**Bayesian Optimization for the control of storm water networks.**

**Main Contributions**

1. Bayesian optimization strategy/Bandit algorithm for the controlling storm water network.
2. Novel objective function formulation that effectively captures the shape and magnitude of the hydrograph.
3. Off the shelf control methodology for shaping the response of the storm water network.

**Figures:**

1. Bayesian Optimization Overview
2. Single ponds + Convergence property
3. Bayesian Optimization controlling a small water network - 2 ponds
   1. This shows where we cannot use simple reward function, specifically Euclidian distance.
   2. Show how DTW is better.
4. Larger example (AA)
   1. Problem with DTW in scaling
   2. Equivalent control with Bayesian Optimization as RL

**Organization:**

1. ***Introduction:***

For control objectives like peak shaving, you might not need dynamic control. We have observed in RL paper that if you want to control the water shed to maintain the flows below a threshold, you can just the valve setting to a constant value.

1. ***Bayesian Optimization***

This led us to the hypothesis, can you use Bayesian optimization to do this. Because,

* 1. Its gives you uncertainty bounds on the performance
  2. More effective than GA
  3. It is useful for systems where you cannot afford to run too may simulations, as it is the case larger networks such as Detroit.

This has been successfully used in the facebook and uber for lots of stuff.

1. ***Objective function:***

While running them on various scenarios, we noticed that performance of the Bayesian Optimization is depended on the how good the objective function is. Because it only uses this valve as a basis for optimization.

We found that when we use Euclidian distance, there are multiple scenarios where good solutions are skipped because they are shifted in time or slight elongated. Hence, we need a metric that is robust to these issues.

This is where DTW is useful. This is a metric used in the measuring the similarity in large time series, specifically in speech and music retrieval.

1. ***Synthetic Network:***

We show the sensitivity of the solution to the objective function. Specifically compare Euclidian distance and DTW. This shows that you need DTW for which scenarios and when ED is sufficient and where it is not.

We can use parallel network for this.

1. ***Ann Arbor Network:***

This shows, how the solution from Bayesian Optimization compares to the other control approach, specifically RL. It is faster and, in this case, more effective. But the problem is that it won’t scale to storm event, like RL did. You would have to re-run the optimization for each rain event

1. ***Discussion points:***

This is a good control approach, but it assumes that we have access to the model that effectively represents the storm water network.

This cannot use sensor reading to make decision like RL or other control approaches.

Ideally, you would use this prime your system and then use other control approaches to fine tune the performance of the network during the storm event.

You would can use this method directly of the shelf, unlike the other methods you don’t have worry about finetuning a lot of hyper paraments. All you need a storm water model and a good objective function.

Though DTW is a good objective function, it is not differentiable hence it might be limited in the use for other methods. But there is an alternative formulation of DTW that you can use for approaches that need to differentiation.