Data-Driven Model Predictive Control For Real-Time Stormwater Management

Jingyun Ning, Benjamin D. Bowes, Jonathan L. Goodall, Madhur Behl

Abstract— **Low-lying coastal cities across the world are increasingly seeing flooding due to climate change and accompanying sea-level rise. Many such cities rely on old and passive stormwater infrastructure which cannot cope up with the increasing flood risk. One potential solution for addressing coastal flooding is implementing active control strategies in the stormwater systems. Existing stormwater control mostly relies on rule-based strategies, which are not sufficient to manage the increasing flood risk. Model predictive control (MPC) for stormwater management has received attention for this problem. However, building physics-based models for MPC in stormwater management is very cost and time prohibitive. In this paper, we propose a data-driven approach, which utilizes unstructured state-space models for system identification and predictive control implementation. We demonstrate our results using two real stormwater network configurations, one from the Norfolk, VA region and another model of Ann Arbor region, MI, respectively using the SWMM simulator. Our results indicate that MPC outperforms rule-based strategies by up to 60% for the Norfolk system and up to 90% for the Ann Arbor system in flood management.**

Stormwater, Real-time control, Model Predictive Control, System Identification

I. Introduction

In much of the United States, flooding is occurring and is a growing source of significant economic loss, social disruption, and housing inequality over the past decade . This is amplified in coastal cities due to sea level rise ; global mean sea level has risen about 8 inches since 1880, with a third of that happening in the last 25 years [1]. This exacerbates flooding risk in cities where the tide level can be above stormwater outlets and may slow or block drainage to the pipes leading to flooding.

There are mainly three approaches to address the increasing threat of flooding: (i) Using locally placed stormwater control measures to prevent stormwater from entering the stormwater system, (ii) expanding the capacity of existing infrastructure, and (iii) implementing more advanced control strategies [2]. Creating new stormwater control measures may not be feasible in developed cities and expanding existing infrastructure can be extremely disruptive and costly. Therefore, we focus on developing a data-driven model predictive control (MPC) strategy for urban flood mitigation.

Real time control (RTC) has become a promising strategy in nuisance flooding mitigation [3]. The implementation of RTC in a stormwater system requires three major components: (i) sensors (e.g., rain gauges, water level sensors, flow meters), to provide real-time input information of system states; (ii) a stormwater system model, to precisely estimate the behaviors of real-world stormwater system; and (iii) actuators, like valves, to manage the outflow from the system.

The current state of the art for RTC of stormwater system is rule-based control (RBC) [4]. This type of control is based on both observed and forecast conditions. For example, a valve on a pond can be opened prior to a storm to ensure enough capacity to store the stormwater and prevent flooding. RBC is transparent to users, but is generally limited to the coverage of the scenarios specified by the rules. An alternative to rule-based strategies is to use MPC.

However, The biggest challenge to implementing MPC is that building control-oriented models using physics-based techniques is extremely cost and time prohibitive. This includes hydrologic and hydraulic modeling, and evaluation of the stormwater drainage system including: stormwater inlets, pipes, ponds, outfalls, etc.. In many cases topographic surveys need to be conducted to obtain this information and additional sensors have to be deployed to identify measures to fill or mitigate data gaps. Finally, thousands of parameters need to be tuned using historical rainfall, tidal surge, or combination rainfall and surge events for which input data and flooding impacts are known and available [5]. This effort can amount to **\$100k-300k** per watershed for a city to build the physics-based model from scratch, and can take **3-6 months** depending on what is needed to verify in the field with surveys. For a city like Norfolk, Virginia, this can amount up to millions of dollars for modeling cost alone.

To address the modeling and rule-based limitations above, the contribution of this work is in implementing MPC for urban flood control but using data-driven state-space models as opposed to the physics-based models used in previous work. The proposed MPC approach formulates the control problem as an optimization problem, which focuses on flood mitigation during storm events.

