# Bayesian Optimization for Control of Stormwater Networks

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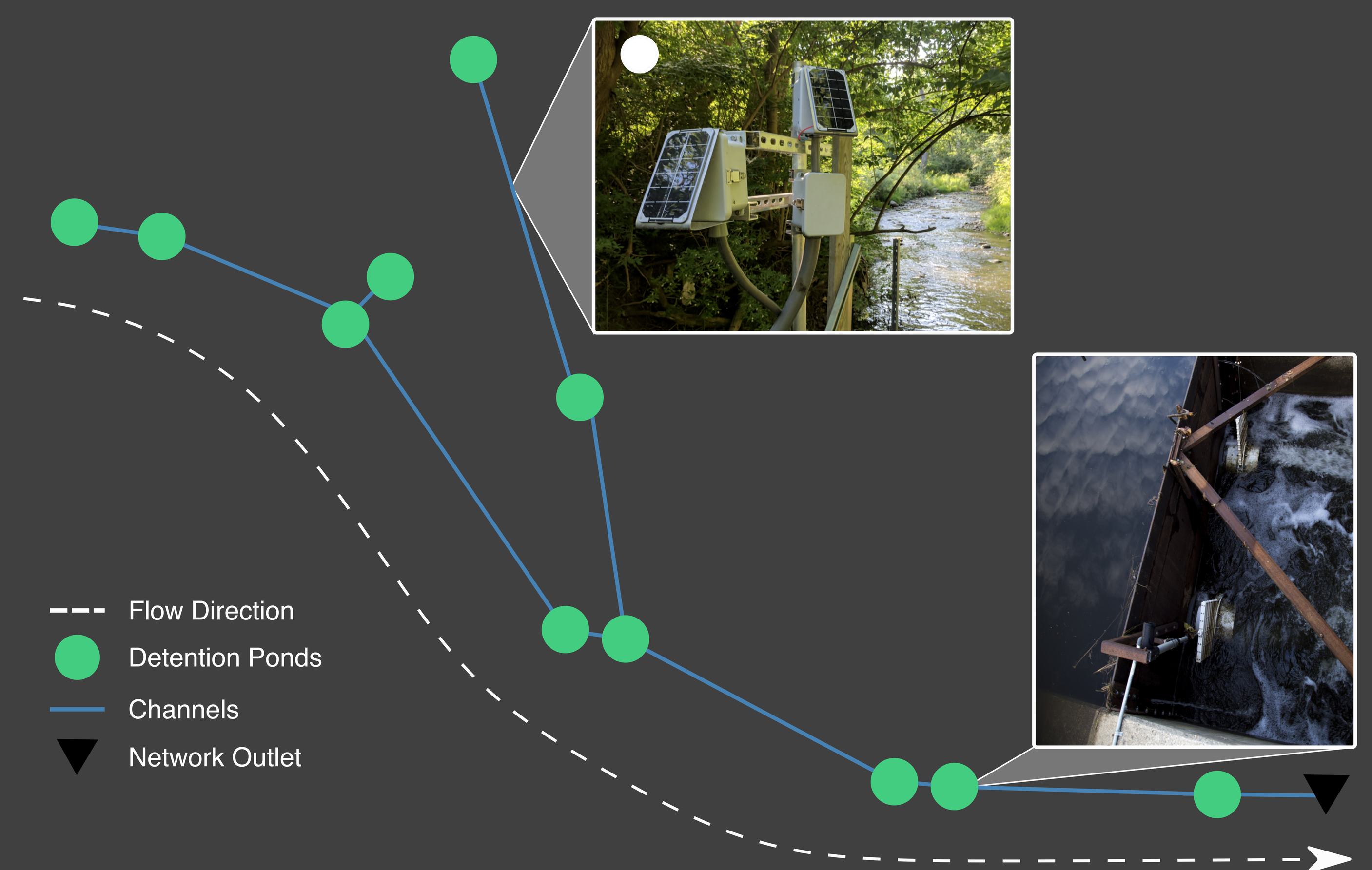
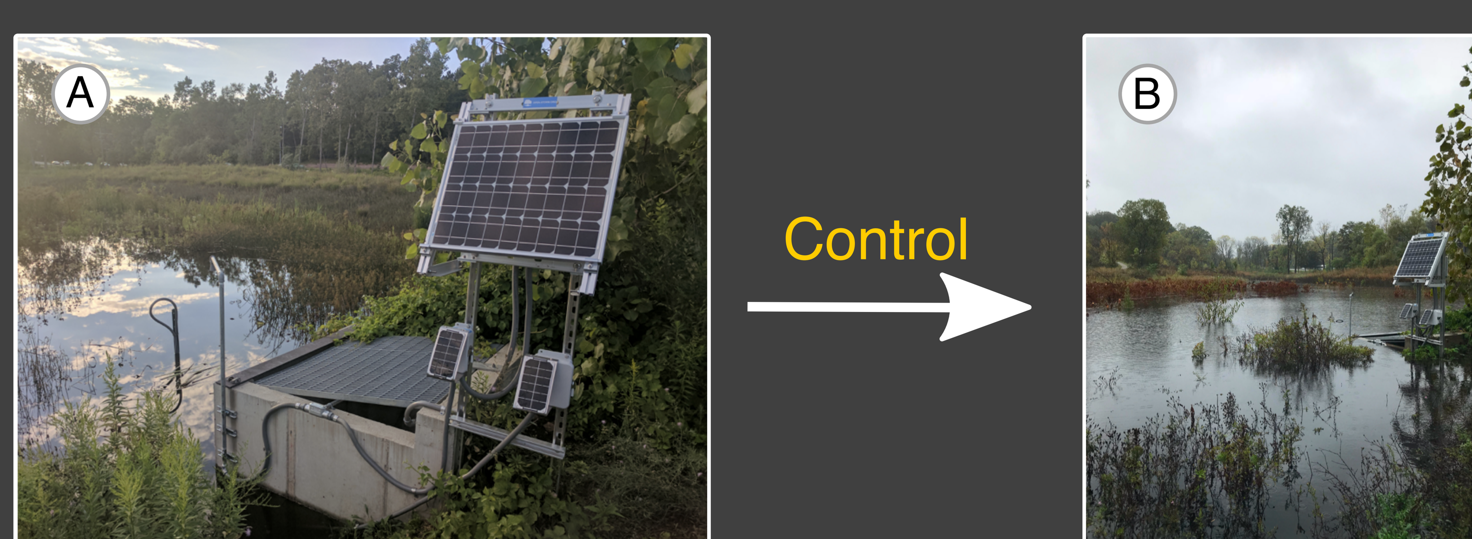
## Smarter Stormwater Networks

