Toward Intelligent Control of Urban Stormwater Management Systems

Shadab Shishegar[1], Reza Ghorbani[2], and Yalda Saadat[3]

[1]University of Hawaii at manoa
[2]University of Hawaii at Manoa
[3]University of Maryland College Park

November 21, 2022

Abstract

Today's global challenges, like climate change and urbanization, combined with the growing population in urban areas have exposed conventional urban stormwater infrastructures to a great risk. Although an emerging need for a change in the urban stormwater managerial paradigm has shifted the decision-makers attention to add new objectives to the stormwater management traditional regulations, there are still limited proper solutions to accommodate the urban runoff dynamics over the watershed and enable an adaptive, distributed and sustainable control of stormwater infrastructures. These concerns can be resolved if intelligence is added to the conventional urban systems to balance the network flow dynamics and environmental demand. This paper provides a conceptual discussion to investigate a novel high-performance, adaptive, and intelligent stormwater control optimization architecture as a sustainable solution against the varying environment.

TOWARD INTELLIGENT CONTROL OF URBAN STORMWATER MANAGEMENT SYSTEMS

Shadab Shishegar[1,*], Reza Ghorbani[1], Yalda Saadat[2]
[1] Mechanical Engineering, University of Hawaii, Manoa, 2540 Dole St. – Holmes Hall 201, Honolulu HI, USA
[2] Department of Civil and Environmental Engineering, University of Maryland, 4298 Campus Dr, College Park, MD, US
[*]Corresponding Author: Shadab@hawaii.edu

Key Points:

- A novel adaptive and intelligent stormwater control optimization architecture is conceptualized
- The presented architecture is unique as it allows flow management based on runoff dynamics and the optimal control of storage units over the stormwater management network.
- This concept substantially improves stormwater management systems adaptation against environmental variabilities, strategies for system level storage, and the infrastructure for next generation smart stormwater network options.

A B S T R A C T:

Today's global challenges, like climate change and urbanization, combined with the growing population in urban areas have exposed conventional urban stormwater infrastructures to a great risk. Although an emerging need for a change in the urban stormwater managerial paradigm has shifted the decision-makers attention to add new objectives to the stormwater management traditional regulations, there are still limited proper solutions to accommodate the urban runoff dynamics over the watershed and enable an adaptive, distributed and sustainable control of stormwater infrastructures. These concerns can be resolved if intelligence is added to the conventional urban systems to balance the network flow dynamics and environmental demand. This paper provides a conceptual discussion to investigate a novel high-performance, adaptive, and intelligent stormwater control optimization architecture as a sustainable solution against the varying environment.

Keywords: Adaptive storm water management; Smart City; Control architecture; Sustainability; AdaptiveDynamic Programming; Model Predictive Control

1. Introduction

Rapid urbanization has significantly altered the hydrologic cycle in urbanized watersheds, making stormwater runoff a great challenge for municipalities. Climate Change (CC) also poses additional challenges to urban sustainability by inducing significant changes in precipitation patterns. These challenges, combined with the growing population in urban areas, have exposed urbanized area's traditional stormwater infrastructures to a great risk. Severe downpours have significantly increased in terms of frequency and intensity, and they will become even more frequent and intense in the future according to the projections (Giorgi et al. 2019). This causes greater and quicker urban runoff that consequently is followed by a dramatic increase in the risk of flooding as well as discharging a huge amount of runoff pollutants to the downstream areas around the world. These varying meteorological conditions call for a sustainable and adaptive solution, while the conventional urban infrastructures are only able to provide a static approach to this evolving challenge.

Recognizing the need for a change in the urban stormwater managerial paradigm, federal, state, and local regulations joined 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 not only the safety of citizens and protecting the public and private properties during rainstorms but also the quality of stormwater runoff discharges to the nation's streams. To achieve these objectives, various control structures could be considered whether at the source (e.g., green roofs or infiltration trenches), over the drainage network (e.g., storage units, perforated pipes), or in the downstream areas (e.g., stormwater basins). A stormwater management system can only achieve these objectives by integrating both quality and quantity controls (Shishegar et al. 2019b).

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 retention) and / or runoff volumes (by infiltration) as well as to improve the quality of water (by sedimentation). Stormwater basins are currently the most used BMPs which are generally designed and operated locally, irrespective of the operation of other structures, or the conditions of other components in the watershed. The United States 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 the modern stormwater management goals at the watershed-level (EPA 2008). Recently, Shishegar et al. (2018) demonstrated that the study on integrating the entire watershed at system-level and the feedback with the operational-level decisions is still an open research area and research is needed to design management systems that are adaptable and robust to climate change.

Advances in technologies and the appearance of the Internet of Things (IoT) have enabled pervasive progress in system component connectivity that allows transitioning the existing stormwater management systems to economic cyber-physical utilities that would facilitate real-time control (RTC) of urban runoff dynamics in a sustainable managerial approach as well as enhancing the resilience of urban infrastructure against climate change. In such a revolutionary vision, the utilities would oversee the interconnection, aggregation, and integration for stormwater distribution network while maintaining reliability and resilience for its dynamic performance. Although the reconstruction of stormwater management infrastructures based on new emerging socio-environmental needs 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. In contrast, a cyber-based autonomous stormwater control framework can realize predictive and adaptive model-optimizer-controller architecture to control the urban stormwater facilities that respond to the varying environment and even react promptly to the potential extreme events. The potential benefits of such an approach for controlling urban stormwater infrastructures have led us to conceptualize a sustainable and intelligent stormwater management architecture as an integrated dynamic framework for autonomous control of the stormwater infrastructures. As compared to current practices, this intelligent architecture offers three distinct capabilities: 1) It implements emerging dynamics and intelligent control to enable maximum utilization of the network capacity and decide on the optimal control strategy such that the intertemporal socio-environmental preferences are met in terms of storm flow volume and quality 2) It operates in real-time in a sense that it continually receives the historical and observed data as well as the spatio-temporal predicted meteorological data and decides how to manipulate the actuators based on their local system's capacity, preference, and compatibility and finally 3) It has the ability to learn not only from the historical data but also from a model that updates itself for the events that have never been experienced.

Currently, stormwater management networks are controlled either statistically or partially dynamically utilizing limited local data; they are mostly based on some predefined rules for controlling the end-of-the-network outflows. Although this type of control is relatively easy to implement, it imposes large operating problems even during normal weather conditions, which results in environmentally unfriendly consequences such as stream pollution, waterbody erosion, excessive hydraulic shocks, and probable flooding with associated damages and increased maintenance (Colas et al. 2004).

Modern sustainable stormwater management systems are efficient if they have optimal real-time quality and quantity control performance at all levels of the network (such as detention pond, reservoir, sub-catchment, and the watershed) to be able to instantly adapt its operation to the changing environment. To guarantee high operational feedback that continually provides a proper response to the environmental events, the system components should perform based on predictive algorithms. One of the main challenges in urban stormwater management is that the optimal performance at the local scale does not necessarily represent the optimal performance at the system scale; for instance, the peak flow reduction in a single stormwater management unit may induce critical conditions in the downstream watercourse, resulting in a sharp final hydrograph for the whole watershed (Kerkez et al. 2016). Thus, there is an essential need for Just-in-Time and Just-in-Place predictive and adaptive model-optimizer-controller architecture with dynamic and stochastic optimizer to control the flows and network capacity to allow the SWM network to respond to these global challenges and to realize an adaptive control. At the large-scale system-wide point of view, no classical static control method would be applied any longer if we were able to build a sustainable, reliable, predictive, and highly efficient urban stormwater management system; and this is due to the dynamics induced by a) the varying state of the environment including, the evolving urbanization and the climate variability, b) stochastic precipitation forecasting data and c) dynamic hydrologic cycle including infiltration, evaporation and groundwater dynamics. Hence, the need for designing an optimal economically motivated control strategy that can adapt to the existing network, considering the underlying SWM system limitations and acting on all network levels seems necessary. Developing such system-wide optimization and control is paramount and critical for urban SWM modernization and will satisfy environmental sustainability as a key element of future smart cities.

In this regard, some major questions address the need to advance knowledge and relevant understanding of the stated issues. The impact of the proposed solutions for the control, optimization, modeling, should be in such a way that it will provide answers to major impending questions including:

- How should urban stormwater runoff be managed to achieve the objectives of environmental sustainability?
- What are the prospects for achieving the goal of climate change impacts mitigation from large-scale managerial insight?
- What are the implications for urban runoff management and sustainable development?
- How can we mimic the pre-development hydrologic cycle without reconstruction of stormwater management infrastructures?
- What is the role of advanced technologies in facing urbanization and climate change as two stormwater management major challenges?
- Can we continuously monitor and report the capacity and flow control available to enhance real-time system operation in presence of environmental variability, extreme events, system contingency, and other events?
- Is it possible to integrate the controllers and optimization framework for real-time monitoring and control of stormwater?
- How can local controllers perform to serve the global objectives of an SWM system?
- How will the hydraulic/hydrologic model of a large-scale stormwater management network be designed and optimized to fulfill the water quality and quantity requirements?
- What are the impacts of uncertain sources such as meteorological forecasting error, measurement error, communication disruption, modeling error, and time delays on the performance of SWM systems?
- Can we successfully include the stochastic prediction data into the optimal flow control that further aid the dynamic flow distribution and detention process and account for the availability of enough volume capacity in the network storage components like a stormwater basin? Can we continuously monitor inflow variability and precipitation forecast accuracy to improve the above estimates and operating strategies?