The key research contributions of this paper are:

1) We demonstrate the use of a data-driven unstructured state-space identification technique to estimate input-output behavior.
2) We formulate flood mitigation as a data-driven MPC

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problem and implement a receding horizon controller using a data-driven model.
3) We evaluate the baseline RBC and MPC performance using both a simple model derived from the coastal city of Norfolk, Virginia, and a large-scale model derived from the city of Ann Arbor, Michigan.

II. Related work

Performance of MPC relies deeply on the accuracy of model used in the optimization problem. Without an accurate model, MPC will not generate reasonable control decisions. In the hydrological cycle, rainfall-runoff plays an important role by returning excess rainfall to the oceans and controlling water flows into stormwater systems. Modeling rain-runoff helps gain a better understanding of hydrologic phenomena and how changes affect the hydrological cycle [6].There are typically three modeling techniques: (i) physics-based model, (ii) grey-box model, and (iii) data-driven model.

1) Physics-based model (white-box model): Physics-based modeling is based on the first-principles, which requires thorough knowledge of physics related to the entire hydrological processes. An example of early development of physics-based models is the MIKE-SHE model [7]. A recent study utilizes EPA-SWMM5 to build a physics-based model for MPC on flood mitigation [8]. A physics-based model can adequately represent the spatial and temporal variations of the real system, however, it does not scale due to the amount of data, sensors, and retrofits needed required.

2) Grey-box model: Grey-box models interpret runoff process based on simplified governing physics equations. A semi-distributed grey-box model, called Hydrologiska Byrans Vattenbalansavdelning (HBV) hydrology model [9], was developed in 1976 and recent studies on river Demer have also showed the impact of MPC flood control based on grey-box modeling [10]. Grey-box models have simple model structures, and are easier to calibrate than physics-based models. They are useful when computation time is limited and catchment characteristics are not analyzed in detail.

3) Data-driven model: As known as the black-box model, which means very little is known about the internal processes that control how runoff results are determined [11]. These models approximate real-world systems based on statistical relationships between inputs and outputs. Vafakhah et al. provided an evaluation of data-driven techniques, including the ANN, ANFIS, ARX and ARMAX models for rainfall-runoff modeling [12]. The disadvantages of data-driven models are the lack of interpretability, and the non-linear relationship between inputs and outputs increases the difficulty of the implementation of MPC on data-driven models.

In this paper, we design a data-driven state-space model, which combines the advantages of physics-based models and data-driven models. Therefore, is able to represent stormwater system dynamics using physical variables without the need of redundant physics equations or expert knowledge of stormwater systems.

III. Problem statement and Methods

We now describe the problem statement in this work followed by explanations of the methodology (i) system identification, (ii) RBC strategies, and (iii) MPC formulation.

A. Problem statement

We present a system identification methodology, which uses an unstructured linear state-space model to estimate the system dynamics. The modeling approach does not require expert knowledge of stormwater systems since the identified model is built only on the input-output relationship.

After creating a system dynamic model, we formulate MPC as an optimization problem for flood control. The objective is to minimize the flood volume at each storage unit (St_i) and junction node (J_i) by minimizing the least squared error of depth level and set-point level of St_i and J_i. We also implement RBC strategies to compare with MPC and evaluate their performance.

Following steps are taken to formulate the flood mitigation problem.

1) Implement RBC strategy inspired by real-world stormwater control as baseline scenario.
2) Use SWMM5 models of sites 1 and 2 to obtain data for system identification from simulation under different RBC strategies.
3) Use N4SID unstructured state-space identification to estimate stormwater system dynamics.
4) Formulate MPC problem for flood management based on the identified state-space model.
5) Evaluate the effectiveness of MPC for SWMM5 models for site 1 and 2, and compare with RBC strategy.

B. System identification

To determine the control policies for a stormwater system, we need to have knowledge of the system dynamics. System identification is a useful technique to help us obtain a mathematical model to precisely estimate the system behaviors.

We use unstructured state-space model for stormwater system identification. Specifically, we construct a multiple-input, multiple-output (MIMO) linear time-invariant state-space model, as shown in Eq. 1, from input-output storm event data to estimate the system behaviors.

