addition, the data-driven methods of rainfall-runoff modeling are embedded into the proposed framework via developing a multi-dimensional neural network algorithm to estimate runoff flow rates at the inlet of each stormwater basin. This supervisory framework aggregates data of historical and observation data of precipitation at small to larger units over the watershed to learn and make the framework independent of hydrological processes that govern the rainfall-runoff transformation. This black-box algorithm reduces the complexity of simulation and allows defining significantly smaller time-steps to generate flow set-points at each local site. In general, by retrofitting the conventional stormwater management systems with some simple equipment, the proposed autonomous stormwater control framework can be realized for an enhanced predictive and adaptive performance of the urban stormwater facilities in respond to the varying environment, and even react promptly to potential extreme events. The major conclusions of the outlined study can be summarized as follows:

- The proposed real-time control optimization model resulted in minimization of peak flows imposed to the downstream watercourse by generating an optimized flow schedule for all the local stormwater systems at the system-level;
- The flow planning generated by the dynamic control approach significantly mitigated the erosive potential of urban runoff on natural streams such that a mean 47 % reduction in velocity of discharged water is reported comparing to the static control approach;
- The quality of discharged water can be enhanced by regulating the detention time at each basin via the designed global quality control rules;
- Integrating smart dynamic models to the stormwater infrastructures enables an adaptive performance for all system components faced with environmental variabilities through process of optimization and automation;
- Significant reduction in outflow variations and the steady nature of the generated flow rates allowed a minimum movement of system regulators at the outlet of the basins that can lead to less depreciation and longer durability of the equipment;
- The integration of optimization and rule-based approach at system-level provides the stormwater management infrastructures with a dynamic performance that preserve the safety of the stormwater basins over the watershed by respecting the capacity limitations of the network;
- The proposed distributed optimization and control paradigm provides an economic alternative to the cost prohibitive urban infrastructure replacement solution;

- Investigating the performance of the system in presence of uncertainties engaged with precipitation forecasting data proved that the dynamic nature of the proposed framework allows rapid recovery of the system after a miss-operation caused by prediction error; this accounts for the resiliency of the system controlled and operated based on the developed smart RTC approach;
- The global scale benefits resulting from the implementation of the smart framework provides the stormwater management infrastructures with enhanced operational efficiency and greater level of service;
- This global adaptive measure is in line with the sustainability defined as the main objective of smart cities;
- The developed octonion-valued neural network, as a multi-dimensional forecasting algorithm, enables rapid and accurate estimation of input parameters to use in real-time control of stormwater systems; and
- The advantages of the proposed dynamic approach highlight the importance of implementing smart automatized decision-support tools to control the urban stormwater in a changing environment.

The adaptive urban stormwater management is an inter-disciplinary topic that concerns many real-world applications in such diverse areas as urban drainage system, intelligent systems, complex system modeling and optimization, smart cities, sustainability and reliability. In addition, making the existing urban infrastructures adaptive to the environmental instabilities has direct impact on public health and security through supporting cleaner streams; creating more sustainable cities; protecting the environment; reducing the risk of flooding to protect people and properties; and finally enhancing the quality of life for the society. Integrating advanced technologies and IoT-enabled devices into stormwater management techniques can open new opportunities for other natural resources management systems to operate dynamically against the emerging challenges of the 21st century including water and energy scarcity, extreme climatic events, and food insecurity. Having all this in mind, although the proposed smart predictive algorithm has the ability to significantly control the urban stormwater and mitigate its unfavorable environmental impacts, there are a number of open problems to enhance the dynamic control approach. For example, the study of uncertainties linked to the rainfall predictions was carried out only by evaluating the performance of the proposed approach in uncertain situations. The uncertainty analysis could be more than a performance evaluation by integrating stochastic programming methods to the proposed optimization algorithm that enables generating more reliable control set-points in unpredictable situations. In addition, although the control of water quality was realized by developing some generalized rules which provided effective outflow schedule during dry periods, it would be more advantageous to design a single optimization algorithm to generate optimized outflow set-points for both dry and wet periods. This RTC optimization algorithm should consider both quantity and quality requirements while respecting the hydraulic/hydrologic constraints of the problem. Also, in order to better represent the hydraulic/hydrological characteristics of the studied system, the proposed mathematical formulation could be further developed/extended to a mixed-integer or non-linear programming optimization model. Furthermore, since the studied cases do not take into account the time of the flow in the river between the various outflows, the delay in the river could be taken into account in the control approach by adding a simple routing function to consider even the cases where the stormwater basins are not close. A real implementation of the proposed approach could also be considered as the next step of this study in order to measure its benefits using water quantity and quality sensors installed at the outlet of the studied basins and over the receiving watercourse. Furthermore, in order to improve the rainfall-runoff modelling process, a metacognitive component could be added to the proposed OVNN-forecaster to enable self-regulation of the network parameters during the learning process. This capability provides an enhanced learning process by selecting more critical samples to train the model. In all cases, keeping the computational efficiency of the algorithm to achieve less running time yet more accurate predictions, should be taken as the highest priority.

From a broader point of view, the further study directions could be twofold. The first part would be to enhance the developed algorithms to address other aspects of the stormwater management network such as resiliency and reliability through regulating the flow rates not only at the outlets of network but over the pipes and BMPs installed over the watershed. In addition, the benefits of this real-time monitoring and control of flow rates in large stormwater management network can be investigated with diverse use of field-deployed IoT devices, sensors and control valves. In the second part, enabling the stormwater system to interact with other components of a smart city (e.g. smart buildings, smart transportation, smart agriculture, etc.) to create an interdisciplinary interconnected city could be the next step to study. One step further, it will be more interesting to study the economic benefits of an optimal system operation which minimizes the total cost (capital, maintenance and savings). This direction opens opportunities toward more multidisciplinary research in the topic and to practical integration of environmental, mechanical, and control disciplines.

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