- How can we enable the local controllers to learn from the real-time data stream and stored data to intelligently respond to an event?
- Can we provide regulations to better manage the balance between optimal detention times and overflow prevention while minimizing the outflow fluctuations in a stormwater storage facility?
- How should people participate in the planning, control, and management of urban stormwater to reconcile ecosystems and develop interventions?

2. Research Background

The next generation of dynamic optimal stormwater system controllers should be capable of monitoring the studied system and external changes at various operating scenarios and develop appropriate control objectives with overall goals of adaptability and sustainability in mind (Kerkez et al. 2016; Wong and Kerkez 2016, 2018; Mullapudi et al. 2017; Bartos et al. 2018; Shishegar et al. 2018, 2019a). Extensive investigations have been done on different applications including control systems and power networks (Kamal et al. 2013; Zeinalzadeh 2013; Sariri et al. 2016; Zeinalzadeh et al. 2016; Motalleb et al. 2017; Smidt et al. 2018; Thornton et al. 2020), parallel computation and optimization (Schwarzer 2011; Schwarzer and Ghorbani 2013; Motalleb et al. 2016; Reihani et al. 2016), stormwater management systems (Shishegar et al. 2018, 2019a), and robust control (Kamalasadan and Ghorbani 2012; Kamal et al. 2014; Tavakkoli-Moghaddam et al. 2016) to add adaptivity and sustainability to the related infrastructures.

Table 1- Optimization Techniques Applied to SWM Systems in Conjunction with the Proposed Method

Example	Control Approach						Uncertainty		Objective		Study focus	
	Static	Dynamic										
		Global	Local	Predictive	Reactive	Intelligent	Deterministic	Stochastic	Quality	Quantity	Design	Operation
(Rauch and Harremoës 1999; Gaborit et al. 2012; Shishegar et al. 2019a)			✓	✓			✓		✓	✓		✓
(Shamsudin et al. 2014)	✓							✓	✓	✓	✓	
(Yeh and Labadie 1997; Giacomoni and Joseph 2017)	✓						✓		✓	✓	✓	
(Tung 1988; Perez-Pedini et al. 2005; Baek et al. 2015; Cano and Barkdoll 2016)	✓						✓			✓	✓	
(Chang et al. 2011)	✓							✓	✓		✓	
(Mobley et al. 2014)	✓						✓			✓	✓	

(Che and Mays 2015)			✓	✓			✓			✓	✓	
(Jia et al. 2016)		✓		✓			✓			✓	✓	
(Fu et al. 2008; Verdaguer et al. 2014)	✓		✓		✓		✓		✓		✓	
(Pleau et al. 2000; Duchesne et al. 2004)		✓		✓			✓			✓	✓	
(Joseph-Duran et al. 2014)	✓							✓		✓	✓	
Proposed study		✓		✓		✓		✓	V	✓		✓

The proposed concept methodology is broad and the optimization architecture is the key in this investigation. The use of optimization techniques in the stormwater management field is an emerging area of research. Since the pioneering work by Behera et al. (Behera et al. 1999), the optimization of SWM systems has received the researchers' attention, and algorithms have been proposed for solving the related problems (Papageorgiou n.d.; Butler and Schütze 2005; Dotto et al. 2012; Christofides et al. 2013; Ocampo-Martinez et al. 2013; Saber-Freedman 2016). However, most of them investigated these systems at the design-level (Emerson et al. 2005; Dietz 2007; Visitacion et al. 2009; Mannina and Viviani 2009; Afshar 2010; Sun et al. 2011; Park et al. 2012; Krebs et al. 2013; Tao et al. 2014; Verdaguer et al. 2014; Montaseri et al. 2015; Saber-Freedman 2016; Mao et al. 2017)) and the feedback at the operational-level is rarely considered (Shishegar et al. 2018) (Table 1). Among the studies on the operation of SWM systems, a good number are rule-based systems, meaning that they defined a set of rules to manipulate the system regulator to improve the final performance of the system (Gaborit et al. 2012). One problem with these systems is the fact that the trial-and-error method was used to come up with the thresholds for the designed regulations (Bartos et al. 2018; Shishegar et al. 2019a) and also the proposed rules are designed to address one but not many other SWM systems' desired objectives. The results obtained by pre-defined rules are not necessarily optimal and they cannot consider the global performance of the catchment. This calls for generic formulations with the ability to consider all types of systems with different physical and spatial characteristics. This motivates us to employ mathematical optimization methods as one of the most effective methods to design solutions for realizing modern intelligent stormwater management systems.

Among a few studies that address operational-level optimization of SWM systems, Shishegar et al. (2019) presented a smart predictive decision-making framework for real-time control of the SWM basin such that an optimization algorithm is integrated with the implemented control rules to enable optimal quality and quantity control performance for the basin. Although this approach showed a significant improvement in the peak-flow reduction and detention time of the basin, it serves the stormwater system only at the local-level. While the optimized performance of a single basin does not necessarily result in an optimal performance at the system-level. In an effort to design a system-level control algorithm, it is shown in (Wong and Kerkez 2018) that an urban watershed network can be modeled using a linear quadratic regulator for controlling the water flows. This approach demonstrates to be efficient in balancing the flood mitigation and flow reduction, however, it poses further challenges for the SWM system when faced with environmental variabilities due to the reactive operation of the system's components.

Static optimization appears in most of the stormwater management studies such as when the location and size of a detention basin are modeled using discrete programming techniques to minimize the risk of flooding (Yeh and Labadie 1997) or when the optimal storm sewer network is designed where the nodal elevations of the network are taken into account as the decision variables (Afshar 2010). In (Kerkez et al. 2016) it was proposed to consider the watershed-scale control of water management systems dynamically in real-time, which was extended (Wong and Kerkez 2016). Nonetheless, the results fail to present a solution for the water quantity control performance of the meshed stormwater network, due to focusing only on characterizing the urban pollutographs. Recently, a predictive real-time control framework presented (Shishegar et al. 2019a), where the dynamic control of water quality and quantity was applied locally to several examples, and possible explanations were discussed. We proposed to apply this approach to develop the optimization architecture, yet at the catchment-scale, to ensure a global dynamic control performance for managing the urban stormwater. As it is shown in Table 1, the proposed study provides an intelligent global predictive dynamic control while considering the uncertainties engaged in the problem. Besides, all important aspects of stormwater management practices are included as the system objectives in the proposed architecture that realize an enhanced performance for the storm network in terms of quality and quantity. Furthermore, intelligence has never been studied in stormwater management literature which makes this investigation a unique opportunity for transforming the conventional stormwater networks to smart and modern systems that adapt the operation to the great vision of sustainable and smart cities. Most importantly, the proposed intelligent architecture targets the feedback with the operation level of the system and not the design level, an ability which helps the municipalities to build a highly efficient, adaptive and economic storm network without the need to execute the cost prohibitive replacement of existing in-place infrastructure.

To ensure system-wide dynamic and optimality, it is of importance to implement and link the optimization algorithms at each layer of the SWM network to local controllers. This conceptual research aims to understand the link between a multi-agent optimization model and optimal controllers at all layers of the stormwater drainage network. *However, the global optimality of storm flow over the network is important, and in general, a network needs to be resilient to be able to bounce back after disruptive events (Saadat et al. 2019). This can be achieved by linking the optimization model with local intelligent controllers at all layers of the drainage network.*

3. Solution Approach: Stormwater Intelligent Management (swIm)

An efficient solution to actively manage the distributed SWM systems could be considered a control, optimization, and communication architecture that integrates spatio-temporal precipitation data and real-time control decision set-points into a network of distributed stormwater system assets. In this approach, a unique solution will be investigated that allows a) a dynamic flow scheduling system based on both short-term (weather prediction) and long-term (climate change) precipitation data, b) real-time optimization that can be integrated with several quality control rules, c) an infrastructure that enables interaction between local and supervisory controllers and d) a multi-disciplinary managerial approach to control detention time, erosion and flooding across the network. So here, we investigate the proposed architecture by which the innovative notion of learning in real-time control of stormwater management systems will be introduced, where IoT-enabled devices utilize data-driven models to train real-time and historical data to discover the hydraulic attributes of the network in terms of availability, flexibility and response behavior against the adverse and undesirable environmental events. The new technological concept would have the potential to significantly reduce the system-level issues related to network capacity and water quality, and also allows for adaptive management of urban stormwater, making the municipal SWM network ready for high-volume flash runoff during extreme weather. This technology would be capable of controlling stormwater drainage networks globally, predictively, and adaptively to enhance the flexibility and resilience of the stormwater system and build an intelligent framework that serves the future smart and sustainable cities.