In any system identification problem for state-space models, the goal is to estimate the values of state matrices: A, B, C, and D. In a physics-based model, these matrices are built based on physical parameters such as properties of catchments, storage nodes, or pipes. However, there is no need for state matrices to have physical interpretation in unstructured state-space models; the goal is to find the elements of state matrices that can best explain the data.

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \tag{1}$$

C. Control strategies

For data collection of system identification procedure, we implement different RBC control strategies, including: (i) bang-bang control, (ii) linear control and (iii) step-wise control. These strategies are inspired by rule-based controllers used in the real world. In addition, to demonstrate the capability of MPC, we implement RBC adopted from [13], shown in Fig. 1. We use passive control as baseline control strategy and compare the performance of flood control.

1) Passive control: Passive control is when no real-time control is involved, and runoff regulators, such as weirs, gates, and valves, are controlled by fixing to a certain static setting. The valves are fully opened under passive control during simulation, thus the discharges from storage nodes were drained by gravity alone.

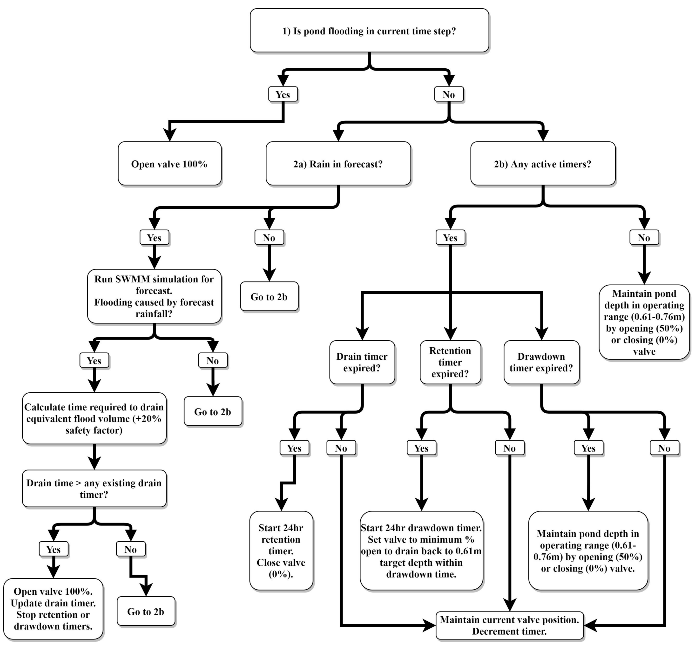

Fig. 1. Rule-based control strategy implemented based on documented industry-standard methods. The depth of pond is kept between 0.61-0.76m by implementing an "if-then" rule-based model to control the valve positions.

2) RBC strategies: For RBC strategies, logical rules are used to control the openings of valves, such rules can be based on experience and knowledge gained over time. RBC strategies change the valve position based on changes of model states, such as depths of storage and junction nodes. We design three RBC strategies to obtain data for system identification, included: (i) Bang-bang control, (ii) Linear control, and (iii) Step-wise control.

Bang-bang control switches between two states, fully opened and fully closed. This control strategy has been used widely in flood control, [14]. We implement the Bang-bang controller based on the status of storage node depth. Linear control strategy changes the valve positions depending upon the water level in St_i and J_i. The changing rate of positions depends on the current flooding volumes. Step-wise control is similar to the linear control, but changes the valve positions by a random amount at each time step.

We also adopt a more sophisticated RBC strategy, see in Fig. 1 [13], which was implemented based on documented industry-standard methods [15]. In this strategy, the valve positions are switched among 0%, 50%, and 100%, the depths of storage nodes are kept between 0.61-0.76m by implementing an "if-then" rule-based model to control the valve positions. Forecast of rainfall event is used for making control decision.

D. Model predictive control

Fig. 2 shows the workflow of the proposed MPC system. Firstly, we use EPA Stormwater Management Model version 5 (SWMM5) to build a simulation model of real-world stormwater system. The SWMM5 model will provide input data (i.e. forecast of precipitation, tide) to the system identification state-space model. After that, MPC formulates an optimal control policy to the plant based on prediction outputs from the state-space model every time step.

