Model predictive control of stormwater basins coupled with real-time data assimilation enhances flood and pollution control under uncertainty

Jeil Oh[a], Matthew Bartos[a]

[a]*Department of Civil, Architectural, and Environmental Engineering, University of Texas at Austin, Austin, 78712, TX, USA*

Abstract

Smart stormwater systems equipped with real-time controls are transforming urban drainage management by enhancing the flood control and water treatment potential of previously static infrastructure. Real-time control of detention basins, for instance, has been shown to improve contaminant removal by increasing hydraulic retention times while also reducing downstream flood risk. However, to date, few studies have explored optimal real-time control strategies for achieving both water quality and flood control targets. This study advances a new model-predictive control (MPC) algorithm for stormwater detention ponds that determines the outlet valve control schedule needed to maximize pollutant removal and minimize flooding using forecasts of the incoming pollutograph and hydrograph. We illustrate that, compared to rule-based controls, MPC more effectively prevents overflows, reduces peak discharges, improves water quality, and adapts to changing hydrologic inputs. Moreover, when paired with an online data assimilation scheme based on Extended Kalman Filtering (EKF), we find that MPC is robust to uncertainty in both pollutograph forecasts and water quality measurements. By providing an integrated control strategy that optimizes both water quality and quantity goals while remaining robust to uncertainty in hydrologic and pollutant dynamics, our study paves the way for real-world smart stormwater systems that will achieve improved flood and nonpoint source pollution management.

Keywords: Model predictive control, Real-time control, Data assimilation, Smart stormwater systems

1. Introduction

Management of nonpoint source pollutants has long been recognized as one of the most critical challenges in stormwater engineering (Harrington et al., 1985; Patterson et al., 2013; Hammer, 1992). Today, a majority of water bodies in the US are classified by the Environmental Protection Agency (EPA) as *impaired*, with the primary drivers of impairment being nonpoint source pollutants like sediments, nutrients, and sewage (U.S. Environmental Protection Agency, 2017; Rowny and Stewart, 2012). Stormwater engineers have traditionally managed these contaminants through the use of stormwater best management practices (BMPs) like detention basins, which provide temporary storage of water to reduce peak discharge rates, prevent streambed erosion, and remove contaminants through sedimentation (Li et al., 2019; Liu et al., 2014; Wilson et al., 2015). However, recent research has called into question the ability of static BMPs to adequately respond to the changing hydrologic conditions caused by climate change and urbanization (Tirpak et al., 2021; Hathaway et al., 2014). On one hand, stormwater ponds must be designed to prevent flooding during large storm events, which necessitates larger storage volumes and outlet pipes. At the same time, larger pipes lead to erosive discharges that impact aquatic habitats downstream. Moreover, given the effect of the first flush—with high levels of pollutants carried by runoff early in the event—very limited treatment can be achieved under design practices that prioritize localized flood control by maximizing conveyance (Middleton and Barrett, 2008). Balancing between conflicting water quality and flood control objectives with a single static design remains a fundamental dilemma in urban drainage engineering.

In recent years, *smart stormwater systems* have emerged as a promising new approach to urban drainage management that addresses many of the shortcomings of static BMP design. Drawing on advances in the *Internet of Things*, smart stormwater systems use distributed sensors and actuators to dynamically reconfigure stormwater infrastructure for the purposes of improved flood and pollution control (Kerkez et al., 2016; Bartos et al., 2018). Real-time control (RTC) of stormwater detention basins using actuated outlet valves, for instance, increases available storage capacity prior to storm events, thereby reducing flashy flows downstream and improving sedimentation of pollutants. Smart stormwater systems have been shown to improve pollutant removal, mitigate urban flooding, reduce combined sewer overflows, and drastically reduce the size of stormwater ponds needed to achieve desired levels of treatment and flood control performance (Muschalla et al., 2014; Wong and Kerkez, 2018; Mullapudi et al., 2017). Despite the promise for real-time controls to solve urban flooding and water quality problems, optimal control strategies for stormwater basins are as of yet poorly explored. In particular, fundamental questions remain concerning (i) how stormwater ponds should be controlled in real-time to meet both water quality and flood control objectives, and (ii) how real-time control strategies can be made robust to the uncertainty inherent in real-world rainfall and pollutant inputs.

Most research on real-time stormwater pond control has focused on water quantity targets, such minimizing overflows and floods (Wong and Kerkez, 2018), shaving hydraulic peaks (Kearney et al., 2011), or increasing hydraulic retention time (HRT) in basins (Shishegar et al., 2019a). Though many studies demonstrate that water quality can be improved by RTC, water quality is only presented as the result of the control and not as the decision variable (Carpenter et al., 2014). In a few recent studies, control strategies have explicitly included water quality as a parameter. Sharior et al. (2019) incorporate water quality into control rules for an outlet valve based on pond height and Total Suspended Solids (TSS) concentration. In this scheme, the valve remains closed until the pond water level or TSS concentration reaches an upper bound, at which time the valve is opened and the pond is drained. Akin et al. (2022) also integrate real-time turbidity data into control decisions and test their control strategy in a real-world deployment to improve the quality of effluent (Akin et al., 2022). In addition, Bowes et al. (2022) propose a deep reinforcement learning-based control strategy for flood mitigation and pollutant treatment at the system level (Bowes et al., 2022).

While previous work shows the power of RTC for improving water quality, more work is needed to achieve holistic stormwater management strategies that handle competing water quality and quantity goals under real-world uncertainty. First, more adaptive alternatives to rule-based control are required. Predetermined rule-based approaches require pre-knowledge of the system and trial-and-error tuning to set specific thresholds for control, and may underperform when novel conditions are encountered. Rule-based controls also struggle to balance between multiple competing objectives, and have few built-in capabilities for handling uncertainty. In addition, incorporation of more dynamic control actions is necessary. Prior work largely focuses on binary (on/off) control (i.e. totally opened or completely closed gates), which limits the range of possible outcomes and may even may cause oscillations in the gate position near thresholds, leading to increased operational cost and wear-and-tear (Gaborit et al., 2013). Most importantly, reactive control systems that base control actions only on current and past sensor observations must to be upgraded to incorporate predictions. Predictive control based on weather forecasts has been shown to outperform reactive control for flood attenuation because it enables current control actions to be adjusted to reflect future inputs and thus prevent stormwater ponds from overflowing (Shishegar et al., 2019b; Gaborit et al., 2016; Xu et al., 2020). However, taking into account pollutant dynamics in the control of stormwater infrastructure is a difficult task given the uncertainty in water quality predictions.

Model predictive control (MPC) provides a method to overcome the aforementioned limitations, especially under uncertainty in rainfall and pollutant forecasts. MPC is an optimization-based method that has been successfully implemented in many industries—including chemical plants, robot control, and autonomous vehicles—as an effective tool to drive future optimal control strategies from a system model and forecasts of external inputs with constraints on controls and states (Camacho and Alba, 2013). For a given forecast window, MPC uses the system's current state as the initial state and solves a finite horizon open-loop optimal control problem to determine the optimal control action at each time step. This optimization yields an optimal control sequence, and only the first control in this sequence is applied to the system (Mayne et al., 2000). This process is repeated as the prediction horizon recedes. MPC's receding horizon strategy confers on it an inherent robustness to uncertainty (De Nicolao et al., 1996; Magni and Sepulchre, 1997). Within the field of water resources engineering, MPC has been mainly applied in urban drainage systems, especially for CSO control (Cembrano et al., 2004; Ocampo-Martinez et al., 2013; Lund et al., 2018; Joseph-Duran et al., 2015; Puig et al., 2009; Sun et al., 2020). However, due to the nonlinearity of the dynamics of water quantity and quality, most studies depend on approximate linear models (Sun et al., 2020, 2021) or HRT as a surrogate for water quality (Shishegar et al., 2019b). We consider a nonlinear model predictive control (NMPC) strategy to take into account the nonlinearity of the combined hydraulic and quality models. In addition to the advantages of linear MPC, such as enabling constraints on decision variables, NMPC can compute optimal control moves under nonlinear costs and constraints.