More precisely, this introduced novel concept consists of a stormwater control optimization architecture (swIm) which is high-performance, adaptive, and intelligent that balances the network flow dynamics and environmental demand in real-time over multiple levels of the stormwater management system, incorporating meteorological conditions, water quality, and network reliability requirements. This novel SWM architecture involves hydraulically linked flow optimization routines across a three-layer hierarchy of a SWM network: Catchment, sub-catchments, and local scale. Model Predictive Control (MPC) and Adaptive/Approximate Dynamic Programming (ADP) methods joined with integrated Real-Time Optimal Flow (RT-OF) model and quality control rules to meet the requirements of municipal regulations with different performance criteria. The distributed architecture also accommodates runoff dynamic into stormwater storage units operation over the storm sewer network which is connected to a cloud-based data of system parameters, environmental states, and generated set-points, to enable transferring it from a static-state to an adaptive, distributed, and dynamic network. Moreover, this distributed optimization and control paradigm provides an economic alternative to the cost-prohibitive urban infrastructure replacement solution. Most importantly, it allows the network operators to learn from historical events for generating optimal flow schedules when facing unexpected extreme precipitations, which finally realizes sustainable and predictive management of urban stormwater.

3.1. Conceptual Architecture

In the introduced multi-layer architecture, taking the hydraulic/hydrologic constraints into account, the methods of rainfall-runoff modeling are embedded into the optimization problem. Furthermore, a supervisory control concept is presented at three layers, which aggregates many small units to larger units and supervision of local controllers. This approach reduces the complexity of the optimization problem and allows defining significantly smaller time-steps to generate flow set-points at each local controller. Also, it augments existing infrastructure with intelligent control algorithms and more complex infrastructure (to add flexibility to the network) and thus allows network controllers to manage the flow appropriately between time-critical and non-time-critical contingencies. Fig.1 illustrates the overall schematics of the three-layer optimization architecture. As illustrated in Fig.1, there are three hierarchical levels for this optimization and control architecture. From bottom to top, the first level is the local actuators. At this level, the main focus is on dynamic control with the objective function to minimize the peak discharge at the outlets to mitigate the hydraulic shocks on the receiving streams and attenuate the flow hydrograph. At this level, all urban hydrology components incorporate the processes of higher flow transformation and the calculation of runoff towards the pipes. Subsequently, the hydraulic components simulate the flow in pipes in the SWM network. All of these processes can be simulated by the Stormwater Management Model (SWMM) (Rossman and Huber 2016) which is still the most widely used model in the scientific community and by urban hydrology engineers in North America. Thus, this model will be used to calculate the parameters associated with local storage facilities and finally generate the optimal outflow through the site-scale optimization model. At the catchment level (can be called system, global, or network level, too), the control will be on interactions between different local sections in terms of flow sharing to realize a balance between the available network capacity and the flow volume. It is assumed that system-wide planning has been already done on the system for sitting and sizing the detention facilities. The optimal stormwater flow at this level

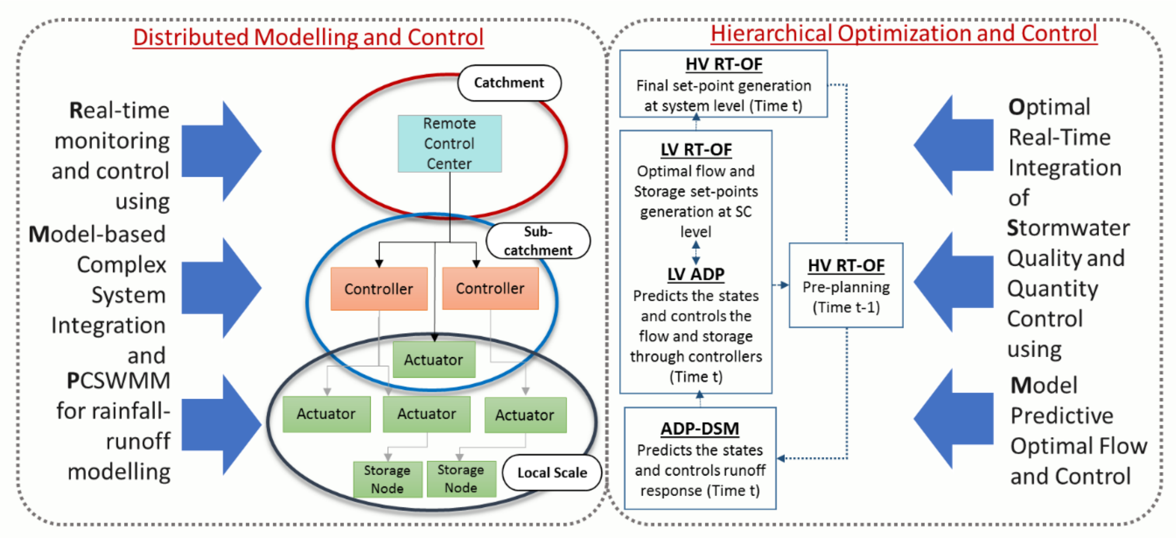

Figure 1: Conceptual Integration of Distributed Modeling and Control and Hierarchical Optimization and Control

updates the flow variables to better utilize the distributed system capacity through sub-catchment level controllers. Both the local level management and the system-wide management are in collaboration at the sub-catchment level where the performance of locally generated set-points are 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. This approach allows significantly faster solution time while reduces the efforts needed to apply on-line large-scale optimization algorithms which could be called only when required.

The main purpose of the introduced intelligent architecture is to provide real-time optimization and control at all layers in the SWM network and realizes a) efficient real-time management of urban runoff at all levels of the SWM system; b) integration of quality control rules with hierarchical quantity control optimization algorithms for system-level management; and c) adapts to the environmental variability by embedding predictive and learning abilities along with intelligence to the system controllers. This technical concept is a unique hierarchical-distributed modeling, control and optimization architecture that involves a) a core analysis and integration of next-generation design, operations management, and control initiatives; and b) integrated optimization architecture for system-level flow dynamics using model-predictive control. Given all the aspects outlined above, the specific objectives to realize the intelligent architecture approach over multiple layers of the stormwater management network can be categorized into four parts:

Objective 1) To propose an optimization architecture and real-time control algorithms to control the whole network of stormwater management systems, and design test case scenarios to validate the hydraulic/hydrologic performance of the architecture on a standard case study with precipitation of different characteristics from short and intense storm events that can produce rapid runoff in urban areas, to long but less intense events that may produce a slower response in urban watersheds but result in high flows in the river, and even flooding.

Objective 2) To develop the model predictive control algorithm and test it based on real-world data developed in collaboration with the City and County of Honolulu in hydraulic/hydrologic simulations (SWMM). Then, a comparison analysis between the performance criteria resulted from the meteorological forecasting data (predictive control) and those of observation data (reactive control) should be conducted.

Objective 3) To introduce a methodology that takes into account the uncertainties associated with the rain forecasts in the stormwater RTC algorithms and then evaluate the robustness of the control against these uncertainties.

Objective 4) To design and develop a process for creating a standard test-bed that simulates, synthesizes, and tests project findings, methods, technologies and could be also employed to validate other proposed investigations on SWM networks.

3.2. *Key contributions of the conceptual methodology*

The key contribution of the swIm approach is the ability of the global stormwater network optimization, on a predictive and dynamic basis. This is through implementing model predictive approximate dynamic programming based controllers and massively distributed optimization architecture which enables the intelligent control of the SWM network to operate efficiently and satisfying various modern network-level objectives optimally, with global sustainability. Other contributions include the ability of the overall optimization algorithm and the predictive control framework to adapt based on environmental variability and provides a novel method for real-time and predictive implementation so that maximum water flow control can be achieved at the same time satisfying the SWM system metrics (peak-flow reduction, pollutant removal, flow attenuation, response-time to extreme events, erosion control, etc.). Specifically: a) <u>Proposed adaptive control architecture</u> benefits from having system-centric controllers (controllers that are adaptive based on system and environmental changes) which provide a hierarchical-distributed framework for stormwater network control. This optimal control algorithm is capable of changing the characteristics based on value priority scheme from stochastic to deterministic control, b) <u>Proposed distributed real-time flow optimization</u> can perform predictable and stochastic modeling of large scale system architectures whose components have the ability to learn from historical data to perform efficiently in response to any type of external event and, c) <u>the distributed processing of RT-OF</u> can make the architecture highly dynamic, stochastic which improves accuracy, speeds up and controls resolution.

3.3. *Methodology*

The key concept of integrated optimization and predictive control is the treatment of network storage nodes as a stormwater basin that interacts between the local discharge/storage management (DSM) side and the network side. The local discharge/storage side can be termed as a controllable flow side and the network side as a stormwater flow optimization side. The interaction between these two sides (Fig.2) provides dynamic stochastic optimal stormwater flow architecture with controllable options. At the local discharge/storage side, controllable and movable outlets are included. The controllable release/detention at this side is represented as U_C. At the system side, water flow interactions and the optimal flow are included and represented as U_G. Depending on the hierarchical level the objective function for control and optimization changes at the various storage network nodes described below:

1- At the level of the local nodes, the management and the optimization of water flow is less critical than the global level. The most important requirement at this level is the optimal water quality management features that control the detention time to allow the settling process concerning storage unit capacity and the ability to transfer the flow based on real-time data capturing. Two types of nodes can be considered at this level; downstream storage units (stormwater basin) and the intersectional storage nodes each with different physical characteristics.