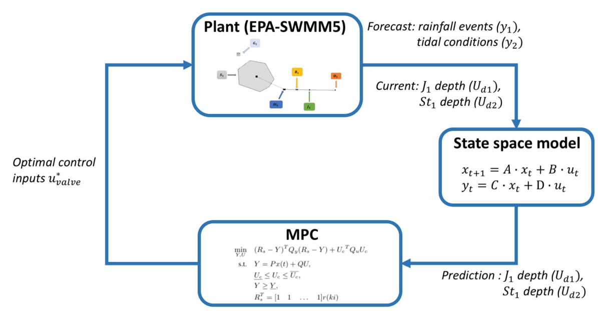

Fig. 2. System workflow. SWMM5 represents the ground truth of stormwater systems.

The control policy of MPC is found by solving the QP optimization problem. The advantage of MPC over the rule-based control is the ability to adjust the actuators based on forecasts of model input, such as rainfall events and tidal conditions. We use a control time step of 6 min and a prediction horizon of half an hour (5-step ahead) as same as control horizon, these values are the best combination to provide the most accurate estimation of system dynamics in system identification process. The objective is to minimize the flood volume by reducing the least square error between current depth value and set-point value of each storage node. Eq. 2 shows the MPC formulation procedure:

$$
\begin{aligned}
\min_{Y,U} \quad & (R_s - Y)^T Q_y (R_s - Y) + {U_c}^T Q_u U_c \\
\text{s.t.} \quad & Y = Px(t) + QU, \\
& \underline{U_c} \le U_c \le \overline{U_c}, \\
& Y \ge \underline{Y}, \\
& R_s^T = [1 \quad 1 \quad \dots \quad 1] r(ki)
\end{aligned} \tag{2}
$$

Where, $U = \begin{bmatrix} U_d & U_c \end{bmatrix}$; $P = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \vdots \\ CA^{N_p} \end{bmatrix}$;

$$Q = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2B & CAB & CB & \dots & 0 \\ \vdots & & & & \\ CA^{N_p-1}B & CA^{N_p-2}B & CA^{N_p-3}B & \dots & CA^{N_p-N_c}B \end{bmatrix}$$

with N_p the prediction horizon, N_c the control horizon, $A \in \mathbb{R}^{n_x \times n_x}$ the state matrix of state-space model, $B \in \mathbb{R}^{n_x \times n_u}$, the input-to-state matrix of state-space model, $C \in \mathbb{R}^{n_y \times n_x}$, the state-to-output matrix of state-space model, $\underline{U_c}$ and $\overline{U_c}$ the operational limits on the inputs, $R_s \in \mathbb{R}^{N_p \times 1}$, data vector that contains the set-point information, $r(ki) \in \mathbb{R}^{N_p \times N-P}$ the set-point depth of each St_i and J_i, $Q_y \in \mathbb{R}^{n_y \times n_y} \geq 0$ and $Q_u \in \mathbb{R}^{n_u \times n_u} \geq 0$ two diagonal weighting matrices of input and output, respectively, $U_d \in \mathbb{R}^{2N_c \times 1}$ the disturbance input vector such as precipitation and tide data, $Y \in \mathbb{R}^{N_p \times 1}$ the output vector, and $U_c \in \mathbb{R}^{N_c \times 1}$ the control vector.

The objective of MPC in both sites is to not only minimize the flooding, but also maintain a desired water level at each storage unit before releasing into the receiving environment. In site 1, the goal is to control the flooding in both St_i and J_i. We first specify a set-point depth value for each storage node, then we use the least squares method to calculate the difference between set-point values and current water levels of storage nodes. After that, we use linear programming method to minimize these difference, and thus minimize the flood volumes. We repeat the same procedure in site 2, except the objective is only to manage the flooding of St_i, which means the output vector $Y = \begin{bmatrix} St_i\ depth \end{bmatrix}$ at site 2.