To that end, this study develops an optimal control strategy for a stormwater basin to maximize its flood and pollution control considering the nonlinearity of water system dynamics. Control is implemented using NMPC based on a mass balance and continuously stirred tank reactor (CSTR) representation. To account for real-world uncertainty in the pollutograph forecast, an Extended Kalman Filter is implemented to estimate the contaminant concentration in the pond at each time step by assimilating simulated turbidity sensor data into the model. The proposed optimization approach offers an adaptable way to minimize floods and maximize runoff treatment without building additional infrastructure. The fundamental contributions of this paper are the following:

- We derive a new methodology for optimal control of stormwater detention ponds that explicitly incorporates water quality parameters into the control objective and strategy.
- We show that when combined with data assimilation, the control strategy remains robust to uncertainty in both the pollutograph forecasts and sensor measurements.
- We demonstrate that, as compared to rule-based control, the MPC-based control strategy is more successful at (i) preventing overflows, (ii) slowing and reducing the peak outflow, and (iii) improving water quality.

2. Material and methods

In this section, we derive, implement, and evaluate a model predictive control algorithm for improving water quality in stormwater detention basins. First, a physically-based model is derived to simulate the hydraulics and contaminant dynamics within a real-world stormwater pond. Drawing on this model, a model predictive control algorithm is developed to determine the optimal outlet valve control strategy needed to reduce downstream pollutant loads and reduce erosion at the outlet while at the same time preventing overflows within the pond. To account for uncertainty in the pollutograph forecast, the control strategy is combined with an Extended Kalman Filter, which adaptively estimates the internal contaminant concentration in the pond based on simulated turbidity sensor data. Finally, the MPC-based control strategy is evaluated against two rule-based control strategies, accounting for uncertainty in both the pollutograph forecast and the measured contaminant concentration in the pond.

2.1. Study area

Our study focuses on an urban watershed located in Ann Arbor, Michigan (Fig. 1). This watershed and its stormwater infrastructure are the subject of a long-term monitoring project (Bartos et al., 2018), and the catchment has been previously investigated in multiple studies on real-time sensing and control of urban drainage infrastructure (Wong and Kerkez, 2018; Bartos and Kerkez, 2021). The watershed is approximately 4 km^2 in area and consists of multiple stormwater basins that receive runoff from mostly urbanized, impervious sub-catchments. We concentrate specifically on the central basin, which is the largest basin in the network and the location where the two major tributaries merge.

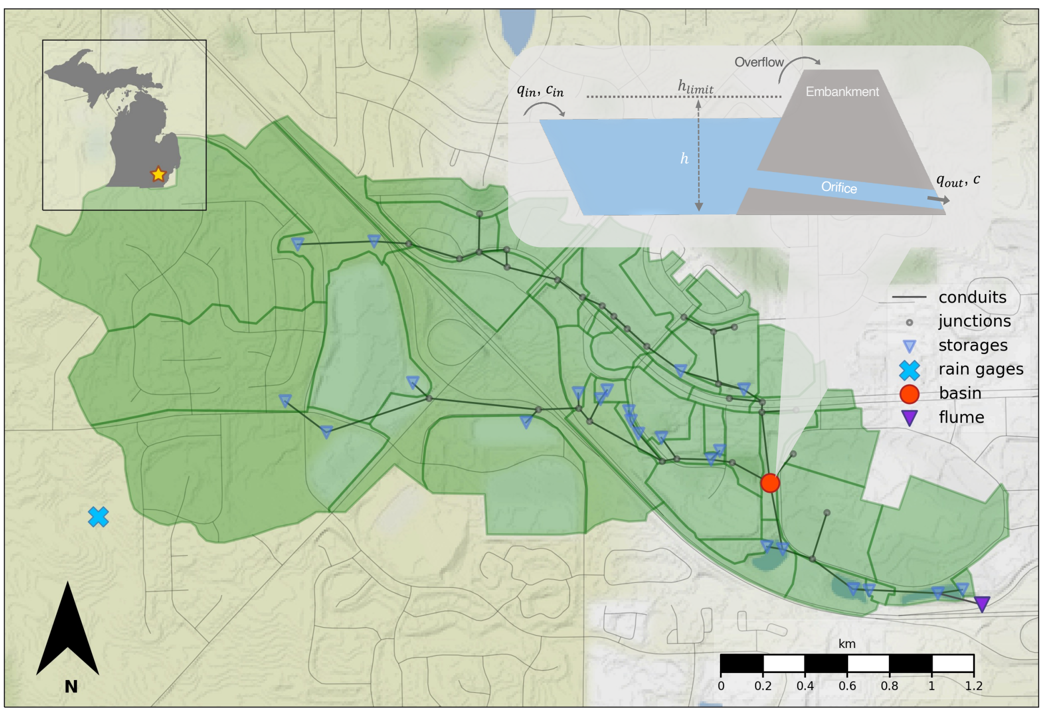


Figure 1: Overview of study area and stormwater system with subcatchments and network topology of the case study.

2.2. Hydraulic model

A hydraulic model is derived to simulate the dynamics of the water within the detention pond under free-flowing inlet conditions and orifice control at the outlet. The hydraulic model for the stormwater pond is based on a mass balance, where the change in storage is equal to the difference between inflow (q_{in}) and outflow (q_{out}). The surface area of the basin at each time step (A) is computed using the storage curve based on the basin water depth (h). It is assumed that precipitation, evaporation, and infiltration within the basin are negligible.

$$A\frac{dh}{dt} = q_{in} - q_{out} \tag{1}$$

At the outlet of the pond, a controllable orifice is installed to regulate the outflow rate, such that $q_{out} = \theta C_d A_d \sqrt{2gh}$; where θ is the orifice opening ratio (from 0 to 1), C_d is the orifice discharge coefficient, A_d is the orifice area, and g is the gravitational acceleration.

2.3. Water quality model

Drawing on the hydraulic model developed in the previous section, a coupled water quality model is derived to model contaminant fate and transport within the pond. The water quality model, formulated here for TSS, can be expressed as a pollutant mass balance considering sedimentation as a first-order reaction (Krajewski et al., 2017). It is assumed that the pond itself behaves as a CSTR, which means the effluent concentration is equal to the concentration in the pond:

$$V\frac{dC}{dt} + C\frac{dV}{dt} = C_{in}q_{in} - Cq_{out} - kCV \tag{2}$$

where C is the concentration in the effluent and in the pond, and k is the first-order rate constant. The treatment constant, k, of the stormwater pond is assumed to be 90% as specified in the Storm Water Management Guidebook of the Michigan Department of Environmental Quality Land and Water Management Division (Menerey, 1999).

The catchment's runoff quantity and TSS concentration are simulated using a pre-calibrated SWMM model with build-up and wash-off processes. The build-up of TSS on subcatchments defined as:

$$B = C_1(1 - e^{-C_2 t_d}) \tag{3}$$

where C_1 is the maximum build-up possible (mass per unit area), C_2 is the build-up rate constant, and t_d is antecedent dry days.

The subcatchment wash-off function is based on the event mean concentration (EMC):

$$W = \text{EMC} \tag{4}$$

where EMC refers to a flow-weighted average concentration during a rainfall-runoff event. The EMC is calculated by dividing the entire mass of the pollutant load by the total volume of the runoff (McCarthy et al., 2018).

Parameters for the build-up/washoff model are taken from a calibrated model described in a previous study (Wong and Kerkez, 2018; CDM Smith, 2015). Parameters for each land use are listed in Table 1.

Land uses	Build-up		Wash-off
	C_1	C_2	EMC
Commercial	12	5	25
Industrial	27	0.5	21
Residential	21	0.3	29

Table 1: Parameters for build-up and wash-off used in the SWMM model.

