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A Benchmarking Framework for Control of Smart Stormwater Networks

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Abstract: While the smart stormwater community has successfully implemented real-time control of stormwater networks, these successes are currently network-specific. Thus, there exists a need for direct and rigorous comparison of control methodologies used across different networks. To address this need, we have developed a benchmarking framework that allows for evaluating control methodologies on a variety of real-world inspired stormwater networks with corresponding delineated benchmark scenarios, thereby facilitating direct performance comparisons. We present five of these networks and their corresponding scenarios, along with the open-source computational toolbox that is hosted online and is built to accelerate ease of use.

Keywords: Benchmarking; Smart stormwater networks; Real-time control

Introduction

Recent accessibility of low-cost sensors, microcontrollers, and wireless communication technology has made it possible for stormwater systems to be retrofitted with an assortment of sensor nodes and actuators that allow for inexpensive stormwater control interventions (e.g. hydraulic valve operated by cellular-connected actuator). These smart stormwater systems have enabled real-time sensing of weather changes and subsequent operational control decisions to be fully automated. Additionally, as rapid urbanization and a changing climate continue to stress urban watersheds beyond their original design capacities, these technologies have allowed for alternative, low-cost, and adaptive remedies when faced with such dynamic threats (Kerkez et al., 2016; Mullapudi et al., 2017).

However, given the emerging nature of the smart stormwater systems field (García et al., 2015; Meneses et al., 2018; Vezzaro et al., 2014), there currently does not exist a framework to (i) objectively and rigorously compare the performance of the control methodologies behind these smart stormwater interventions, and (ii) assess the generalizability of the control methodologies across a diverse set of networks and storm events.

To address this void of benchmarking standards, we have developed a framework that consists of:

1. Anonymized stormwater networks that include:
    a. A variety of control objectives and event drivers (e.g. storm events), and
    b. A corresponding delineated individual event scenario specifically defined for the direct comparison and evaluation of control algorithm performance,

which are packaged in

2. An open-source python library that can be used for evaluating the performance of the control algorithms on these networks,

and are then

3. Hosted online for instantaneous comparison to the performance of other submitted solutions.

We distinguish our benchmarking approach from previous efforts (Schütze et al., 2018; Saagi et al., 2017) first, by utilizing open source software forthrightly and providing extensive documentation such that it is accessible particularly for those outside the field of stormwater control; and, second, by focusing the stormwater control problem solely on *algorithm implementation* of control, thus streamlining the ability to measure and directly compare different control strategies. The details for each component of our framework are presented below.

Material and Methods

Anonymized stormwater networks and corresponding benchmarking scenarios. Five diverse stormwater networks have been developed as initial benchmarking networks, each of varying size and function. For each of these networks, corresponding delineated scenarios are defined that include distinct control objectives, driving events (e.g. storm events), controllable network components and constraints, and quantifiable performance measures. The performance of control algorithms in these scenarios is evaluated using the performance measure. This measure allows for the objective comparison of each control algorithm's performance in a scenario.

For example, Scenario gamma evaluates the ability of a control algorithm to drain its corresponding stormwater network (Figure 1a) as quickly as possible, while simultaneously avoiding flooding and minimizing erosion. A brief overview of the five networks and their corresponding scenarios can be seen in Table 1. We also provide "toy" control problems that represent three idealized stormwater networks that can be used for unit testing the control algorithms prior to launching into a full-scale simulation.

Simulating Stormwater Networks. To accompany the benchmarking scenarios, we have developed a standalone python computational toolkit that manages the computational components (i.e. runoff generation and flow routing) of these scenarios, allowing for focus to be on the development and deployment of control algorithms. This toolkit uses EPA-SWMM (Rossman et al., 2014) wrapped in PySWMM (*PySWMM*, 2019) as its backend for simulations of stormwater networks.

Online hosting. To encourage widespread adoption of and contribution to this benchmarking framework, the stormwater networks, corresponding benchmarking scenarios, and computational toolbox are all hosted online (http://open-storm.org/benchmarking). The online portal is built such that testing and comparison of new control algorithms can occur automatically.

Results

To demonstrate the utility of this benchmarking framework, we apply and compare two control algorithms on two benchmarking scenarios; specifically, we compare Bayesian Optimization and a Genetic Algorithm for real-time control of Scenarios gamma and delta (Table 2). Though the results indicate that these two control algorithms perform similarly well in both of these scenarios, this objective comparison is enabled by the benchmarking framework.

Conclusions and Discussion

While this benchmarking framework has only recently been developed, we believe it will be used widely and extensively in the near future, with encouragement for other researchers to submit their own anonymized stormwater networks and scenarios. Its use will further enable control interventions to be developed and implemented, while also minimizing the prior need to first master stormwater simulation. Additionally, “competitions” will be coordinated to encourage novel solutions to complex stormwater control needs. Finally, it will assist in bridging the knowledge gaps between water resources engineers unfamiliar with real-time control, and control engineers unfamiliar with stormwater systems.

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Figures and Tables

Table 1 The benchmarking framework includes five benchmarking scenarios of various size, type, and control objectives.

Benchmarking Scenario	Subcatchment Area and Number of Control Assets	System Type	Control Objective(s)
Scenario alpha	0.12 sq km; 5 controllable weirs	Residential combined sewer network	Minimize total combined sewer overflow volume
Scenario beta	1.3 sq km; 1 storage unit and 1 detention basin, both with controllable outlet valves, and 1 controllable pump	Urban separated sewer network with outflow influenced by tidal conditions	Minimize total network flooding
Scenario gamma	4 sq km; 11 detention ponds with controllable outlets	Urban separated sewer network	Channel flows below threshold; Avoidance of pond flooding
Scenario delta	1.7 sq km; 5 controllable detention ponds	Residential network in which detention ponds also function as waterfront	Maximize utilization of ponds while avoiding flooding
Scenario epsilon	67 sq km; 11 controllable in-line storage dams	Urban combined sewer network	Constant total suspended solids load at network outlet; Avoidance of network flooding

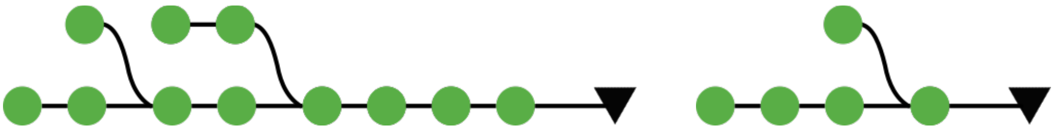

Figure 1 The topology of the networks in Scenarios (a) gamma and (b) delta include controllable assets (nodes) that drain to a downstream waterbody (triangle). These assets can be controlled in real time during a storm event to achieve the respective scenario objectives.

Table 2 Comparison of two control algorithms across benchmarking scenarios as quantified by performance measures. Performance measures are normalized to values of the uncontrolled cases; a value of zero would indicate perfect achievement of the control objective.

Scenarios	Control Algorithm		
	Uncontrolled	Bayesian Optimization	Genetic Algorithm
Scenario gamma	1.000	0.626	0.611
Scenario delta	1.000	0.218	0.224