IV. Experiment Setup

We now describe implementation of MPC on two stormwater sites . Recall that we are only using the SWMM models as representations of the ground truth for the systems. Our MPC methodology and implementation does not depend on the knowledge of SWMM in any manner.

A. Stormwater sites description

1) Site 1 - Norfolk, Virginia - Hague model: The Hague neighborhood is a subsection of the Norfolk city and its SWMM model was presented in [8]. This model consists of 2 subcatchments, and 2 rain gages provide precipitation data for subcatchments, respectively. Rainfall-runoff drains into two storage units, and outflow from each storage unit is controlled by a valve. The valves of the storage units meet at junction node J_1 and flow through a junction node J_2, before leaving the system through the outfall.

2) Site 2 - Ann Arbor model: We use a calibrated SMWW model from a stormwater system in Ann Arbor, Michigan, to test the scalability of our method. This model is adopted from [16], it is composed of 19 subcatchments, 11 storage nodes, ranging in volume from 370 to 32,000 m^3, 11 junction node, and four rain gages. No tide level is present in this model.

B. Simulating storm surge events

To simulate stormwater events, we rely on the use of the US National Oceanic and Atmospheric Administration (NOAA) database [17]. The US NOAA database allows us to specify the intensity and duration of the simulated storm event. Each storm event in this paper is sampled at a 6-min resolution and serves as the rainfall time series input for the SWMM models.

In order to create an extreme storm event, and to investigate the effectiveness of MPC on flood mitigation, we selecte a 50-year 12-hour rainfall event(6.76 in) [18], which means this event lasts 12 hour and happens once every 50 years. The drainage through the outfall is also influenced by the tide level of this site, which is the observations from the Sewells Point tide gauging station operated by NOAA [19].

For site 2, we select a storm event of 10-year 12-hour rainfall event, which has an average cumulative rainfall of 3.46(in) in Southeast Michigan.

C. System identification procedure

In the system identification process, Eq. 3 is learned to estimated both two models, except there is no tide input in the Ann Arbor model.

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{3}$$

where,
$y = \begin{bmatrix} St_i\ depth \\ J_i\ depth \end{bmatrix}$, $u = \begin{bmatrix} u_d \\ u_c \end{bmatrix}$, $u_d = \begin{bmatrix} Rainfall \\ Tide \end{bmatrix}$,
$u_c = \begin{bmatrix} Valve\ openings \end{bmatrix}$

1) Site 1 - Norfolk, Virginia - Hague model: In this model, input data includes: (i) rainfall data, provided by each rain gage G_i, (ii) tidal level data, collected from the Sewells Point tide gauging station, and (iii) valve positions of each valve R_i. The output data is the depth values of storage units, St_i.

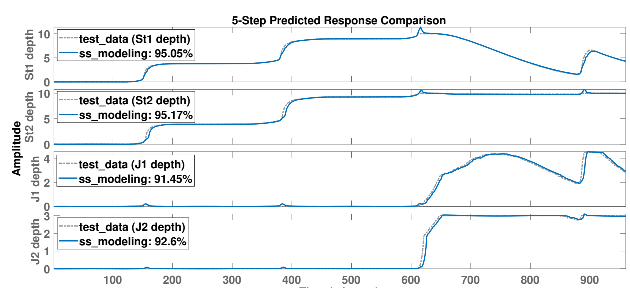

Fig. 3. Predicted system response against the original measurement data in the abstract Hague model. (prediction horizon: 5 steps)

We split the data into training and testing sets: the training set is composed of 13-day, 6-min sampling time, (3120 samples) data, and the testing set is composed of 4-day, 6-min sampling time, (960 samples) data. We implement N4SID subspace algorithm on frequency-domain data [20] with MOESP weighting algorithm [21], and focus on minimizing the prediction error between measured and predicted outputs. The identified state-space model had 5 orders and 5

TABLE I
PREDICTED SYSTEM RESPONSE AGAINST THE ORIGINAL MEASUREMENT DATA IN ANN ARBOR MODEL. (PREDICTION HORIZON: 5 STEPS)

Nodes	Prediction
St_1	91.99%
St_2	83.11%
St_3	98.08%
St_4	98.28%
St_5	83.33%
St_6	98.28%
St_7	95.92%
St_8	94.88%
St_9	90.50%
St_{10}	97.70%
St_{11}	96.35%

states. Prediction results are shown in Fig. 3, which indicate that the identified model has the ability to accurately predict the system dynamics at least 5 steps ahead.