2- At the sub-catchment level, the local storage management and stormwater flow management are equally important. The objective of this level is to establish an optimal interaction between the local and systems-level while looking at regional network safety in terms of overflow prevention and pollutant load reduction.

3- At the catchment level, the main objective is to develop a stochastic optimal water flow architecture that includes both quality and quantity control strategies. Flow fluctuations control is the second priority which is considered to minimize the depreciation of the systems components facilities as well as the providence of energy consumption.

Fig.2 illustrates the proposed stormwater network node concept. As shown, Q_{Gt} and V_{Gt} are desired outflow rate and desired storage volume at each node respectively, ε_i, ϑ_i represents released flow and detained volume and ϵ_i represent losses due to evaporation and infiltration. Thus the storage level in the node x_i can be represented as a function of the flow balance as:

$$Q_{Gt}\Delta t + 2V_{Gt} = I_t\Delta t + I_{t-1}\Delta t + 2\vartheta_i - \varepsilon_i\Delta t - \epsilon_i \quad \forall t = 1, \ldots, L$$

where V_t represents the volume of water in the node at time step t (m^3).

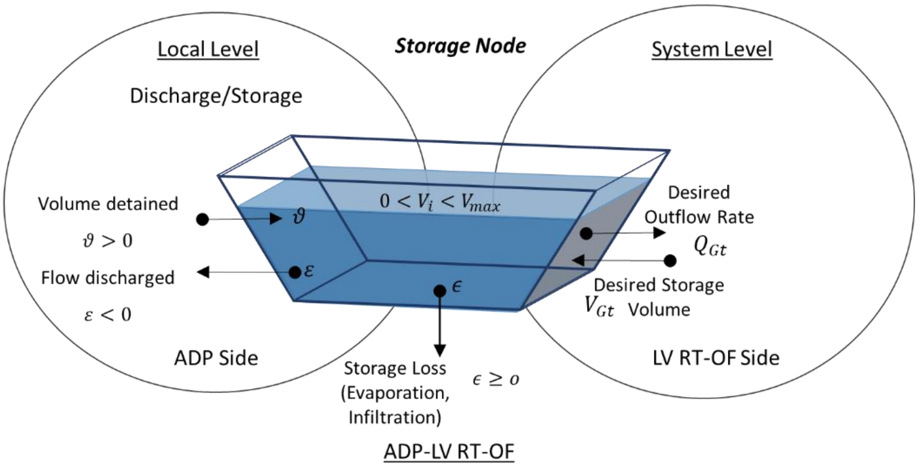

Figure 2- Illustration of Storage Node and Interaction of ADP and LV RT-OF.

It should be noted that The state of the system is estimated by ADP and the status is distributed to the LV RT-OF for optimization. LV RT-OF then commands the desired flow rates and storage volume trajectories.

Considering all possible variations in flow and storage, the overall functional representation of the optimization and the control architecture at three levels is defined as follows:

1) ADP DSM (Fig.1) focuses on dynamic flow management with storage control options. The input to this controller is the system-level flow variables for the respective local actuator.

2) The High Volume Real-Time Optimal Flow (HV RT-OF) delivers the network side flow variables for each controller node (Fig.1).

3) After performing an optimal flow response, the ADP DSM provides updated and actual flow rates and storage volumes to the upper-level nodes. This actual flow and volume at the local level replaces the previously estimated and aggregated set-points which are used for final flow optimization (Fig.4).

4) At the Low Volume Real-Time Optimal Flow (LV RT-OF) and ADP controller structure, the inputs are the pre-planning catchment level inflow and the updated volumes and flow from the local level. The optimal storm flow then calculates the updated U where U is $U_G + U_C$. U_C is adjusted based on the control functions of the ADP.

5) The final output at the controller level is then transmitted to the HV RT-OF.

6) At the HV RT-OF level, the U from the controller will be utilized for generating the final flow set-points.

LV RT-OF updates each Δt and the optimization problem is solved for the horizon of kΔt. ΔT=mΔt is the update time over the control horizon for HV RT-OF. The planning horizon time is LΔT (Fig.3).

To implement the optimization and control architecture, the SWM network of closed pipes, storage,

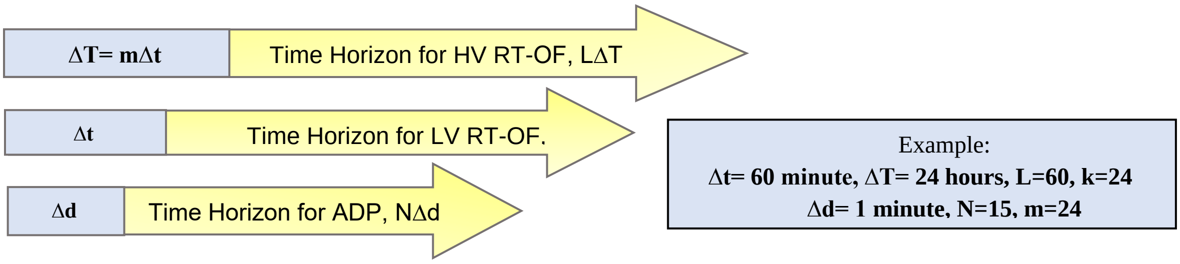

Figure 3- Computation and time horizon demonstration for different units.

gates, pumps, controllers, etc. needs to be modeled and integrated. Modeling the system is conducted using SWMM by U.S. EPA (Rossman and Huber 2016). A large-scale SWM network can be modeled in PCSWMM software to simulate the hydraulic/hydrologic processes of a watershed that contains hundreds of thousands of components, to perform an integrated analysis for design, operations management, monitoring, and control. Hydrological/hydraulic simulations will provide water levels and retention times in the stormwater basin, flow rates, and output velocities of storage units as well as peak flows, water levels, and velocities in the river, based on the valve opening values determined by the optimization problem. This simulation feature makes it possible to decompose complex system problems both hierarchically (vertically) and horizontally into relatively simple re-composable pieces.

Figures 4 and 5 illustrate the implementation architecture of the concept methods. Fig.4 shows the level of the local nodes, in which the proposed method allows us to control the active and reactive storage management considering sub-catchment level changes. Fig.5 illustrates the proposed system at the catchment scale that integrates the sub-catchment controllers to a remote control station with the help of optimization algorithms. The controllers will be interacting with local actuators and higher-level components at the sub-catchment level and ADP DSM interacts with quality control rules through the communication network.

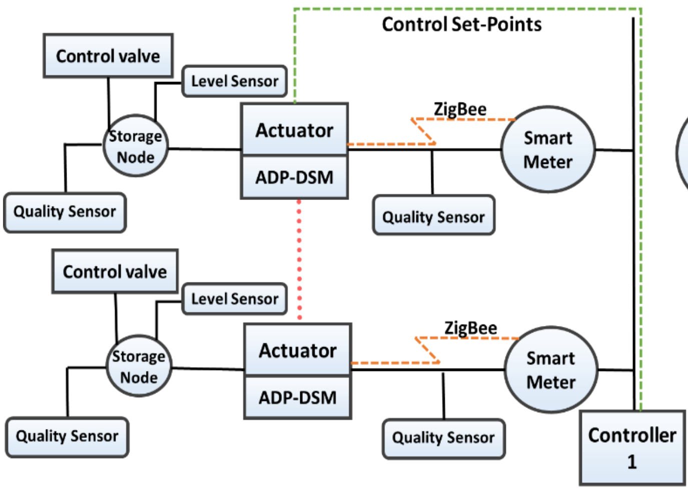

Figure 4- Implementing sub-catchment level control and optimization routine on the SWM network model.

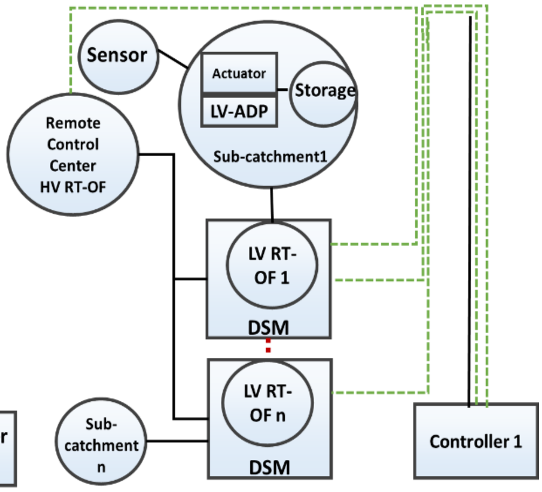

Figure 5-Implementing system level control and optimization routine on the SWM network.

3.3.1.ADP-DSM at the local level

Assume at time ‘t-1’, an upcoming storm event is predicted which requires the storage nodes to create available volume. So, the local controllers decide to generate the outflow set-points based on the remaining time until the next rain event, the required volume, and the emptying time of the storage volume. We call this a pre-planning condition at time ‘t’. At the local level with real-time control and monitoring, first, Approximate Dynamic Programming (ADP) will be used to construct discharge/storage management (DSM). ADP DSM inputs are the simulated inflows to the network nodes that are resulted from the runoff journey over the network ($I_{i,t}$). The objective of the ADP DSM is to perform dynamic management between detained volume, the outflow discharge, and the runoff dynamics through an agent-based learning process from the environment.