2.4. Model Predictive Control

Using the models described in the previous section, a model predictive control algorithm is derived to determine the optimal valve control strategy needed to minimize the total pollutant mass delivered downstream while at the same time reducing peak outflow and preventing the pond from overflowing. In general terms, given a dynamical model of the detention pond along with forecasts of the incoming hydrograph and influent concentration, the MPC algorithm determines the valve control strategy needed to optimize an objective function over a future prediction horizon. At each control time step, the optimal control action is determined over the prediction horizon (here $T = 24$ hours) based on the current state of the system and future inputs into the system. Once the optimal control action at the current time step is applied, the prediction and optimal control computations are recalculated recursively as the prediction horizon moves one step forward. The

MPC optimization problem is defined formally as follows:

$$\begin{aligned}
\min_{\mathbf{u}} \quad & \mathbf{J}(\mathbf{x}, \mathbf{u}, \mathbf{d}) \\
\text{s.t.} \quad & x(\tau+1) = f(x(\tau), u(\tau), d(\tau)) \\
& x(\tau) \in \mathcal{X}, \quad \tau = t, \ldots, t+T \\
& u(\tau) \in \mathcal{U}, \quad \tau = t, \ldots, t+T-1 \\
& x(0) = x_0
\end{aligned} \tag{5}$$

where $\mathbf{J}$ is the objective function, $x(\tau) \in \mathbb{R}^{n_x}$ is the states of the system at time step τ, which represent both the water level and TSS concentration of the pond; $\mathbf{u} \in \mathbb{R}^{n_u}$ is the vector of manipulated variables, which represent the controlled valve opening ratio; $\mathbf{d} \in \mathbb{R}^{n_d}$ is the sequence of disturbances including incoming runoff and TSS concentration of the runoff. The function $f(\cdot)$ denotes the system dynamics which are Eqs.(1) and (2). $\mathcal{X}$ and $\mathcal{U}$ are linear constraints in the states and the inputs. Here, physical constraints are imposed on both the maximum allowable water height ($0 \leq h \leq h_{\max}$), and the valve opening ratio ($0 \leq \theta \leq 1$).

In this study, we formulate the objective function to enhance the two main functions of stormwater ponds: (i) slowing and reducing stormwater discharges, and (ii) lowering pollutant loads. The objective function of the NMPC optimization is formulated as follows:

$$J = w_1 \sum_{\tau=t}^{t+T} \|q_{out}(\tau) - \overline{q}_{out})\|^2 + w_2 \sum_{\tau=t}^{t+T} \|c(\tau) q_{out}(\tau)\|^2 + w_3 \|h(\tau+T)\|^2 \tag{6}$$

where the constant parameter $\overline{q}_{out}$ is the average outflow over the prediction horizon, w_1, w_2, w_3 are tuning weights that reflect the priority among conflicting objectives and can be adjusted to meet the importance set by the system operators.

The first objective term minimizes the peak outflow rate from the pond. The peak outflow is reduced by minimizing the difference between the outflow and the average outflow over the prediction horizon. The second term minimizes the cumulative pollutant load over the horizon. The last term minimizes the water level at the end of the horizon, which provides a driving force to encourage the pond to fully drain.

2.5. Data assimilation with Extended Kalman Filtering

The MPC control strategy described in the previous section is combined with an Extended Kalman Filter to estimate the contaminant concentration within the pond and ensure that control remains robust in the face of measurement and forecast uncertainty in real-world applications. Effective control of water quality requires knowledge of the contaminant concentration within the stormwater pond. In real-world situations, however, this contaminant concentration is difficult to know with certainty. Pollutograph forecasts based on build-up and wash-off models are highly uncertain. Turbidity sensors deployed in the stormwater pond may provide real-time estimates of TSS concentration, but these estimates are based on site-specific correlations and are thus also uncertain. To overcome these problems and enable real-world implementation, we derive a state estimation scheme that uses an Extended Kalman Filter to continuously estimate the TSS concentration within the pond from noisy turbidity sensor data.

The Extended Kalman Filter (EKF) recursively estimates the TSS concentration within the pond by combining estimates from a process model together with estimates obtained from sensor data. This procedure ensures that the process model stays 'up-to-date' with the true behavior of the system. The EKF estimates the state of a nonlinear system based on a successive linearization of the system with respect to previous estimates of the state (Julier and Uhlmann, 2004; Lee and Ricker, 1994). For sensor fusion, the Extended Kalman filter has two stages: prediction and update. The system model, Eqs. (1), (2), and the observation model can be expressed as the difference equation with additive white process noise, w_k, and measurement noise, v_k:

$$x_{k+1} = f(x_k, u_k) + w_k \tag{7}$$

$$y_k = h(x_k) + v_k \tag{8}$$

The filter is initialized with the initial state $\hat{x}_{0|0} = E[x_0]$ and covariance $P_{0|0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]$. Based on the previous state estimate $\hat{x}_{k|k}$, its covariance matrix $P_{k|k}$, and the input u_k, we compute the estimate of the new state $\hat{x}_{k+1|k}$ and its covariance matrix $P_{k+1|k}$, respectively:

$$\hat{x}_{k+1|k} = f(\hat{x}_{k|k}, u_k) \tag{9}$$

$$P_{k+1|k} = F_k P_{k|k} F_k^T + Q_k \tag{10}$$

where the Jacobian matrix $F_k = \frac{\partial f}{\partial x}\big|_{\hat{x}_{k|k}, u_k}$ and Q_k is the covariance matrix of the process noise.

Once a sensor measurement is obtained, it is used to adjust the latest estimate of the system state. First, we compute the measurement residual $\tilde{y}$

and its covariance matrix S:

$$\tilde{y}_{k+1} = y_{k+1} - h(\hat{x}_{k+1|k}) \tag{11}$$
$$S_{k+1} = H_{k+1} P_{k+1|k} H_{k+1}^T + R_k \tag{12}$$

where the Jacobian matrix $H_{k+1} = \frac{\partial h}{\partial x}\Big|_{\hat{x}_{k+1|k}}$ and R_k is the covariance matrix of the measurement noise.

Then, we can compute the Kalman gain:

$$K_{k+1} = P_{k+1|k} H_{k+1}^T S_{k+1}^{-1} \tag{13}$$

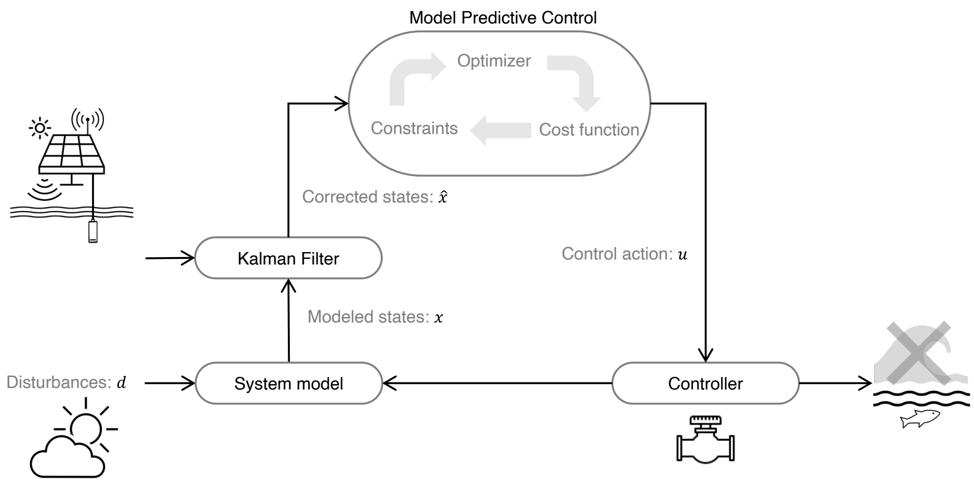
Using the Kalman gain, we can update the state estimate and its covariance matrix, respectively:

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1} \tilde{y}_{k+1} \tag{14}$$
$$P_{k+1|k+1} = [I - K_{k+1} H_{k+1}] P_{k+1|k} \tag{15}$$