2) Site 2 - Ann Arbor model: The training set is composed of 10-day, 6-min sampling time, (2400 samples) data, and the testing set is composed of 4-day, 6-min sampling time, (960 samples) data. The estimated state-space model has 12 orders in site 2, and it is able to precisely estimate the system behaviors. Prediction results are shown in Table I.

V. DATA-DRIVEN MPC EVALUATION

We have evaluated and compared the effectiveness of both RBC strategies and MPC in flood management.

A. Site 1 - Norfolk, Virginia - Hague model

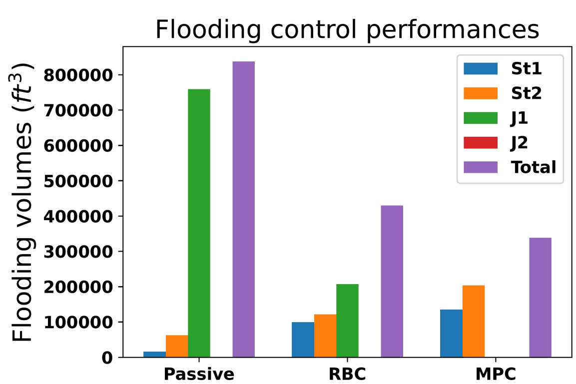

Fig. 4. Simulation results of localized flooding volume at each node and total flooding volume. Noted that flooding has never occurred at J_2.

Results of flooding volumes at different nodes and total volumes across different control strategies are shown in Fig. 4. MPC is the most effective approach to mitigate flooding, which reduces total flooding volume around 60% of passive control, and 21% of RBC.

In addition, we have compared the computational cost of our approach to a physics based MPC approach presented in [6]. Details are shown in Table II. Both approaches are implemented on the same SWMM model with the same 24-hr storm event duration. However, The wall-clock time of our proposed MPC is 500 times faster than the MPC

TABLE II
MPC COMPUTATIONAL COST COMPARE BETWEEN PHYSICS-BASED MODELING AND DATA-DRIVEN MODELING

Modeling	**Time step**	**Prediction horizon**	**CPU cores**	**wall-clock time**
Physics	15-min	1-hr (4-step)	8	214.7-min
Data-driven	6-min	30-min (5-step)	6	**0.4-min**

TABLE III
TOTAL FLOODING VOLUMES (ft^3) UNDER DIFFERENT CONTROL STRATEGIES

	MPC	**Passive**	**Bang-bang**	**Linear**	**Step-wise**
Full	**42837.9**	536693.2	228496.4	330526.7	369069.8
Best	**42028.1**	536693.2	227054.3	292649.4	305121.7

based on physics-based modeling approaches, with fewer CPU cores. One of the advantages of data-driven modeling is its computational effectiveness because it only relies on the input-output relationship to form the model without complex physical parameters or governing equations involved.

B. Site 2 - Ann Arbor model

We evaluate the performance of flood management across different control strategies with different configurations: fully controlled by 11 valves (full) and configurations of best performance (best). The results are shown in Fig. 5, with details shown in Table III. Specifically, MPC reduces total flooding volume around 92% compared to passive control, 81% of bang-bang control, 85% of step-wise control, and 86% of linear control policy.