The stormwater network node dynamics allows analyzing the amount of runoff required to be detained and the volume that needs to be discharged at that instant. The storage node dynamics can be represented as the mass balance equation at the system level. This can be represented as $Q_{i,t}\Delta t + 2V_{i,t} = I_{i,t}\Delta t + I_{i,t-1}\Delta t + 2V_{i,t-1} - Q_{i,t-1}\Delta t - \epsilon_t \quad \forall t = 1, \dots, m\Delta t$ where the volume of water in storage i at time t is $V_{i,t} \geq 0$, the inflow rate to storage i at time t is $I_{i,t}$ and, the outflow rate from the storage i at time t is $Q_{i,t}$ and, $0 \leq Q_{i,t} \leq Q_{max}$ where Q_{max} is the maximum allowable outflow. The capacity of each storage is limited and formulated as $\sum_t (I_t - Q_t)\Delta t + V_0 \leq V_{i,max}$ where $V_{i,max}$ is the maximum capacity of the storage i.

A model is used to select the fill/discharge cycle of the SWM storage unit. Based on this control selection, a model predictive controller works on the water storage regulation by controlling the amount of flow rate at the outlet of each node. The result of this interaction is the updated storage volume at the time instant. The updated volume ($V_{i,t}$) is fed to the optimization model. The objective of the optimization policy is, given the residual water volume profile and real-time data capturing, to find the optimal fill/discharge/idle schedule at each time-step which minimize the total outflow $\sum_i \sum_t (Q_{i,t})$.

3.3.2. HV RT-OF/MPC Structure at the catchment Level

The final planning stage will be executed by the HV RT-OF agent, which is optimizing the flow rate result under the network conditions. The objective of the optimization here is to perform dynamic management between end-of-the-network storage (we assume all the storage units at the downstream area are detention basins), the outflow discharge, and the runoff dynamics.

The HV-OF mainly works on the system level storage dynamics. At this level, the outflows represents the downstream discharges resulting from a simple abstraction of the whole stormwater drainage network (lumped approach) which enables a faster resolution time for the optimization algorithms. The ADP controller that solves the optimization problem for one horizon length starts the overall optimization cycle. Then ADPs are calculating DSM trajectories. Weather forecasting data to estimate future precipitation intensities across the watershed is provided by the remote control center for the horizon length. This data is also used as inputs to the hydrologic and hydraulic model to predict flow rates (and water levels if necessary) at different sites in the system. These flow rates and future water levels are calculated at the time step chosen for a time equivalent to the response time of the entire watershed (often called the forecast horizon). When there is not any inflow to the network (dry period) the control is based on the performance of quality control regulations, which are formulated based on $t_e = V_{req}/Q_{max}$, Where t_e is the emptying time of the storage until the availability of the storage volume V_{req} at maximum outflow Q_{max} (s). These rules define the outflow rates according to the thresholds identifying the detention time windows. In stormwater management studies the minimum desired detention time for allowing the sedimentation is 20 hours (Carpenter et al. 2014). On the other hand, there is a 40 hour limit as the maximum detention time after which almost no more settling process is realized (Gaborit et al. 2012).

ADP formulation using DHP method with state estimation run at each Δd =LΔt

---

$$\boldsymbol{x(k+1) = F[x(k), u(k), k], k = 0, 1, \ldots}$$

$$\boldsymbol{J[x(i), i] = \sum_{k=1}^{\infty} \gamma^{k-i} U[x(k), u(k), k]}$$

$$\boldsymbol{J^*[x)] = \min_{u(k)} \{U(x(k), u(k)) + \gamma J^*(x(k+1))\}}$$

$$\boldsymbol{u^*(k) = arg J^*[x)]}$$

Bellman's optimality for continuous-time case

$$\boldsymbol{x(t+1) = F[x(t), u(t), t], t \geq t_0}$$

$$\boldsymbol{J[x(i), i] = \int_{k=1}^{\infty} U(x(\tau), u(\tau)) d\tau}$$

$$\boldsymbol{-\frac{\partial J^*(x(t))}{\partial t} = \min_{u} \left\{ U(x(t), u(t)) + \left(\frac{\partial J^*(x(t))}{\partial x(t)}\right)^T \times F(x(t), u(t), t \right\}}$$

$$\boldsymbol{= U(x(t), u^*(t), t) + \left(\frac{\partial J^*(x(t))}{\partial x(t)}\right)^T \times F(x(t), u^*(t), t)}$$

Dual Heuristic Programming

Where:

x: State vector of the system

u: Control action

F: System function

U: Utility function

γ: Discount factor

J: Cost function

$u^*(k)$: Optimal control at time k

$\hat{J}$: The output of the critic network

E_D: Error measure of DHP over time

W_C: parameters of the critic network

k: Time-step

$$\min \{\|E_D\| = \sum_k E_D(k) = \frac{1}{2}\sum_k \left[\frac{\partial\hat{J}(k)}{\partial x(k)} - \frac{\partial U(k)}{\partial x(k)} - \gamma\frac{\partial\hat{J}(k+1)}{\partial x(k)}\right]^2\}$$

$$\frac{\partial\hat{J}(k)}{\partial x(k)} = \partial\hat{J}[x(k), u(k), k, W_C]/\partial x(k)$$

Integrated Predictive Quantity and Quality control formulation at each time-step for the time horizon of LΔt

$$Min\left\{\sum_i \sum_t (Q_{i,t} + \xi * pp_{i,t} + \varphi * qq_{i,t})\right\}$$

Subject to:

$$\sum_t (I_{i,t} - Q_{i,t})\Delta t + V_{i,0} \le V_{i,max} \quad \forall i = 1,2,\dots,N$$

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

$$V_{i,t} \ge 0 \quad \forall t = 0,1,\dots,L \;\&\; \forall i = 1,2,\dots,N$$

$$0 \le Q_{i,t} \le Q_{i,max} \quad \forall t = 0,1,\dots,L \;\&\; \forall i = 1,2,\dots,N$$

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

$$pp_{i,t} \ge 0 \quad \forall t = 0,1,\dots,L \;\&\; \forall i = 1,2,\dots,N$$

$$qq_{i,t} \ge 0 \quad \forall t = 0,1,\dots,L \;\&\; \forall i = 1,2,\dots,N$$

Where:

$Q_{i,t}$= outflow (decision variable) from storage node i at time step t (m³/s);

$pp_{i,t}$= negative variation of the set-point (continuous variable) associated to storage node i;

$qq_{i,t}$= positive variation of the set-point (continuous variable) associated to the storage node 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 storage node i at time step t (m³/s);

$V_{i,t}$= volume of water in the storage node i at time step t (m³);

$V_{i,max}$= maximum volume capacity of storage node i (m³);

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

$V_{i,0}$= initial volume of water in storage node i (m³);

$Q_{i,max}$= maximum allowable outflow from storage node i (m³/s);

N= number of controlled storage node in the drainage network.

Having these mathematical models and the time until the start of the next predicted storm event $t_{next\ rain}$, the rules are defined as $if\ t_{next\ rain} \le t_e \rightarrow\ Q_t = Q_{max}$, $if\ t_e < t_{next\ rain} \le t_e + 20h \rightarrow Q_t = Q_{max} * \frac{t_e}{t_{next\ rain} - t_f}$, $if\ t_e + 20h < t_{next\ rain} < 40h + t_e^{max} \rightarrow Q_t = Q_{max} * \frac{t_e + 20h}{t_{next\ rain} - t_f}$ or $if\ t_{next\ rain} \ge 40h + t_e^{max} \rightarrow$ for $\forall\ t < 40h\ \ Q_t = 0$ and for $\forall\ t \in (40h, 40h + t_e^{max})\ Q_t = Q_{max} * \frac{t_e}{t_e^{max}}\ \ \forall\ t \in (40h, 40h + t_e^{max})$, Where t_f is the time that the previous rainfall event finished (s), t_e^{max} is emptying time of the whole basin at the maximum outflow Q_{max} (s) and V_{req} is the required storage volume for the next coming rainfall event to avoid any overflow in the basin (m³) (Shishegar et al. 2019a). Distributing the resulting flow trajectories in both wet and dry periods, the LV RT-OF at each sub-catchment computes the data for the actual horizon length including the storage volume, and flow rates (ADP formulation). With the feasible sub-catchment flow trajectories, the system-level optimization process calculates the final flow planning (Integrated predictive formulation).

