Executive Summary

The *Open-Storm Detroit Dynamics* team is a utility-university partnership, bringing together the University of Michigan and the Great Lakes Water Authority (GLWA). Our goal is to enable the next generation of smart storm and sewer collection systems, which dynamically reconfigure themselves to changing inputs. This will be achieved by ingesting real-time sensor feeds to control distributed assets, such as valves, pumps, and gates. Without requiring new construction, this will dynamically 'redesign' existing infrastructure in real-time to reduce CSOs and improve flows going to the treatment plant. We have a passion for open source and we freely share all of our findings and algorithms on open-storm.org, with the goal of allowing others to apply them to systems across the country.

For the LIFT Challenge our team is submitting a novel real-time, market-based control approach to dynamically reconfigure inline storage dams and CSO basins. The algorithm is applied to GLWA's system and accompanied with a real-time dashboard and decision support tool for operators. Given the novel nature of our control algorithms, our LIFT challenge relies on simulations. However, GLWA will be implementing these control tools this year.

Application of our real-time control approach offers the potential to significantly improve the existing GLWA wastewater and CSO management system by reducing both the occurrence of CSOs and peak flows going to the treatment facility. These benefits can be achieved without new construction, rather by relying entirely on existing infrastructure, which promises to free up significant capital savings for future investments.

We show that significant CSO reductions can be achieved – as much 100 million gallons per storm event – by using a cloud-hosted, market-based control algorithm that requires only measurements of water levels and flows at few locations in the sewer system. Unlike other control approaches, our approach can be implemented with just a few sensors and can be modeled using existing SWMM models. This makes it possible for just about any community to adopt real-time control without expert knowledge. To communicate control recommendations from our controller to the stormwater operator, the team designed a decision support dashboard. Our dashboard is web-based and not only gives real-time readouts of measurements from across the stormwater system, it also gives control recommendations to the user as determined by the market-based control algorithm.

All algorithms, cloud infrastructure, and control models will be shared open source and available to the public free of cost under the GNU License. Supporting documentation and the interactive dashboard can be found at www.github.com/klab/LIFT.

Thank you for your time and consideration of our submission.

Regards,

Gregory Ewing

Team Lead, Open-Storm Detroit Dynamics

gregjewi@umich.edu

Team: Open-Storm Detroit Dynamics

Name	Title	Organization	Email
Wendy Barrott	Program Director R&D	GLWA	Wendy.Barrott@glwater.org
Christopher Nastally	Manager – CSO Control	GLWA	Christopher.Nastally@glwater.org
Branko Kerkez	Assistant Professor	University of Michigan	bkerkez@umich.edu
Sara Troutman	Student, Ph.D. Candidate	University of Michigan	stroutm@umich.edu
Abhiram Mullapudi	Student, Ph.D. Candidate	University of Michigan	abhiramm@umich.edu
Gregory Ewing[1]	Research Scientist	University of Michigan	gregjewi@umich.edu

No changes to the team have occurred during the duration of the Challenge.

We are a utility-university partnership, with the participating utility being the Great Lakes Water Authority (GLWA) and the partner the University of Michigan. Our group brings together years of experience in the operation and management of city-wide stormwater infrastructure and novel research in real-time control of intelligent water systems. Our research group is internationally recognized in the area of smart water systems and, specifically, for the real-time control of separated stormwater systems (tinyurl.com/bkerkez). For this LIFT challenge we bring this expertise and tool to bear on GLWA's combined sewer systems.

Problem Statement

The Great Lakes Water Authority (GLWA) is a regional water and sewer authority that services nearly 40 percent of the water customers in Michigan, including the City of Detroit and its surrounding suburbs (approximately 3.9 million customers). Due to many stressors, such as aging infrastructure, changing populations, and rapid development in the service area, the sewer and stormwater conveyance system is strained well beyond its design. As a result, the combined sewer system experiences frequent and unpermitted combined sewer overflows to the Detroit River. To combat these persistent untreated outflows, and with a vision to create more controlled inflows into the wastewater treatment facility, GLWA launched a project in late 2017 with the University of Michigan's Real-Time Water Systems Lab to investigate the application of real-time sensing and dynamic control on existing infrastructure. The desired outcomes of dynamic, real-time control are to:

- Maximize current storage utilization by dynamically controlling pumps, valves, and gates
- Reduce Combined Sewer Overflows
- Equalize flows to the Wastewater Treatment Plant

Since construction of new CSO basins and green infrastructure may cost over a billion dollars, real-time control presents a great opportunity to stretch the performance of existing assets.