Unlike the current state-of-the art stormwater solutions, these "smarter" stormwater networks retrofitted with sensors and actuators have the ability monitor the state of the network in real-time and dynamically adapt their response to individual storm events.




The ability to control the response of stormwater assets during a storm event enables us to enhance the performance of the existing infrastructure by maximizing its utility (i.e. increasing the amount of stormwater capture).




By choosing to hold water in an asset (A in the above figure) by anticipating an incoming storm event, storage utilization in the asset can be maximized (B in the above figure) to achieve network scale benefits.

## Control of Stormwater Networks

Controlling stormwater networks (often with hundreds of assets) to achieve complex network-wide objectives is not straightforward, as the decision process has to account for the network topology and the cascading impacts of spatially distributed assets. In this work, we propose an automated framework based on Bayesian optimization for identifying an optimal control strategy for controlling stormwater networks and illustrate its performance on a single asset.

## Bayesian Optimization

Bayesian optimization identifies an optimal solution by interacting with the system and learning a surrogate objective function. This approach uses gaussian processes (GP) for modelling the surrogate.

$$f(\mathbf{x}) \sim \mathcal{GP}\left(m(\mathbf{x}), k\left(\mathbf{x}, \mathbf{x}'\right)\right)$$

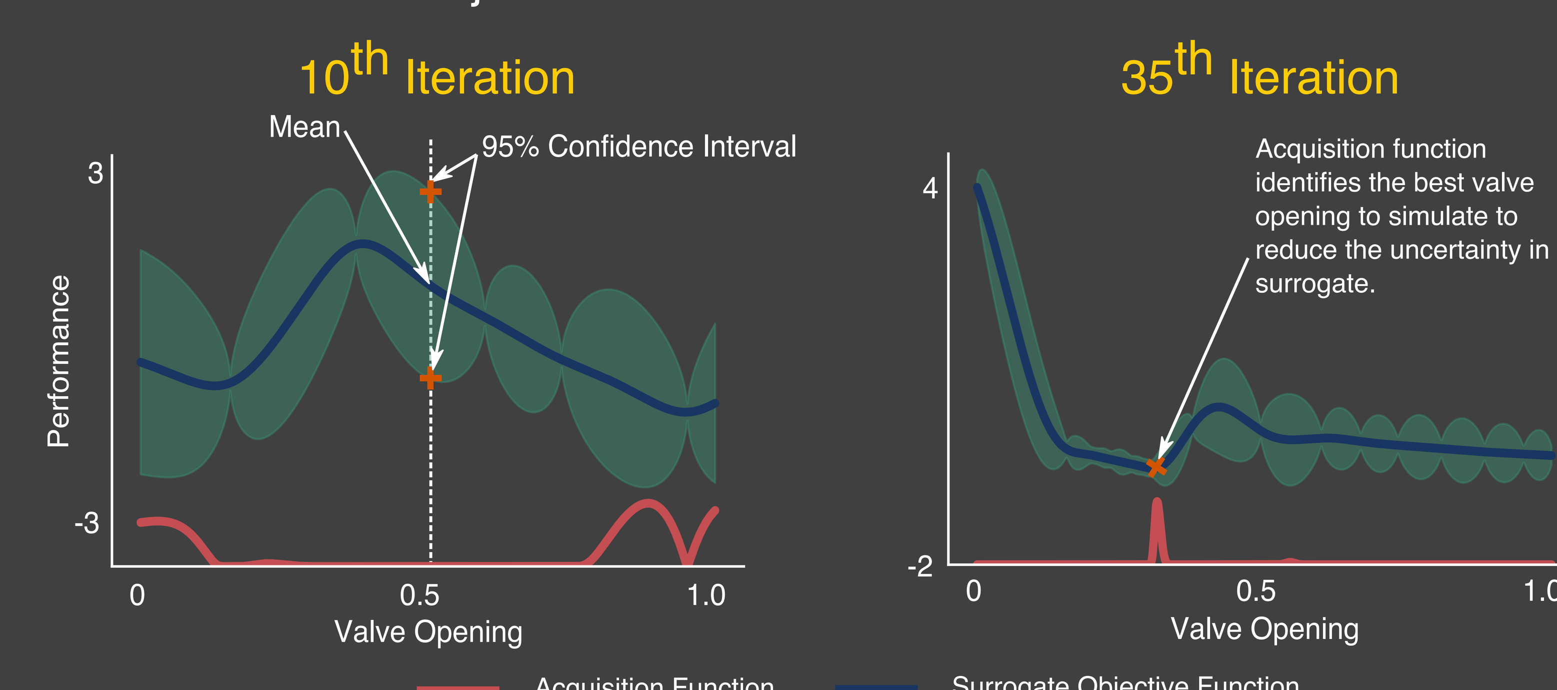
Rather than just predicting an estimate, GP learns to predict the uncertainty associated with these predicted estimates. These uncertainty estimates are then leveraged by the Bayesian optimizer using an acquisition function to effectively learn the surrogate. The algorithm for Bayesian optimization is presented below.