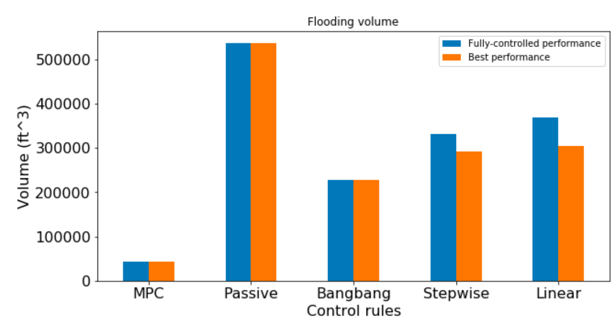

Fig. 5. Flooding management performance under different control strategies. MPC reduced most flooding volume among all RTC.

To further evaluate the effectiveness of MPC, we adopted the evaluation metrics from [16], see Eq. 4. The performance is evaluated by combining the volume of flooding along with the overflow ($Q_{i,outflow} = 15ft^3/s$) at each storage node across the duration of an entire storm event.

$$P = \sum_{nodes} \sum_{step} Q_{i,fl}(t) + \alpha \cdot max(Q_{i,out}(t) - Q^*_{i,max}, 0) \quad (4)$$

Where, α, is a weighting parameter that can be tuned to reflect the relative importance of each objective (localized flooding vs. downstream erosion, e.g.). In this evaluation, since we focus on flooding control, α is set to be 0.1. $Q_{i,flood}(t) \in \mathbb{R} \geq 0$ is the flooding rate of each storage node at time t, $Q_{i,outflow}(t) \in \mathbb{R} \geq 0$ is the outflow rate.

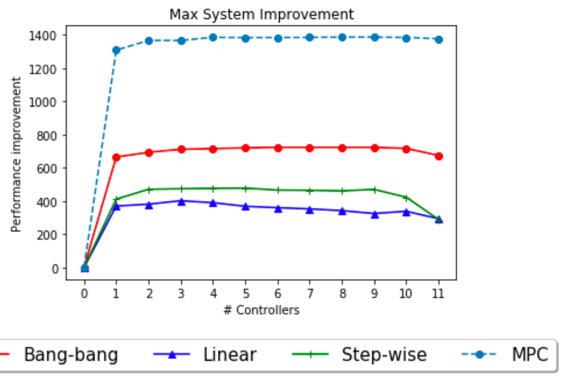

Fig. 6. Performance of different real-time control strategies in Ann Arbor model. MPC had the best performance among all control strategies.

TABLE IV
FLOOD MANAGEMENT PERFORMANCE OF PASSIVE AND MPC ON DIFFERENT INTENSITY OF STORM EVENTS

Control	Storm event	Rain depth (in)	Flood volume (ft^3)
Passvie	10 yr, 12 hr	3.2	536693.2
MPC	100 yr, 12 hr	5.1	519096.7

The performances P for both MPC and RBC strategies are evaluated using a 10-year, 12-hr storm. In addition, we use the same storm event to evaluate the different model configurations, ranging from only one node being controlled to all 11 storage nodes being controlled in coordination. As the results show in Fig. 6, the system with 4 nodes being controlled tends to have the best performance.

Additionally, we implement MPC for different precipitation intensities to explore its max capability of flood management. As shown in Table IV, our proposed MPC has the ability to cope with a much rarer storm event, 100yr-12hr, and reach similar total flood volume as a ten times more common event, 10yr-12hr, under passive control. This result proves that MPC has the ability to overcome an extreme storm event.

VI. Conclusion

This paper presents the use of data-driven MPC for the problem of minimizing stormwater flooding. We use system identification to learn an unstructured state-space dynamical model of the system. The control problem is to manage the opening of valves that directly affect upstream and downstream flooding. We evaluate the effectiveness of MPC and RBC strategies on real-world stormwater systems in Norfolk, VA and Ann Arbor, MI, respectively. As shown in section V, MPC outperforms all other strategies for the abstract Hague model and Ann Arbor model, respectively. Therefore, our proposed data-driven state-space models can be effectively used for real-time flood mitigation for stormwater management. In the future, we plan to explore other data-driven methods of system identification as well as scale our proposed MPC flood control approach on stormwater systems with more complicated structures. Long-term storm events will be used to test our MPC system in the future.

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