4. Preliminary Results

Many overflow structures are located on the studied watershed in the southeast of Canada and several overflows are observed, particularly in the municipal area. Between 1984 and 2017, more than 160 floods were recorded in this territory. Also, 59% of the shorelines of the studied streams at this watershed are considerably degraded, particularly affected by erosion and the high concentration of phosphorus in the sediments while its quality is degrading by its passage from the city. 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 summer, higher temperatures, lower water levels, and sudden severe storms will be more probable in the future. This makes this area an interesting case study for the primary evaluation of the proposed framework. Fig.6 illustrates the optimal discharge/storage schedule of downstream storage units. Employing the integrated quality and quantity control framework, the flow schedule is optimized in such a way that the water is detained during the dry periods or less intense storm events and discharged during the wet periods. For some hours the outlet actuator is idle ($Q = 0$ and $V = 0$). This is the time at which either the settling process has been already realized or there is not any upcoming storm event predicted. This enables an optimal quantity and quality control performance for the local actuators while providing scheduled flow rates for the sub-catchment controllers based on the optimal management set-points.

Second, the performance of the RT optimization architecture is assessed in practice, by reproducing the impacts of climate change on the precipitation data series of the next 30 years, based on the proposed methodology demonstrated by Ouranos (2015). In this case, as the system receives high runoff inflows on May 23 (Fig.7.a), the optimization architecture decides to assign a flow rate at a low percentage in the wet period (May 23-26) to prevent any overflow in the storage node. 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 RT strategy prioritizes the quantity control measures (avoiding overflow) over the quality control ones (retaining water). Looking at the water volume variation (Fig.7.b), it can be seen that the storage capacity of the basin reaches its maximum. In this case, although detaining water could result in improving the quality of discharged flow, 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 performance in mitigating the peak flows for the illustrated period in Fig.7, is calculated as 78%. This preliminary result shows that the system is responding well to the climate variations while considering SWM infrastructure limitations, to satisfy all system constraints, and enhance both quality and quantity control performances. These results can be extended to the whole network of stormwater management at the watershed level to control the operations of each single storage node to achieve the global optimality.

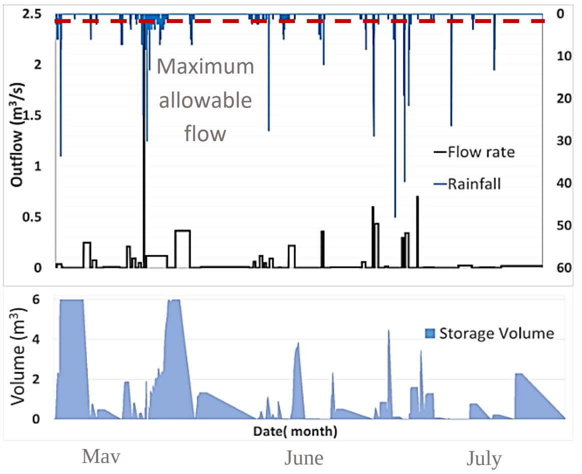

Figure 6- Dischaarge/storage Schedule During Three Months

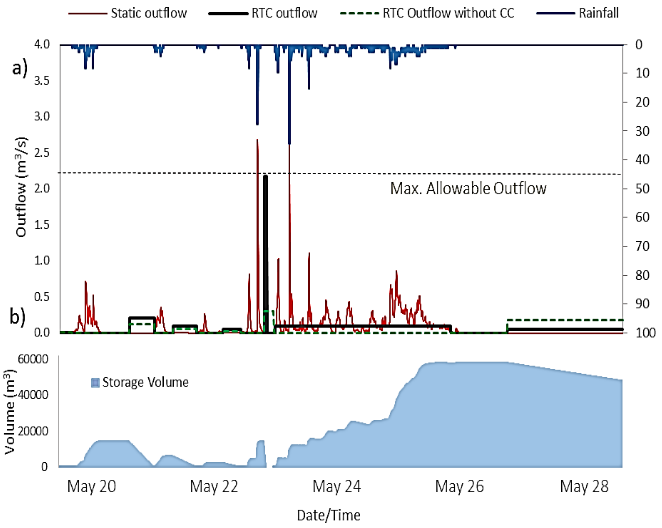

Figure 7- a) Flow Hydrographs Resulted From Static Control Approach vs. RTC Optimization, b) Detained Volume at the Storage Unit Under Presence of Climate Change

5. Uncertainty Analysis

Investigating rainfall-runoff models has always been engaged with uncertainties that originated from measurement errors in rainfall historical data. The meteorological forecasting data generated based on such historical data are also contaminated by inherent uncertainties engaged in the rainfall time series, and since rainfall is considered as the main input data in rainfall-runoff problems, several deficiencies would be imposed on the performance of the final system. In our study, storage node overflow is the most probable system failure that may occur following the lack of proper uncertainty analysis. Fig.8 shows the performance of smart dynamic control architecture on a single storage node when using rainfall prediction versus observation data. The observation data herein is employed as the perfect prediction input parameter for the model. In studies engaged with meteorological forecasting data, the observation is often used to avoid any forecasting error uncertainties, which helps to simplify the hyper-complexity of spatio-temporal variabilities of rainfall patterns. Hence, the outflow schedule shown obtained under observation data in Fig.8 could be considered as a reliable scenario. As illustrated, a significant rainfall event has not properly been predicted by the forecasting model at around 8 am. Given the variability of the weather condition especially due to climate change, there is a possibility of not providing enough volume capacity in system storage nodes for an upcoming extreme event because of not forecasting it. A failure in on-time discharge of trapped water may result in system failure and storage overflow, which causes an overflow and shallow local flooding. Therefore, before the acknowledgment of the uncertainty, proper reliability analysis and procedures should be developed to further generate a realistic flow rate schedule. In such circumstances, considering stochastic optimization techniques could be beneficial to take into account different scenarios and optimize the imposed failure costs on the system. Even though these kinds of analysis hinder municipalities to economize on system expenses under normalcy, it would provide strong implications for decision-makers to prevent cost-intensive system failures over the urbanized areas.

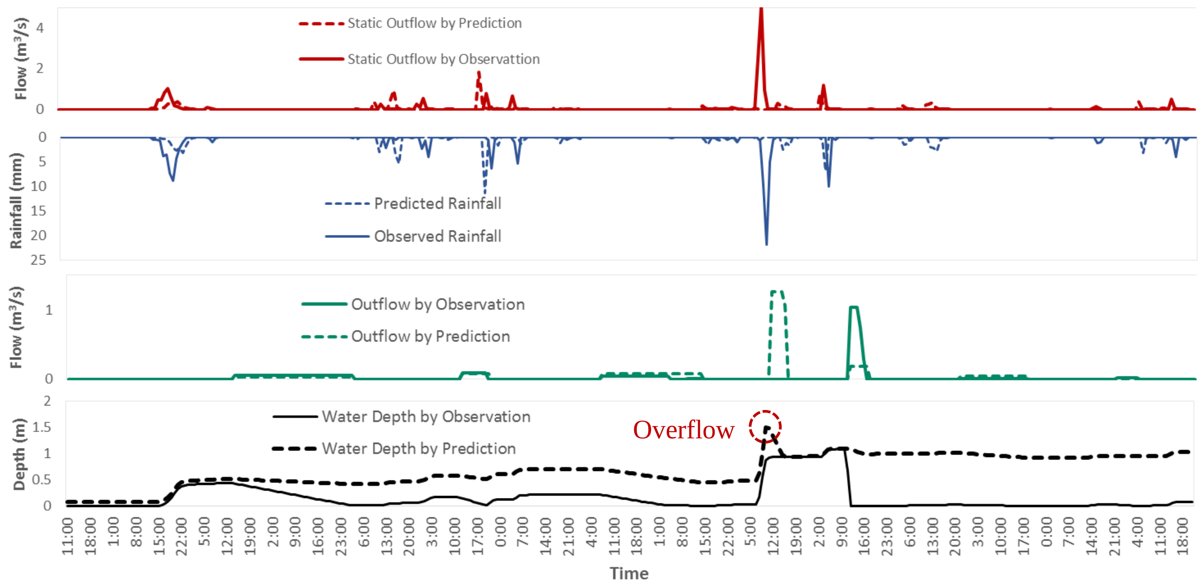

Figure 8- Comparison of Smart Control Approach Performance Under Uncertain (prediction data) and Reliable (observation data) Conditions

6. Conclusion

A novel adaptive and intelligent stormwater control optimization architecture is conceptualized in this paper to balance the network flow dynamics and environmental demand in real-time over multiple levels of the stormwater management (SWM) system. The proposed architecture uses an integrated model predictive control (MPC) with real-time flow control consideration. All the interconnected components act based on the introduced intelligent stormwater control at different levels which realizes adaptive and sustainable management of urban runoff based on climate and urban variability. This platform allows stochastic dynamic optimal control with optimal water flow. Although the proposed methodology is critical, it proves to be the solution for transforming the next generation of urban water networks. Further, the proposed effort will be a first-time venture to provide feasible, scalable, and implementable stormwater system control and optimization infrastructure. This concept advances the state of the art and substantially improves SWM system adaptation against environmental variabilities, strategies for system-level storage, and the infrastructure for next-generation smart stormwater network options.

The presented architecture is unique as it allows flow management based on runoff dynamics and the optimal control of storage units over the stormwater management network. Furthermore, due to the hierarchical agent interaction, this architecture will allow real-time updates of the water flows and allows area controller interactions between local and area controllers.