**Algorithm** Bayesian Optimization

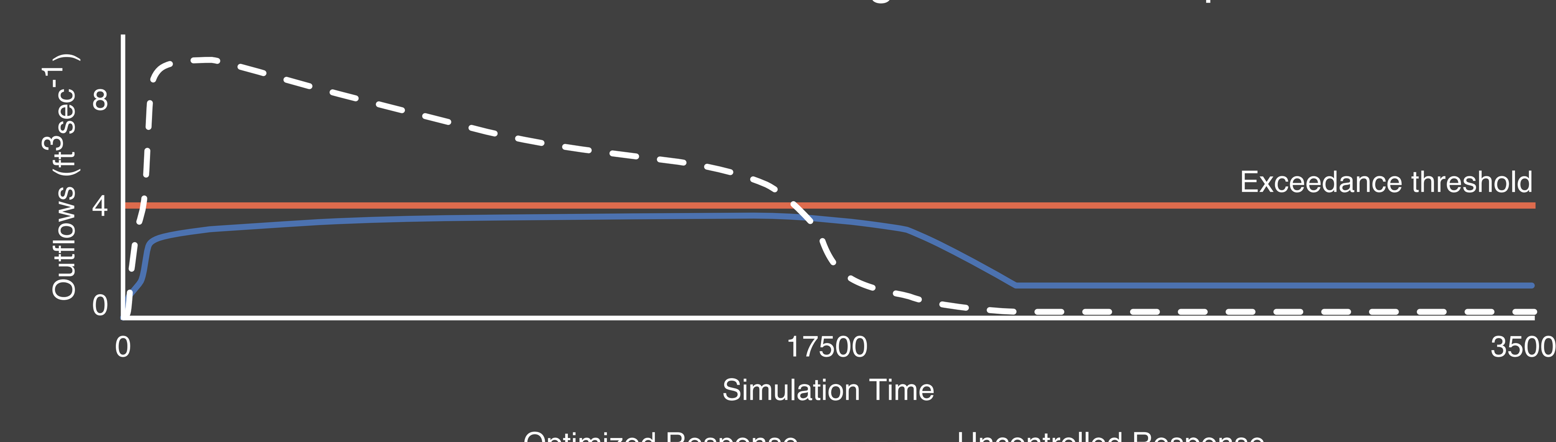
```
1: for t=1,2,3, ... do
2:     Identify x_t by optimizing acquisition function (u) over the
       solution space x_t = argmax_x u(x|D_{1:t-1})
3:     Sample the objective function, y_t = f(x_t) + ε
4:     Augment the data D_{1:t} = {D_{1:t-1}, (x_t, y_t)} and update GP
5: end for
```

## Controlling a Stormwater Asset

In this scenario, we control a single stormwater asset to maintain its outflows for an incoming storm event below an exceedance threshold by regulating the valve at its outlet between 0.0 (closed) to 1.0 (completely open). Bayesian optimization is used to identify the optimal valve position that achieves this objective.