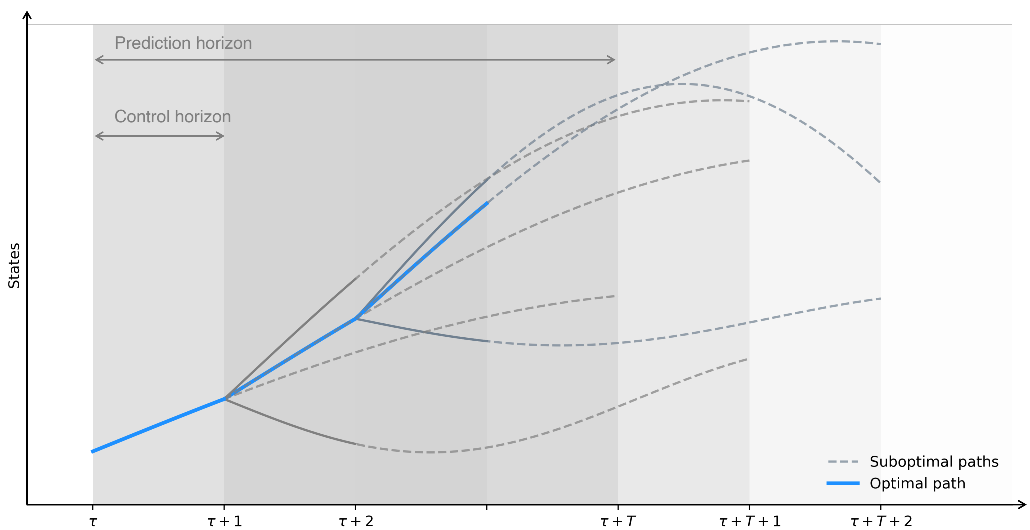
This procedure yields near-optimal estimates of the TSS concentration in the pond, both of which are subsequently used as inputs to the MPC algorithm. Together, these two steps form a combined estimation and control scheme (MPC-EKF).

2.6. Control strategies

This study compares three control strategies, including two rule-based control strategies, and a MPC-based approach. Here, we adopt two rule-based control schemes; one is outflow regulated control (RBC-Outflow) and the other is concentration based control (RBC-Conc). **RBC-Outflow** is a control algorithm that keeps the valve closed and only opens it if the water height exceeds the maximum allowable water level to prevent the pond from overflowing. While discharging water, the valve is adjusted to ensure that outflows do not exceed the desired outflow rate in order to prevent downstream erosion (Mullapudi et al., 2017). **RBC-Conc** is based on the pollutant concentration. Under this scheme, the valve is closed to retain stormwater longer and allow for additional treatment by settling if the concentration is above a threshold. Otherwise, the valve is opened, allowing the water to drain. RBC-Conc also prevents the pond from overflowing by opening the valve when the maximum depth is reached (Sharior et al., 2019; Bowes et al., 2022).



(a) MPC with data assimilation



(b) The receding horizon principle of MPC

Figure 2: The schematic of MPC with data assimilation using Kalman Filter and the receding horizon approach of MPC for optimization.

In addition to the rule-based control strategies, we also present three different model predictive control schemes. The first two MPC cases are based on different influent water quality information. **MPC-True** determines its control actions under perfect influent forecasts, i.e. the MPC controller has access to perfect information about incoming pollutant loads. In contrast, **MPC-False** simulates control actions under an inaccurate forecast, i.e. the MPC controller does not have access to perfect information about incoming pollutant loads. Finally, **MPC-EKF** determines its control actions under inaccurate influent forecasts, but continuously calibrates its process model by assimilating sensor measurements (i.e. the true behavior of the pond) at each time step using EKF. Note that MPC-EKF represents our primary result, while MPC-True and MPC-False are presented for reference. The implementation of these strategies is discussed in further detail in the following section.

2.7. Implementation and evaluation of MPC with EKF

To test the viability of MPC under real-world uncertainty, we assess its performance under three uncertainty scenarios corresponding to a perfect pollutograph forecast (MPC-True), an inaccurate pollutograph forecast (MPC-False), and an inaccurate pollutograph forecast with real-time data assimilation (MPC-EKF), as described in the previous section. Briefly, this procedure uses a pollutograph forecast based on a 'de-calibrated' model run, along with artificial sensor data based on a 'ground-truth' model run with added noise to simulate how the MPC-EKF strategy will perform in practice when the forecast model is imperfect and the sensor data is noisy.

To generate a 'de-calibrated' pollutograph forecast that either overestimates or underestimates TSS runoff concentrations from the sub-catchments, we use constant EMC values that deviate from the true dynamics. Using EMC values has two main advantages: (1) they have simple dynamics compared to build-up and wash-off models, and (2) EMC monitoring data are available for BMPs nationally (Clary et al., 2002). Then, we run the MPC for the first control time step under the 'de-calibrated' forecast. In parallel, we also simulate the system under a 'ground truth' pollutograph forecast, which yields the true behavior of the pond. The MPC-True strategy computes its control action sequence using the ground-truth pollutograph forecast. The MPC-False strategy computes its control action sequence using the de-calibrated forecast. The MPC-EKF strategy also uses the de-calibrated forecast, but continuously updates the estimated contaminant concentration in the pond from synthetic turbidity sensor data. Synthetic sensor data is generated by adding random noise to the output of this 'ground truth' simulation. Given the accuracy of commercial turbidity meters, the measurement sensor noise is assumed to be about $\pm 2\%$ of the reading (YSI Inc., 2022). This sensor data is then fused into the system using EKF, updating the model's states to rectify disparities between the forecast and reality. This procedure repeats recursively at each optimization time step based on the control action from the false forecast, and filtered measurements from the true forecast. This procedure shows how our framework performs under the uncertainty in water quality predictions (Fig. 2).

2.8. Performance evaluation metrics

The metrics used in this paper to evaluate the control performance are (a) overflow volume, (b) peak outflow rate, (c) downstream TSS load, (d) control effort, and (e) outflow flashiness. These metrics are defined mathematically in Table 2.

Performance criteria	Quantitative performance measure
Overflow	$\sum \boldsymbol{A}(h_{\max}) \cdot \max(\boldsymbol{0}, \boldsymbol{h} - \boldsymbol{h}_{\max})$
Peak outflow	$\max(\boldsymbol{q_{out}})$
Cumulative TSS load	$\sum(\boldsymbol{C} \cdot \boldsymbol{q_{out}})$
Control effort	$\sum \|\Delta\boldsymbol{\theta}\|^2$
Outflow flashiness	$\sum \|\boldsymbol{q_{out}} - \overline{\boldsymbol{q}}_{\boldsymbol{out}})\|^2$

Table 2: Performance evaluation metrics and quantitative performance measures. The italic bold font is used for vectors, scalars are denoted by lowercase italic letters.

3. Results

We evaluate the performance of the MPC algorithm in terms of preventing overflow, reducing peak outflow, and minimizing pollutant loads. Compared to conventional rule-based controls, MPC shows better performance in not only preventing the risk of overflows but also in reducing flashy outflows and pollutant loads. Crucially, we show that data fusion via EKF enables MPC to achieve these goals under measurement noise and uncertainty in influent quality predictions that are characteristic of real-world conditions.

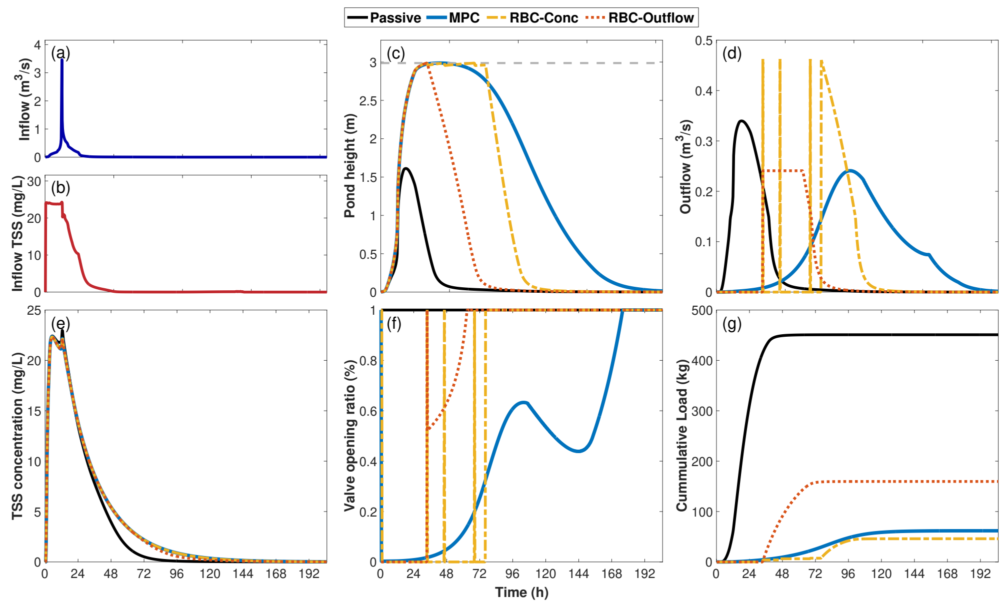


Figure 3: Pond dynamics for the passive system (black), RBC-Conc (yellow), RBC-Outflow (red), MPC (blue) cases, showing (a) inflow, (b) inflow concentration, (c) pond water height, (d) outflow, (e) TSS concentration in the pond, (f) valve opening ratio, and (g) cumulative TSS loads exiting the pond.