The long-term research goal will be twofold. The first part will be to enhance the developed algorithms to address other aspects of the stormwater network such as resilience and reliability. Secondly, the benefits of a large SWM network with a diverse use of IoT devices, sensors, and control valves can be investigated. It is needed to understand and quantify the overall value of the global SWM network optimization. This perspective opens the opportunities for more multidisciplinary research in the topic to integrate environmental, mechanical, and control disciplines.

Acknowledgment

All the preliminary results have been obtained under a Ph.D. program finalized by Shadab Shishegar at the Institut National de la Recherche Scientifique and financial support of FRQNT-Nature and Technology. All the data used in this research is available through Shishegar, et al. 2019b.

REFERENCES

Afshar, M.H. 2010. A parameter-free Continuous Ant Colony Optimization Algorithm for the optimal design of storm sewer networks: Constrained and unconstrained approach. Adv. Eng. Softw. **41**(2): 188–195. Elsevier Ltd. doi:10.1016/j.advengsoft.2009.09.009.

Baek, S.S., Choi, D.H., Jung, J.W., Lee, H.J., Lee, H., Yoon, K.S., and Cho, K.H. 2015. Optimizing low impact development (LID) for stormwater runoff treatment in urban area, Korea: Experimental and modeling approach. Water Res. **86**: 122–131. Elsevier Ltd. doi:10.1016/j.watres.2015.08.038.

Bartos, M., Wong, B., and Kerkez, B. 2018. Open storm: A complete framework for sensing and control of urban watersheds. doi:10.1039/c7ew00374a.

Behera, P.K., Papa, F., and Adams, B.J. 1999. Optimization of Regional Storm-Water Management Systems. J. Water Resour. Plan. Manag. **125**(2): 107–114. doi:10.1061/(ASCE)0733-9496(1999)125:2(107).

Butler, D., and Schütze, M. 2005. Integrating simulation models with a view to optimal control of urban wastewater systems. Environ. Model. Softw. **20**(4): 415–426. doi:10.1016/j.envsoft.2004.02.003.

Cano, O.M., and Barkdoll, B.D. 2016. Multiobjective, Socioeconomic, Boundary-Emanating, Nearest Distance Algorithm for Stormwater Low-Impact BMP Selection and Placement. J. Water Resour. Plan. Manag.: 05016013. doi:10.1061/(ASCE)WR.1943-5452.0000726.

Carpenter, J.F., Vallet, B., Pelletier, G., Lessard, P., and Vanrolleghem, P.A. 2014. Pollutant removal efficiency of a retrofitted stormwater detention pond. Water Qual. Res. J. Canada **49**(2): 124–134. doi:10.2166/wqrjc.2013.020.

Chang, N.-B., Rivera, B.J., and Wanielista, M.P. 2011. Optimal Design for Water Conservation and Energy Savings Using Green Roofs in a Green Building under Mixed Uncertainties. J. Clean. Prod. **In Press,**(11): 1180–1188. Elsevier Ltd. doi:10.1016/j.jclepro.2011.02.008.

Che, D., and Mays, L.W. 2015. Development of an Optimization/Simulation Model for Real-Time Flood-Control Operation of River-Reservoirs Systems. Water Resour. Manag. **29**(11): 3987–4005. doi:10.1007/s11269-015-1041-8.

Christofides, P.D., Scattolini, R., Muñoz de la Peña, D., and Liu, J. 2013. Distributed model predictive control: A tutorial review and future research directions. Comput. Chem. Eng. **51**: 21–41. doi:10.1016/j.compchemeng.2012.05.011.

Colas, H., Pleau, M., Lamarre, J., Pelletier, G., and Lavallée, P. 2004. Practical Perspective on Real-Time Control. **39**(4): 466–478.

Dietz, M.E. 2007. Low impact development practices: A review of current research and recommendations for future directions. Water. Air. Soil Pollut. **186**(1–4): 351–363. doi:10.1007/s11270-007-9484-z.

Dotto, C.B.S., Mannina, G., Kleidorfer, M., Vezzaro, L., Henrichs, M., McCarthy, D.T., Freni, G., Rauch, W., and Deletic, A. 2012. Comparison of different uncertainty techniques in urban stormwater quantity and quality modeling. Water Res. **46**(8): 2545–2558. Elsevier Ltd. doi:10.1016/j.watres.2012.02.009.

Duchesne, S., Mailhot, A., and Villeneuve, J.-P. 2004. Global predictive real-time control of sewers allowing surcharged flows. J. Environ. Eng. **130**(5): 526–534. doi:10.1061/(ASCE)0733-9372(2004)130:5(526).

Emerson, C.H., Welty, C., and Traver, R.G. 2005. Watershed-Scale Evaluation of a System of Storm Water Detention Basins. J. Hydrol. Eng. **10**(3): 237–242. doi:10.1061/(ASCE)1084-0699(2005)10:3(237).

EPA. 2008. Urban Stormwater Management in the United States. U.S. Environmental Protection Agency, Washington, DC.

Fu, G., Butler, D., and Khu, S.-T. 2008. Multiple objective optimal control of integrated urban wastewater systems. Environ. Model. Softw. **23**(2): 225–234. doi:10.1016/j.envsoft.2007.06.003.

Gaborit, E., Muschalla, D., Vallet, B., Vanrolleghem, P.A., and Anctil, F. 2012. Improving the performance of stormwater detention basins by real-time control using rainfall forecasts. Urban Water J. **10**(4): 1–17. doi:10.1080/1573062X.2012.726229.

Giacomoni, M.H., and Joseph, J. 2017. Multi-Objective Evolutionary Optimization and Monte Carlo Simulation for Placement of Low Impact Development in the Catchment Scale. **2**(9): 1–15. doi:10.1061/(ASCE)WR.1943-5452.0000812.

Giorgi, F., Raffaele, F., and Coppola, E. 2019. The response of precipitation characteristics to global warming from climate projections. Earth Syst. Dyn. **10**(1): 73–89. doi:10.5194/esd-10-73-2019.

Jia, B., Simonovic, S.P., Zhong, P., and Yu, Z. 2016. A Multi-Objective Best Compromise Decision Model for Real-Time Flood Mitigation Operations of Multi-Reservoir System. Water Resour. Manag. **30**(10): 3363–3387. Water Resources Management. doi:10.1007/s11269-016-1356-0.

Joseph-Duran, B., Jung, M.N., Ocampo-Martinez, C., Sager, S., and Cembrano, G. 2014. Minimization of Sewage Network Overflow. Water Resour. Manag. **28**(1): 41–63. doi:10.1007/s11269-013-0468-z.

Kamal, E., Aitouche, A., Ghorbani, R., and Bayart, M. 2013. Electrical Power and Energy Systems Robust nonlinear control of wind energy conversion systems. Int. J. Electr. Power Energy Syst. **44**(1): 202–209. Elsevier Ltd. doi:10.1016/j.ijepes.2012.07.009.

Kamal, E., Aitouche, A., Ghorbani, R., and Bayart, M. 2014. Fuzzy Scheduler Fault-Tolerant Control for Wind Energy Conversion Systems. IEEE Trans. Control Syst. Technol. **22**(1): 119–131. IEEE. doi:10.1109/TCST.2013.2246162.

Kamalasadan, S., and Ghorbani, R. 2012. Novel Intelligent Fault-Tolerant Adaptive Control Methodology for Next-Generation Energy Systems. IEEE Control Syst. doi:10.1109/IAS.2012.6374044.

Kerkez, B., Gruden, C., Lewis, M., Montestruque, L., Quigley, M., Wong, B., Bedig, A., Kertesz, R., Braun, T., Cadwalader, O., Poresky, A., and Pak, C. 2016. Smarter stormwater systems. Environ. Sci. Technol. **50**(14): 7267–7273. doi:10.1021/acs.est.5b05870.

Krebs, G., Kokkonen, T., Valtanen, M., Koivusalo, H., and Setälä, H. 2013. A high-resolution application of a stormwater management model (SWMM) using genetic parameter optimization. Urban Water J. **10**(Lid). doi:10.1080/1573062X.2012.739631.

Mannina, G., and Viviani, G. 2009. Separate and combined sewer systems: A long-term modeling approach. Water Sci. Technol. **60**(3): 555–565. doi:10.2166/wst.2009.376.

Mao, X., Jia, H., and Yu, S.L. 2017. Assessing the ecological benefits of aggregate LID-BMPs through modelling. Ecol. Modell. **353**(April 2015): 139–149. Elsevier B.V. doi:10.1016/j.ecolmodel.2016.10.018.

Mobley, J.T., Culver, T.B., and Hall, T.E. 2014. Simulation-optimization methodology for the design of outlet control structures for ecological detention ponds. J. Water Resour. Plan. Manag. **140**(11): 04014031. doi:10.1061/(ASCE)WR.1943-5452.0000420.

Montaseri, M., Hesami Afshar, M., and Bozorg-Haddad, O. 2015. Development of Simulation-Optimization Model (MUSIC-GA) for Urban Stormwater Management. Water Resour. Manag. **29**(13): 4649–4665. doi:10.1007/s11269-015-1082-z.