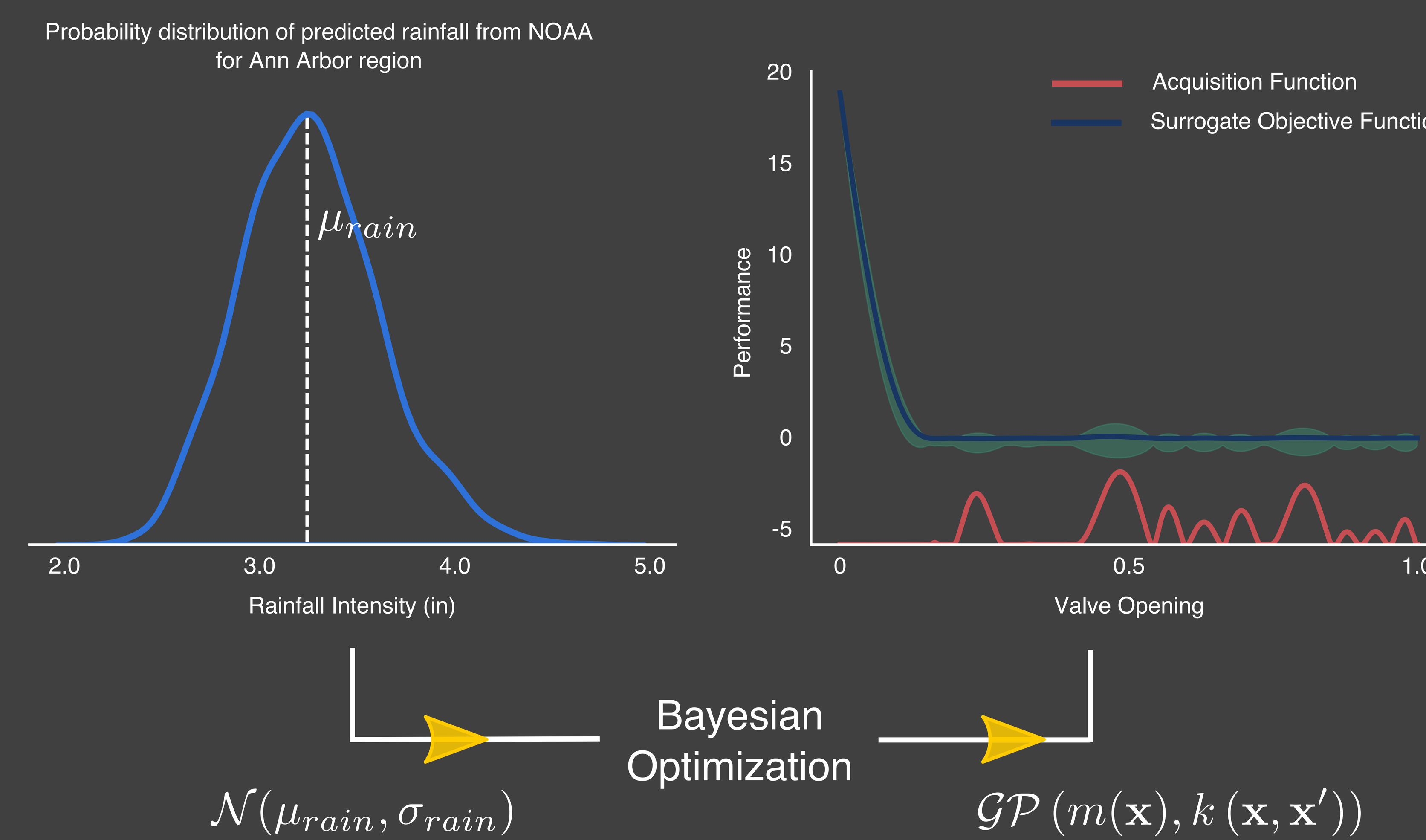



Bayesian optimization identifies the optimal valve position by simulating (a physical model) the response of the stormwater network to various valve positions. Initially, the optimizer has a high uncertainty about the surrogate and, as the number of simulations increase, this uncertainty reduces (illustrated in the above figure). The optimal solution for this scenario identified from the above surrogate function is presented below.




## Quantifying Rainfall Uncertainty

Storm events experienced by the stormwater networks are often highly stochastic. This introduces a high degree of uncertainty that has to be quantified to identify a control decision that is reasonably robust to this stochasticity. Bayesian optimization quantifies this uncertainty (i.e. input uncertainty) by simulating an ensemble of possible storm events.




## Conclusion

Bayesian optimization is a automated data-driven approach for identifying a control strategy that achieves the desired response from the stormwater network. This approach can be used to quantify the uncertainty associated with the storm events and identify robust control strategies. The ability of the Bayesian optimization to identify an optimal control strategy that satisfies the requirement is dependent on the formulation of the objective.

## Acknowledgements

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## References

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