3.1. Control performance

Fig. 3 shows how the passive system, RBCs, and MPC respond to a 10-year, 24-hr design storm event. Compared to the passive system, all three real-time control strategies utilize the pond's capacity more effectively by allowing the pond to fill to its maximum height. However, rule-based controls struggle to reduce the outflow rate and minimize valve control effort.

These limitations are clear for the case of concentration-based control (RBC-Conc). Because the valve is opened above the concentration threshold and closed below, the valve oscillates rapdily between the closed and open positions, with the potential to cause wear-and-tear under real-world operations (Fig. 3f). Moreover, when the valve is opened at a high water level, water is released at a high flow rate—higher even than in the passive system—because the outflow rate is proportional to the water level (Fig. 3d). While RBC-Conc achieves lower TSS loads downstream compared to other control strategies, this performance depends on the concentration threshold. In this example, the threshold is set to achieve a 90% reduction in influent EMC. However, a higher threshold may not allow sufficient treatment, whereas a lower threshold may maximize treatment but at the same time increase the risk of overflow.

In the case of RBC-Outflow, water is released at a constant rate when the water level reaches a user-specified limit. As such, the high outflow rate seen in RBC-Conc is prevented. However, even in this scenario, the issue of how to set the flow rate remains an open question. For the experiment shown in Fig. 3d, the specified outflow rate is set to the same value as the maximum flow rate of MPC. If the maximum outflow rate is set to a smaller value, TSS removal may be improved due to a longer retention time. However, at the same time, this strategy prevents the pond from draining quickly, making it vulnerable to future stormwater events and flooding. As with RBC-Conc, RBC-Outflow may lead to significant flooding due to overflow of the pond.

MPC simultaneously reduces the peak flow and TSS load, while also preventing overflow. Dynamic control by MPC results in a TSS load reduction of 86.3% (from 450 kg to 50 kg) as compared to the passive system. Intuitively, MPC improves pollutant removal by releasing more flow when the pond's TSS concentration is low and decreasing the discharge when the concentration is high. Additionally, MPC shows a 30% reduction in the magnitude of peak flow from 0.34 m^3/s to 0.24 m^3/s. The outflow of stormwater volume is efficiently spread across the event duration and outside of the rainfall time window according to the dynamically controlled outlet valve, resulting in a longer detention time and further treated pollutants in the effluent.

A comparison of relative performance for each stormwater control strategy including the passive system is shown in Fig. 7a. Each control strategy is evaluated in terms of the following metrics: (1) overflow volume, (2) peak outflow rate, (3) downstream TSS load, (4) control effort, and (5) outflow flashiness. All values are calculated as a relative percentage based on the maximum value for each metric. Note that a smaller area represents better performance.

Only MPC outperforms in every aspect compared to the passive system with minimum control effort. Even though RBC-Conc shows the highest performance in TSS load reduction, this outcome comes at the cost of increasing peak outflow and control effort. On the other hand, RBC-Outflow shows better performance in peak flow and control by compensating the detention time and downstream TSS load, but performs poorly at reducing TSS load. Unlike the rule-based control strategies, MPC is able to effectively balance between multiple competing objectives.

3.2. MPC-EKF under uncertainty

To assess its robustness to uncertainty, the MPC-EKF strategy is tested under forecast and measurement uncertainty—both of which are characteristic of real-world stormwater control applications. Fig. 4 shows the performance of MPC-EKF under the uncertainty of both noisy measurements and imperfect forecasts—with influent concentration predicted as a constant value (18.8mg/L). Grey lines represent 100 trials with measurement noise. Even with poor predictions of influent TSS concentrations and the introduction of measurement noise, the performance of MPC-EKF remains robust by fusing the sensor measurements and reorganizing the control strategy at each time step.

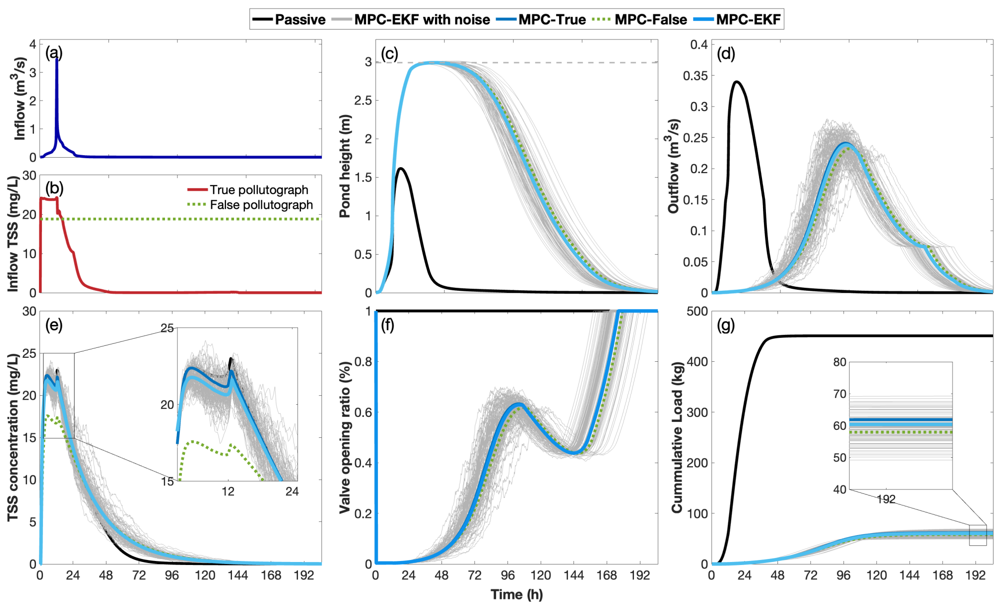


Figure 4: Pond dynamics for MPC-True based on true pollutograph (blue), MPC-False based on false pollutograph (green), MPC-EKF based on false pollutograph but fused sensor data (sky blue), and MPC-EKF with measurement noise (grey).

Although EMC is an important analytical parameter for rainfall-runoff events and can be used to assess water quality impacts from stormwater runoff, it is still based on post-hoc analysis from previous rainfall events. Therefore, there is no guarantee that the same EMC will hold true for every different rainfall event. MPC-EKF is thus tested under different EMC levels. A total of eight scenarios are considered, each with the same conditions as in the previous example (Fig. 4), but with EMCs between 25% and 200% of the previous case. As shown in Fig. 5, no matter what level of EMC is predicted, the pond can be properly controlled through real-time data assimilation. In the beginning, the valve control trajectories of each MPC-EKF are the same as the corresponding MPCs since both have the same predictions. As MPC-EKF assimilates the sensor measurements at each time step, however, the valve control trajectories evolve to be similar to the original EMC level (100%) (Fig. 5b). This result is more explicit in the case of 25% EMC. In this case, the valve opening ratio starts near the level of 0.06 resulting from the predictied concentration, but converges to the level of the 100% EMC case through online state estimation. In other words, real-time data assimilation allows for successful control even with faulty predictions, but faster convergence and better performance can be expected with more precise predictions.