Motalleb, M., Reihani, E., and Ghorbani, R. 2016. Optimal placement and sizing of the storage supporting transmission and distribution networks. Renew. Energy **94**: 651–659. Elsevier Ltd. doi:10.1016/j.renene.2016.03.101.

Motalleb, M., Sreedharan, S., and Sangrody, H. 2017. Power Network Reliability Improvement through Forecasting with Complex-Valued Neural Networks under System Contingency American Journal of Engineering Research (AJER) Power Network Reliability Improvement through Forecasting with Complex-Valued Neural Network. (June).

Mullapudi, A., Wong, B., and Kerkez, B. 2017. Emerging investigators series: building a theory for smart stormwater systems. Environ. Sci. Water Res. Technol. **3**(1): 66–77. Royal Society of Chemistry. doi:10.1039/C6EW00211K.

Ocampo-martinez, C., Cembrano, G., and Quevedo, J. 2013. Application of Predictive Control Strategies to the Management of Complex Networks in the Urban Water Cycle. Inst. Electr. Electron. Eng. **1**(33): 15–41.

Ouranos. 2015. Vers l'adaption. Synthèse des connaissances sur les changements climatiques au Québec. *In* 2015th edition. Montreal, Quebec. Available from https://www.tandfonline.com/doi/full/10.1080/1573062X.2019.1574844.

Papageorgiou, M. (n.d.). Optimal control of large scale combined sewer systems.

Park, M., Chung, G., Yoo, C., and Kim, J. 2012. Optimal Design of Stormwater Detention Basin using the Genetic Algorithm. **16**: 660–666. doi:10.1007/s12205-012-0991-0.

Perez-Pedini, C., Limbrunner, J.F., and Vogel, R.M. 2005. Optimal Location of Infiltration-Based Best Management Practices for Storm Water Management. J. Water Resour. Plan. Manag. **131**(6): 441–448. doi:10.1061/(ASCE)0733-9496(2005)131:6(441).

Pleau, M., Pelletier, G., Marcoux, C., Meunier, C., and Bonin, R. 2000. REAL-TIME CONTROL FOR CSO MANAGEMENT : QUEBEC URBAN COMMUNITY SYSTEM STARTUP. *In* the 29th annual WEAO Technical Symposium and OPCEA Exhibition, Hamillton, Canada. Hamilton. pp. 16–28. doi:10.1017/CBO9781107415324.004.

Rauch, W., and Harremoës, P. 1999. Genetic algorithms in real-time control applied to minimize transient pollution from urban wastewater systems. Water Res. **33**(5): 1265–1277. doi:10.1016/s0043-1354(98)00304-2.

Reihani, E., Motalleb, M., Thornton, M., and Ghorbani, R. 2016. A novel approach using flexible scheduling and aggregation to optimize demand response in the developing interactive network market architecture. Appl. Energy **183**: 445–455. Elsevier Ltd. doi:10.1016/j.apenergy.2016.08.170.

Rossman, L.A., and Huber, W.C. 2016. Storm Water Management Model Reference Manual Volume I – Hydrology. *In* U.S. Environmental Protection Agency. Environmental Protection Agency, Corvallis, Oregan. Available from www2.epa.gov/water-research.

Saadat, Y., Ayyub, B.M., Zhang Y., Zhang D., & Huang H., 2019, "Resilience of Metrorail Networks: Quantification with Washington D.C. as a case study." ASCE. ASME J. Risk Uncertainty Part B. 2019, doi:10.1115/1.4044038.

Saber-Freedman, N. 2016. A Data-Driven Decision Model for Combined Sewer Overflow Management using the Low-Impact Development Rapid Assessment Method. J. Chem. Inf. Model. **53**(9): 1689–1699. doi:10.1017/CBO9781107415324.004.

Sariri, S., Schwarzer, V., Kalisch, D.P.H., Angelo, M., and Ghorbani, R. 2016. Real-Time Data Collection and Processing of Utility Customer's Power Usage for Improved Demand Response Control. *In* Transactions on Large-Scale Data- and Knowledge-Centered Systems XXVII: Special Issue on Big Data for Complex Urban Systems. *Edited by* A. Hameurlain, J. Küng, R. Wagner, A. Anjomshoaa, P.C.K. Hung, D. Kalisch, and S. Sobolevsky. Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 48–63. doi:10.1007/978-3-662-53416-8_4.

Schwarzer, V. 2011. New Opportunities for Large-scale Design Optimization of Electric Vehicles using GPU Technology. 2011 IEEE Veh. Power Propuls. Conf.: 1–6. IEEE. doi:10.1109/VPPC.2011.6043051.

Schwarzer, V., and Ghorbani, R. 2013. Drive Cycle Generation for Design Optimization of Electric Vehicles. IEEE Trans. Veh. Technol. **62**(1): 89–97. IEEE. doi:10.1109/TVT.2012.2219889.

Shamsudin, S., Dan, S., Aris, A., and Yusop, Z. 2014. Optimum combination of pond volume and outlet capacity of a stormwater detention pond using particle swarm optimization. Urban Water J. **11**(2): 127–136. doi:10.1080/1573062X.2013.768680.

Shishegar, S., Duchesne, S., and Pelletier, G. 2018. Optimization methods applied to stormwater management problems: a review. Urban Water J. **15**(3): 276–286. Taylor & Francis. doi:10.1080/1573062X.2018.1439976.

Shishegar, S., Duchesne, S., and Pelletier, G. 2019a. Predictive Real-Time Control Optimization of a Stormwater Management System. IEEE 15th International Conference on Control and Automation (ICCA). IEEE, 2019.

Shishegar, S., Duchesne, S., and Pelletier, G. 2019b. An integrated optimization and rule-based approach for predictive real-time control of urban stormwater management systems. J. Hydrol. **577**: 124000. Elsevier BV. doi:10.1016/j.jhydrol.2019.124000.

Smidt, H., Thornton, M., and Ghorbani, R. 2018. Network Coordinated Evolution: Modeling and Control of Distributed Systems Through Online Genetic PID-Control Optimization Search. *In* Applications of Evolutionary Computation. *Edited by* K. Sim and P. Kaufmann. Springer International Publishing, Cham. pp. 256–271.

Sun, S., Djordjević, S., and Khu, S.-T. 2011. A general framework for flood risk-based storm sewer network design. Urban Water J. **8**(1): 13–27. doi:10.1080/1573062X.2010.542819.

Tao, T., Wang, J., Xin, K., and Li, S. 2014. Multi-objective optimal layout of distributed storm-water detention. Int. J. Environ. Sci. Technol. **11**(5): 1473–1480. doi:10.1007/s13762-013-0330-0.

Tavakkoli-Moghaddam, R., Shishegar, S., Siadat, A., and Mohammadi, M. 2016. Design of a Reliable Bi-objective Relief Routing Network in the Earthquake Response Phase. *In* Procedia Computer Science. doi:10.1016/j.procs.2016.09.372.

Thornton, M., Member, S., Motalleb, M., Member, S., Smidt, H., Branigan, J., Siano, P., Member, S., and Ghorbani, R. 2020. Internet-of-Things Hardware-in-the-Loop. IEEE Trans. Ind. Informatics **14**(11): 5020–5028. IEEE. doi:10.1109/TII.2017.2782885.

Tung, Y.-K. 1988. Multi-Objective Detention Basin Design in Urban Drainage Systems - Tradeoff Between Risk and Cost. Water Resour. Manag. **2**: 57–62.

Verdaguer, M., Clara, N., Gutiérrez, O., and Poch, M. 2014. Application of Ant-Colony-Optimization algorithm for improved management of first flush effects in urban wastewater systems. Sci. Total Environ. **485–486**(1): 143–152. Elsevier B.V. doi:10.1016/j.scitotenv.2014.02.140.

Visitacion, B.J., Booth, D.B., and Steinemann, A.C. 2009. Costs and Benefits of Storm-Water Management: Case Study of the Puget Sound Region. J. Urban Plan. Dev. (4): 150–158. doi:http://dx.doi.org/10.1061/(ASCE)0733-9488(2009)135:4(150.

Wong, B., and Kerkez, B. 2016. Adaptive measurements of urban runoff quality. Water Resour. Res. **52**: 8986–9000. doi:10.1002/2015WR018013.Received.

Wong, B., and Kerkez, B. 2018. Real-Time Control of Urban Headwater Catchments ThroughLinear Feedback: Performa nce, Analysis, and Site Selection. Water Resour. Res. **54**: 7309–7330. Elsevier B.V. doi:10.1016/j.proeng.2014.02.188.

Yeh, C.-H., and Labadie, J.W. 1997. Multiobjective watershed-level planning of stormwater detention systems. J. Water Resour. Plan. Manag. **123**(6): 336–343.

Zeinalzadeh, A. 2013. Optimal Power Flow Problem with Energy Storage, Voltage, and Reactive Power Control.

Zeinalzadeh, A., Ghorbani, R., and Yee, J. 2016. Stochastic Model of Voltage Variations in the Presence of Photovoltaic Systems *. 2016 Am. Control Conf. (978): 5032–5037. American Automatic Control Council (AACC). doi:10.1109/ACC.2016.7526151.