Controlling Stormwater Detention Ponds under Partial Observability

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1 Introduction

Storm water detention ponds play an important role in urban water management by collecting and conveying rainfall runoff from urban catchment areas to nearby streams. Their purpose is not only to avoid flooding but also to reduce stream erosion and degradation caused by the direct discharge of pollutants to the stream.

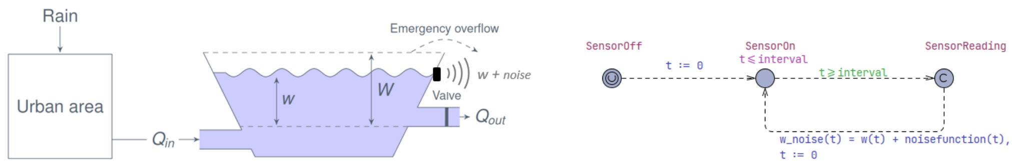
Standard solutions for managing storm water detention ponds employ static controllers to regulate the discharge of water. These types of controllers fail to exploit the full potential of the water system as demonstrated in [2], where formal methods are used to synthesize safe and optimal control strategies using Uppaal Stratego [1]. For synthesizing control strategies, [2] models the water system as a hybrid Markov decision process, based on which reinforcement learning is used to find a strategy that minimizes a cost function balancing the consequences of discharging pollutants to the stream (optimality) with the consequences of pond overflows (safety).

The control strategies synthesized in [2] rely on full observability of the system, including the water height in the pond. In real world settings, the true water height is not known and water measurements are instead based on noisy and potentially faulty sensors leading to incomplete/-partial observability. In this paper, we extend the results in [2] by modeling the storm water detention pond, including the catchment areas and weather forecasts, as a partially observable hybrid Markov decision process, where sensors and sensor noise are explicitly represented. We compare the synthesized strategies with those produced by [2] and we present preliminary analyses of how sensitive the synthesized strategies are wrt. different types of sensor noise. These analyses not only provide insight into the robustness of the control strategies, but can also be used for designing new physical sensor systems, where one typically needs to balance the cost and accuracy of the sensors being deployed.

2 Storm water detention ponds: System model

Storm water detention ponds collect rain water from urban areas, such as streets and parking lots, before discharging the water into streams. The ponds not only help ensure that the rate of water discharge do not exceed stream capacity, but by temporarily retaining water in the pond, urban water pollutants can sediment before entering the stream with possibly damaging ecological consequences. An example of such a pond is schematically illustrated in Figure 1.

For synthesizing a strategy for controlling the discharge of water (Q_{out}) from the pond and into the stream, we rely on the symbolic model checking and reinforcement learning tool UPPAAL Stratego [1]. UPPAAL Stratego provides methods for synthesizing safe and near-optimal strategies for hybrid Markov Decision Processes (MDP), including both timed automata and continuous-space MDPs. To synthesize a safe and optimal strategy, UPPAAL Stratego



(a) (b)

Figure 1: (a) Schematic illustration of a water pond. The actual water height is measured by a (noisy) sensor. (b) UPPAAL Stratego model of the sensor noise.

abstracts the MDP $\mathcal{M}$ into a 2-player timed game, based on which a most permissive strategy σ_S can be found subject to certain safety constraints. Using reinforcement learning techniques, sub-strategies of σ_S can then be generated by optimizing a domain specific optimization objective.

The main (safety) objective of the pond controller is to prevent the pond from overflowing, with adverse affects on both the surrounding environment and infrastructure. The secondary (optimization) objective is to sediment and filter out urban particles collected in the pond in order to prevent contamination of the water environment in the stream. The longer the water is retained in the pond before discharge, the higher the degree of sedimentation of water pollutants.

A detailed description of the fully observed pond model can be found in [2], expressed as a combination of differential equations and timed automata models. Below we focus on extending this model specification to allow for partial observability, in particular the use of noisy sensors for measuring the water height in the pond. The (stochastic) timed automaton *Sensor* (see Figure 1(b)) models the relationship between the actual water height w in the pond and the observed water height w_{obs}. The sensor measures the water height at discrete time intervals, which is captured by the guard $t \geq \mathit{interval}$ between the locations SensorOn and SensorReading. The dynamics of the actual water height is described by a differential equation, taking into account both rain fall and pond control settings [2].

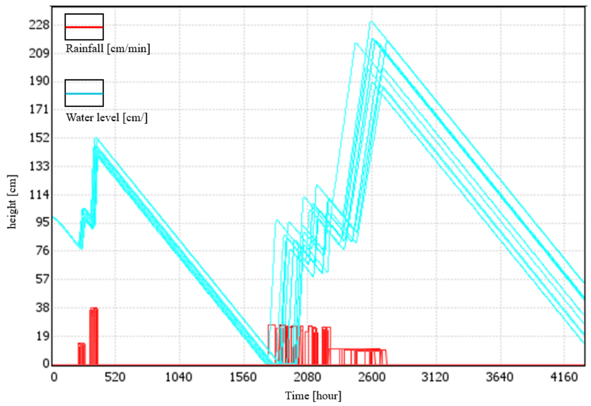
The measurement errors of the sensors can take different forms. In the preliminary analyses reported below we have experimented with an additive noise model [3], where the noise is either uniformly or Gaussian distributed:

$$w_{\text{obs}}(t) = w(t) + \mathit{noise}(t). \tag{1}$$

Specifically, for the uniform noise model, noise is assumed to follow a uniform distribution over the interval $[-\epsilon, \epsilon]$. For the Gaussian noise model, we assume a Gaussian distribution with mean 0 and standard deviation σ, i.e., $\mathit{noise} \sim \mathcal{N}(0, \sigma^2)$. A UPPAAL Stratego implementation of the noise model can be see in Figure 1(b).

3 Experimental results: use case

Figure 2(left) shows 10 simulations runs using a controller guided by a water level sensor with $\sigma = 15.0$. The figure shows the water level in the pond as a function of time. Figure 2(right) shows cost estimates for different sensor configurations expressed in terms of confidence intervals. As the noise level increases, we see that the accumulated cost also increases together with the width of the confidence intervals.



No noise
3073.72 ± 8.89
Gaussian Noise
μ=0, σ = 5.0
3189.92 ± 37
μ=0, σ = 10.0
3323.01 ± 82
μ=0, σ = 15.0
3575.39 ± 138

Figure 2: (Left) Ten simulation runs using a controller based on a $\sigma = 15.0$ water level sensor. (Right) Accumulated costs with 95% confidence intervals under different sensor noise levels.

4 Conclusions and Future Work

In this paper we have reported on preliminary results on synthesizing safe and near optimal strategies for the control of storm water detention ponds based on noise sensor measurements. We have modeled the pond (including the surrounding urban catchment area and weather forecast) using UPPAAL Stratego and we have analyzed the effect of applying different noise models on the synthesized strategies. As part of future work we will calibrate the models wrt. real-life measurements from the Vilhelmsborg Skov pond, south of Aarhus, Denmark. The model will also be extended to encompass multiple ponds and more elaborate sensor systems supporting sensors with limited memory and also allowing for a degree of edge computing. We believe that the techniques and analyses investigated in the present paper are also applicable to other domains beyond storm water detention ponds.

5 Acknowledgments

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