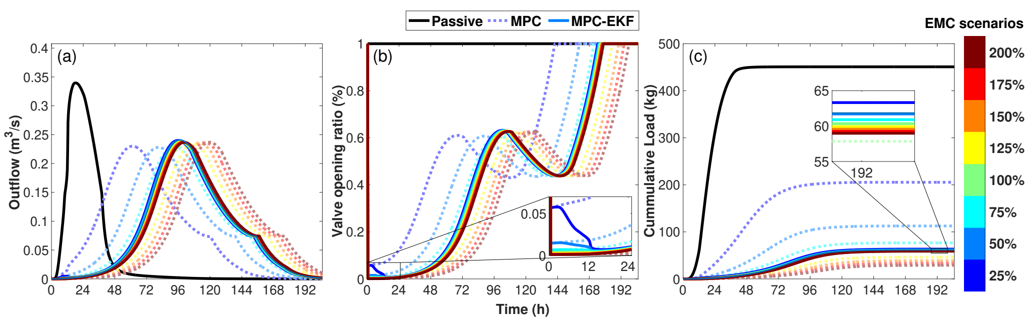


Figure 5: Pond dynamics under imperfect influent TSS concentrations as various constant EMCs scenarios. Dashed lines represent the system performance of MPC without online state estimation and solid lines show the performance of MPC-EKF. Each color corresponds to different EMC scenarios.

3.3. Performance under real-world conditions: a case study

We also apply the MPC-EKF strategy to a real-world storm event recorded between September 6 and September 7, 2021. Precipitation intensity data are collected from a weather station from Weather Underground in our study catchment. This rain event is considered (i) in order to see the behavior of the pond under real-world weather events, and (ii) to evaluate the performance under the back-to-back rainfall events.

Fig. 6 illustrates the pond dynamics for the three control scenarios from the real-world rainfall events, and Table 3 provides a summary of the perfor-

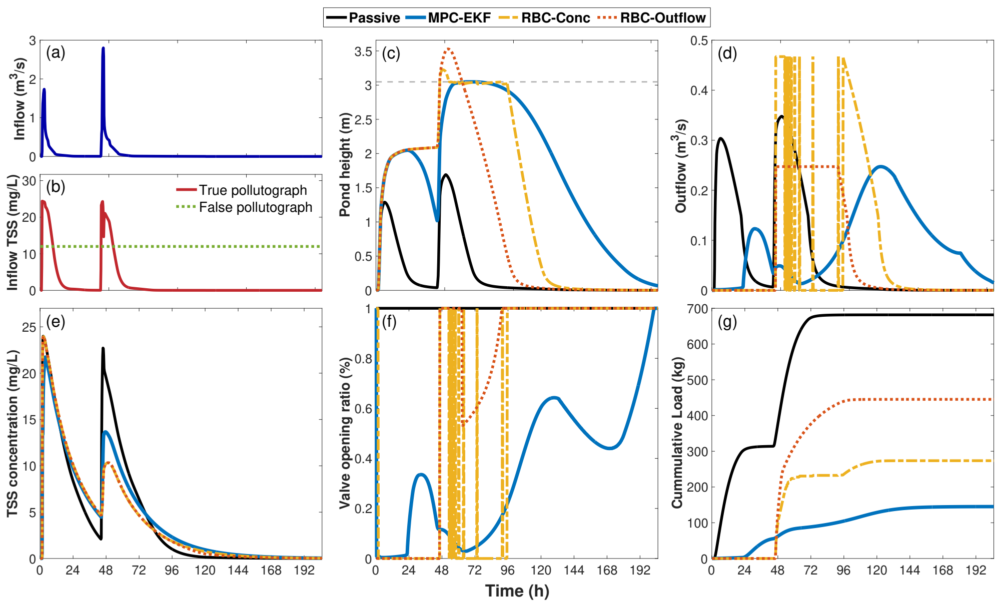


Figure 6: Pond dynamics simulated from September 6 to September 7, 2021. It is assumed that we have imperfect influent TSS concentrations as a constant EMC (12mg/L).

mance for each case. The control strategies and thresholds for RBCs are the same as the previous cases.

Compared to the 10-year, 24-hr design storm event, Fig. 6 clearly shows the drawbacks of reactive control. In the case of rule-based controls, flooding cannot be avoided because the control strategy is reactive, and the valve cannot pre-emptively release water to make room for the anticipated inflow. During the first rainfall event, both RBCs close the valve because the water level in the pond has not reached the threshold (Fig. 6c). However, once the

	Passive	MPC-EKF	RTC-Conc	RTC-Outflow
Overflow volume (m^3)	0	0	2204.2	5994.5
Peak Outflow (m^3/s)	0.35	0.25	0.47	0.25
TSS load (kg)	681.7	138.8	272.9	443.4
Control effort	0	0.99	24	1.22
Outflow flashiness	10.15	5.03	16.47	9.15

Table 3: Performance comparisons among passive, MPC-EKF, and RBC cases for overflow, peak outflow, TSS load, control effort, and outflow flashiness.

second back-to-back rainfall event starts, the water depth reaches the limit and starts to drain water. However, this control action comes too late to handle the inflow, so the water depth exceeds the limit, resulting in overflow and system failure. RBC-Outflow is much worse; a larger amount of overflow occurs because the flow rate that can be discharged is limited (Fig. 6d). Such unwanted spills and control failures also lead to poorer results than the previous design storm event in terms of TSS attenuation, because overflow allows the spill volume to remain untreated (Fig. 6g).

In contrast, MPC-EKF adapts and copes with various hydrological inputs using forecasts. Here, even though the height does not reach the maximum height during the first rainfall event, MPC-EKF decides to intentionally discharge water to secure capacity to cope with the second rainfall event. Even when discharge is unavoidable, the amount of discharge is increased when the concentration is low so that the downstream load is minimized. When the height limit is reached, the valve is slowly opened to release water while maximizing the benefits of water treatment. In this way, MPC-EKF can adaptively maximize the capacity of the pond for both flood and pollution control.

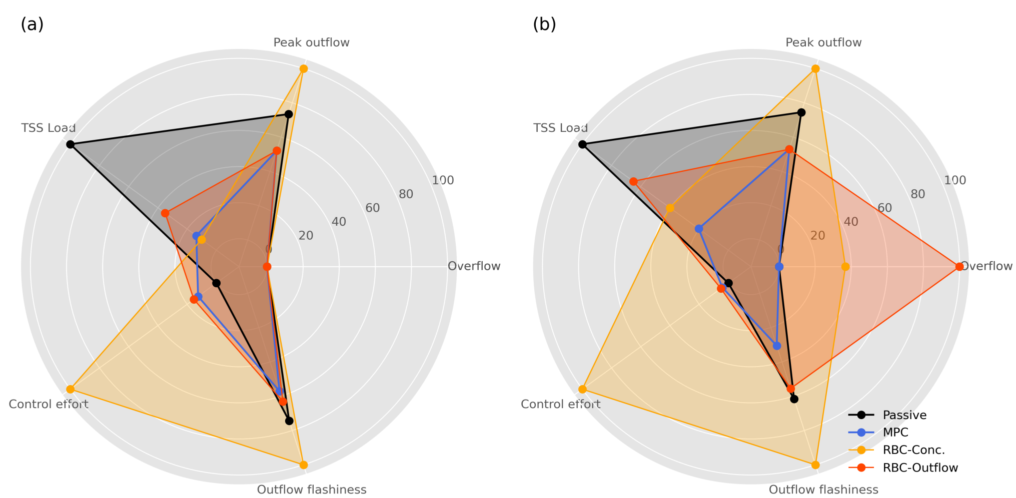


Figure 7: Relative performance (%) comparisons among passive, RBC cases, and MPC for overflow, peak outflow, TSS load, control effort, and outflow flashiness under (a) 10-year, 24-hr design storm event and (b) real-world storm event recorded between September 6 and September 7, 2021.

Fig. 7 summarizes the performance of the pond under (a) design storms and (b) a continuous real-world rainfall event. MPC shows the most balanced performance in both cases, while the RBCs result in large outflows and struggle to balance between multiple objectives. This result indicates that rule-based control is disadvantageous in cases where multiple competing benefits are required, while MPC provides a more flexible framework that can be adapted to meet multiple stormwater objectives.

4. Discussion

With climate change, urbanization, population growth, and aging infrastructure placing increasing stresses on urban water systems, deployment of real-time stormwater control systems will help to manage flooding and pollutant loads while at the same time reducing the need for new stormwater infrastructure expansion. The model predictive control and real-time data assimilation strategy developed in this study provides an adaptive measure to substantially enhance the performance of existing stormwater detention basins through real-time control retrofits. By determining the outlet valve control strategy that optimizes both water quality and quantity goals over a receding time horizon, our approach provides an explicit and adaptable framework that attenuates the total peak flow to the stream and improves water quality through sedimentation. In addition, our approach handles both sensor measurement error and pollutant forecast uncertainty by fusing real-time turbidity data into the process model, thereby demonstrating applicability to real-world stormwater systems where both model and forecast uncertainty are large.

The results of this study show that model predictive control substantially outperforms rule-based control strategies at meeting both water quality and water quantity objectives. Many existing studies focus on rule-based control (either reactive or predictive) which requires operators to establish specific desired thresholds on states such as the pond depth or contaminant concentration. The main drawbacks of RBC in real-world settings with diverse inputs are that (i) *good* thresholds are specifically tuned to one particular storm and study site and thus fail to generalize, and (ii) RBC struggles to balance between multiple competing objectives. While avoiding building complicated if-else conditions for multiple possible scenarios and objectives, our approach provides a simple control logic and explicit control goal, but at the same time remains adaptable to diverse hydrologic scenarios and regulatory goals.

This study also shows that when paired with state estimation techniques (i.e. EKF), model predictive control is robust to uncertainty in pollutant forecasts. This finding is significant, because it shows that our technique can be readily applied to real-world stormwater systems where pollutant dynamics are poorly characterized. Given the uncertainties inherent in runoff pollutant dynamics, precise forecasts of future pollutant inflows are difficult to achieve in practice. However, the findings of this study show that when combined with real-time sensor data (i.e. turbidity measurements within a stormwater pond), our MPC-EKF approach is able to achieve near-optimal flood reduction and pollutant removal benefits, even when initial pollutograph forecasts are inaccurate. This result highlights that combining real-time control with state estimation significantly enhances the viability of real-time stormwater control strategies under real-world conditions.

4.1. Towards real-world implementation

While this study shows the potential for model predictive control to improve stormwater quality, several research questions must be addressed to enable application to real-world stormwater systems. In terms of scalability, future work should consider control of stormwater facilities at the watershed scale. Optimization of control measures at the local level can yield optimal performance for individual sites, but does not guarantee maximum performance at the system level. Hence, future work should extend the framework described in this paper to the watershed scale to provide a global solution for stormwater management. Systematic control of distributed stormwater facilities can coordinate individual elements to achieve city-scale benefits. Similarly, future research should investigate how our method can be integrated into a real-time digital twin stormwater model, which can address the real-world problem of sparsely spaced sensors by estimating the states for ungauged locations, to achieve system-scale control (Bartos and Kerkez, 2021). Furthermore, investigating sensor placement algorithms may be required to decide how many sensors are necessary and where they should be positioned to enhance the performance of stormwater systems (Eulogi et al., 2021; Bartos and Kerkez, 2019).

Another natural extension of our study is the development of control strategies for the removal of different pollutants. This work focuses on TSS as the contaminant of interest. Thus, the stormwater pond is modeled as a continuously stirred tank reactor with first-order reaction kinetics. However, contaminant removal is often subject to much more complicated biological and physicochemical processes. Recent studies have developed a real-time toolkit for complex water quality modeling (Mason et al., 2021) and explored nutrient dynamics in stormwater treatment (Wijesiri et al., 2022; Mason et al., 2022). Such approaches should be incorporated into our control framework, thereby enabling enhanced attenuation and treatment of pollutants like nutrients, microbes, metals, as well as contaminants of emerging concern like microplastics. Such a contribution will enable more complete smart stormwater management by integrating the fields of control theory, hydrology, and aquatic chemistry.

In terms of reliability, uncertainty in weather forecasts should be examined in future work. While uncertainty in water quality measurements and predictions were considered, our approach assumed full knowledge of hydrologic states, mainly to maintain water mass balance to accurately compare the pollutant load and examine the effect of water quality variable for each scenario. However, in practice, weather predictions are subject to significant uncertainty, which might cause adverse impacts like overflows if not accounted for. Thus, the impacts of incomplete knowledge and the resulting compensation of the performance remain to be investigated. Future work may consider the uncertainty in weather forecasts using a robust model predictive control approach (Shang et al., 2019), or a hybrid Markov decision process (Goorden et al., 2021).

5. Conclusion

In this study, we develop a novel approach for active management of stormwater ponds that combines model predictive control with online data assimilation to mitigate flooding and improve water quality. Our approach provides an optimal valve control strategy based on nonlinear model predictive control with a receding horizon window along with an extended Kalman filtering process that enables the assimilation of real-time turbidity sensor data. The resulting model predictive control algorithm substantially outperforms existing rule-based control schemes at reducing pollutant outflows, limiting erosion, and preventing flooding. This study is the first to integrate water quality parameters explicitly into the control objective function and does not require specification of site-specific control rules or thresholds. Moreover, by integrating real-time data, our approach shows strong and stable performance even under noisy sensor measurements and imperfect knowledge of influent pollutant dynamics. These features make our methodology readily applicable to real-world stormwater ponds without the need for extensive model or rule calibration. Dynamically controlled stormwater ponds with MPC-EKF will facilitate environmental restoration, reduce urban flooding, and enable more sustainable and adaptive urban stormwater management for smarter future cities.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the University of Texas at Austin Startup Grant.

Data availability

Code and data links are available at: https://github.com/future-water/mpc-pond

References

Akin, A.A., Hathaway, J.M., Khojandi, A., 2022. Turbidity informed real-time control of a dry extended detention basin: a case study. Environmental Science: Water Research & Technology .

Bartos, M., Kerkez, B., 2019. Hydrograph peak-shaving using a graph-theoretic algorithm for placement of hydraulic control structures. Advances in Water Resources 127, 167–179.

Bartos, M., Kerkez, B., 2021. Pipedream: An interactive digital twin model for natural and urban drainage systems. Environmental Modelling & Software 144, 105120.

Bartos, M., Wong, B., Kerkez, B., 2018. Open storm: a complete framework for sensing and control of urban watersheds. Environmental Science: Water Research & Technology 4, 346–358.

Bowes, B.D., Wang, C., Ercan, M.B., Culver, T.B., Beling, P.A., Goodall, J.L., 2022. Reinforcement learning-based real-time control of coastal urban stormwater systems to mitigate flooding and improve water quality. Environmental Science: Water Research & Technology .

Camacho, E.F., Alba, C.B., 2013. Model predictive control. Springer science & business media.

Carpenter, J.F., Vallet, B., Pelletier, G., Lessard, P., Vanrolleghem, P.A., 2014. Pollutant removal efficiency of a retrofitted stormwater detention pond. Water Quality Research Journal of Canada 49, 124–134.

CDM Smith, 2015. City of ann arbor stormwater model calibration and analysis project.

Cembrano, G., Quevedo, J., Salamero, M., Puig, V., Figueras, J., Martı, J., 2004. Optimal control of urban drainage systems. a case study. Control engineering practice 12, 1–9.

Clary, J., Urbonas, B., Jones, J., Strecker, E., Quigley, M., O'Brien, J., 2002. Developing, evaluating and maintaining a standardized stormwater bmp effectiveness database. Water Science and Technology 45, 65–73.

De Nicolao, G., Magni, L., Scattolini, R., 1996. On the robustness of receding-horizon control with terminal constraints. IEEE Transactions on Automatic Control 41, 451–453.

Eulogi, M., Ostojin, S., Skipworth, P., Shucksmith, J., Schellart, A., 2021. Hydraulic optimisation of multiple flow control locations for the design of local real time control systems. Urban Water Journal 18, 91–100.

Gaborit, E., Anctil, F., Pelletier, G., Vanrolleghem, P.A., 2016. Exploring forecast-based management strategies for stormwater detention ponds. Urban Water Journal 13, 841–851.

Gaborit, E., Muschalla, D., Vallet, B., Vanrolleghem, P.A., Anctil, F., 2013. Improving the performance of stormwater detention basins by real-time control using rainfall forecasts. Urban water journal 10, 230–246.

Goorden, M.A., Larsen, K.G., Nielsen, J.E., Nielsen, T.D., Rasmussen, M.R., Srba, J., 2021. Learning safe and optimal control strategies for storm water detention ponds. IFAC-PapersOnLine 54, 13–18.

Hammer, D.A., 1992. Designing constructed wetlands systems to treat agricultural nonpoint source pollution. Ecological Engineering 1, 49–82.

Harrington, W., Krupnick, A.J., Peskin, H.M., 1985. Policies for nonpoint-source water pollution control. Journal of Soil and Water Conservation 40, 27–32.

Hathaway, J.M., Brown, R.A., Fu, J.S., Hunt, W.F., 2014. Bioretention function under climate change scenarios in north carolina, usa. Journal of Hydrology 519, 503–511.

Joseph-Duran, B., Ocampo-Martinez, C., Cembrano, G., 2015. Output-feedback control of combined sewer networks through receding horizon control with moving horizon estimation. Water Resources Research 51, 8129–8145.

Julier, S.J., Uhlmann, J.K., 2004. Unscented filtering and nonlinear estimation. Proceedings of the IEEE 92, 401–422.

Kearney, M., Dower, P.M., Cantoni, M., 2011. Model predictive control for flood mitigation: A wivenhoe dam case study, in: 2011 Australian Control Conference, IEEE. pp. 290–296.

Kerkez, B., Gruden, C., Lewis, M., Montestruque, L., Quigley, M., Wong, B., Bedig, A., Kertesz, R., Braun, T., Cadwalader, O., Poresky, A., Pak, C., 2016. Smarter Stormwater Systems. Environmental Science & Technology 50, 7267–7273.

Krajewski, A., Sikorska, A.E., Banasik, K., 2017. Modeling suspended sediment concentration in the stormwater outflow from a small detention pond. Journal of Environmental Engineering 143, 05017005.

Lee, J.H., Ricker, N.L., 1994. Extended kalman filter based nonlinear model predictive control. Industrial & Engineering Chemistry Research 33, 1530–1541.

Li, C., Peng, C., Chiang, P.C., Cai, Y., Wang, X., Yang, Z., 2019. Mechanisms and applications of green infrastructure practices for stormwater control: A review. Journal of Hydrology 568, 626–637.

Liu, W., Chen, W., Peng, C., 2014. Assessing the effectiveness of green infrastructures on urban flooding reduction: A community scale study. Ecological Modelling 291, 6–14.

Lund, N.S.V., Falk, A.K.V., Borup, M., Madsen, H., Steen Mikkelsen, P., 2018. Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management. Critical Reviews in Environmental Science and Technology 48, 279–339.

Magni, L., Sepulchre, R., 1997. Stability margins of nonlinear receding-horizon control via inverse optimality. Systems & Control Letters 32, 241–245.

Mason, B.E., Mullapudi, A., Gruden, C., Kerkez, B., 2022. Improvement of phosphorus removal in bioretention cells using real-time control. Urban Water Journal , 1–7.

Mason, B.E., Mullapudi, A., Kerkez, B., 2021. Stormreactor: An open-source python package for the integrated modeling of urban water quality and water balance. Environmental Modelling & Software 145, 105175.

Mayne, D.Q., Rawlings, J.B., Rao, C.V., Scokaert, P.O., 2000. Constrained model predictive control: Stability and optimality. Automatica 36, 789–814.

McCarthy, D.T., Zhang, K., Westerlund, C., Viklander, M., Bertrand-Krajewski, J.L., Fletcher, T.D., Deletic, A., 2018. Assessment of sampling strategies for estimation of site mean concentrations of stormwater pollutants. Water research 129, 297–304.

Menerey, B.E., 1999. Stormwater management guidebook.

Middleton, J.R., Barrett, M.E., 2008. Water quality performance of a batch-type stormwater detention basin. Water Environment Research 80, 172–178.

Mullapudi, A., Wong, B.P., Kerkez, B., 2017. Emerging investigators series: building a theory for smart stormwater systems. Environmental Science: Water Research & Technology 3, 66–77.

Muschalla, D., Vallet, B., Anctil, F., Lessard, P., Pelletier, G., Vanrolleghem, P.A., 2014. Ecohydraulic-driven real-time control of stormwater basins. Journal of hydrology 511, 82–91.

Ocampo-Martinez, C., Puig, V., Cembrano, G., Quevedo, J., 2013. Application of predictive control strategies to the management of complex networks in the urban water cycle [applications of control]. IEEE Control Systems Magazine 33, 15–41.

Patterson, J.J., Smith, C., Bellamy, J., 2013. Understanding enabling capacities for managing the 'wicked problem'of nonpoint source water pollution in catchments: A conceptual framework. Journal of environmental management 128, 441–452.

Puig, V., Cembrano, G., Romera, J., Quevedo, J., Aznar, B., Ramón, G., Cabot, J., 2009. Predictive optimal control of sewer networks using coral tool: application to riera blanca catchment in barcelona. Water Science and Technology 60, 869–878.

Rowny, J.G., Stewart, J.R., 2012. Characterization of nonpoint source microbial contamination in an urbanizing watershed serving as a municipal water supply. Water Research 46, 6143–6153.

Shang, C., Chen, W.H., Stroock, A.D., You, F., 2019. Robust model predictive control of irrigation systems with active uncertainty learning and data analytics. IEEE transactions on control systems technology 28, 1493–1504.

Sharior, S., McDonald, W., Parolari, A.J., 2019. Improved reliability of stormwater detention basin performance through water quality data-informed real-time control. Journal of Hydrology 573, 422–431.

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

Shishegar, S., Duchesne, S., Pelletier, G., 2019b. Predictive real-time control optimization of a stormwater management system, in: 2019 IEEE 15th International Conference on Control and Automation (ICCA), IEEE. pp. 628–632.

Sun, C., Romero, L., Joseph-Duran, B., Meseguer, J., Muñoz, E., Guasch, R., Martinez, M., Puig, V., Cembrano, G., 2020. Integrated pollution-based real-time control of sanitation systems. Journal of Environmental Management 269, 110798.

Sun, C., Romero, L., Joseph-Duran, B., Meseguer, J., Palma, R.G., Puentes, M.M., Puig, V., Cembrano, G., 2021. Control-oriented quality modelling approach of sewer networks. Journal of environmental management 294, 113031.

Tirpak, R.A., Hathaway, J.M., Khojandi, A., Weathers, M., Epps, T.H., 2021. Building resiliency to climate change uncertainty through bioretention design modifications. Journal of Environmental Management 287, 112300.

U.S. Environmental Protection Agency, 2017. National Water Quality Inventory: Report to Congress. Technical Report EPA 841-R-16-011.

Wijesiri, B., Liu, A., Miguntanna, N., He, B., Goonetilleke, A., 2022. Understanding nutrient dynamics for effective stormwater treatment design. Science of The Total Environment 850, 157962.

Wilson, C., Hunt, W., Winston, R., Smith, P., 2015. Comparison of runoff quality and quantity from a commercial low-impact and conventional development in raleigh, north carolina. Journal of Environmental Engineering 141, 05014005.

Wong, B., Kerkez, B., 2018. Real-time control of urban headwater catchments through linear feedback: Performance, analysis, and site selection. Water Resources Research 54, 7309–7330.

Xu, W.D., Fletcher, T.D., Burns, M.J., Cherqui, F., 2020. Real time control of rainwater harvesting systems: the benefits of increasing rainfall forecast window. Water Resources Research 56, e2020WR027856.

YSI Inc., 2022. Exo turbidity smart sensor. URL: https://www.ysi.com/product/id-599101-01/exo-turbidity-smart-sensor. accessed: 2022-09-15.