Considerations

GLWA requires that any solution respect the current maximum operating levels in the sewer and pump system to avoid basement flooding. Further, the solution should not replace the human interface of stormwater operators in the management of the system, but rather provide control recommendations in real-time to achieve the stated outcomes.

Characterization of Intelligent Water System

Currently, GLWA has many of the components in their system to realize dynamic control of their assets. GLWA leadership is committed to intelligent, data-driven solutions and supports infrastructure towards this end. GLWA operates a robust measurement and transmission infrastructure, with minutely and sub-minutely data for flow, level, and precipitation measurements from across the conveyance network and is available in real-time via a web interface. Further, GLWA currently operates their gates, pumps, and valves

[1] Team Lead, Point of Contact

from a centralized command and control center. GLWA has also recently upgraded their in-line storage dams (ISDs) to be remotely operable. Integrating the present – and near-present – capabilities, GLWA is well-positioned to incorporate dynamic control recommendations into their operations. This presents great opportunity to integrate existing sensor and control assets into a truly holistic smart water system, whose *intelligence* will be based on data and control algorithms developed in this LIFT project.

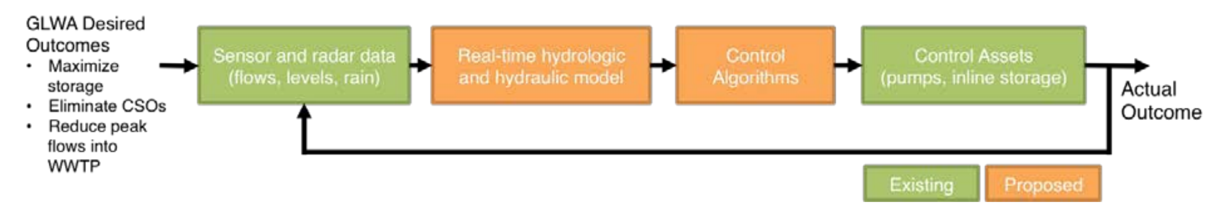
Figure 1. Detroit sewer network is equipped with inflatable in-line storage dams (green circles) that can use storage capacity in the pipes to regulate wet-weather flows.

Plan

Due to the size and complexity of the GLWA collection and interceptor system, a single region and subset of the larger system was chosen as a pilot project. The focus area was selected for the number and size of its controllable assets, including pump stations, in-line storage dams, and a 120-million-gallon retention basin complex. This area has many outfalls that are unpermitted to release untreated CSOs.

Our solution is iterative, using the feedback that exists in the conveyance system to inform control decisions to continually nudge results to a desired state. This idea of feedback is a critical component to the control algorithms that we apply. First, we develop the real-time control approaches in a model space, and then move to the application of these approaches using real-time data across the GLWA footprint. The novelty of our project is the application within a real system in real-time of these control approaches that were designed in the model space specifically for use in stormwater conveyance networks.

We begin by developing control formulations based on historical events. Using these historical events in a local model space with "full knowledge" allows us to develop insights into the dynamics of the system and help inform how to apply our control algorithms on the utility's assets. This process will be followed systematically for all potential control locations within the study area.



Visual summary of proposed approach: The *feedback* control approach continually compares the desired state of the collection system to the actual state using a suite of real-time models that ingest streaming sensor data. A series of control algorithms then makes concrete recommendations that can be used to manually or autonomously control the system to ensure that the system performs optimally.

Concurrently, we develop a web application that ingests data in real-time from GLWA's system. These data will include flow and level measurements, but also states of control points like pump status and percent open for gates and valves. With these data, we run models and analyses that incorporate the insight gained from our control studies of historical storms. The results of these models are control recommendations for operators that can be incorporated into their operations during wet weather and dewatering events.

Implementation

Data and Real-Time QA/QC

Real-time control decisions must be made on the best possible knowledge and sensor data from the GLWA system. Throughout this project, we have used historical rainfall data, flow and level sensor readings from meters across the network. These data are inherently noisy, as is the case with many real-world sensor feeds. To clean the data up for our dashboard and control algorithms, we have developed a real-time quality control (QA/QC) algorithm, which uses modern signal processing and outlier statistics to smooth noisy sensor feeds. Figure 2 shows an example of the QA/QC algorithm applied to a real sensor feed, highlighting the drastic difference between raw and filtered sensor data.

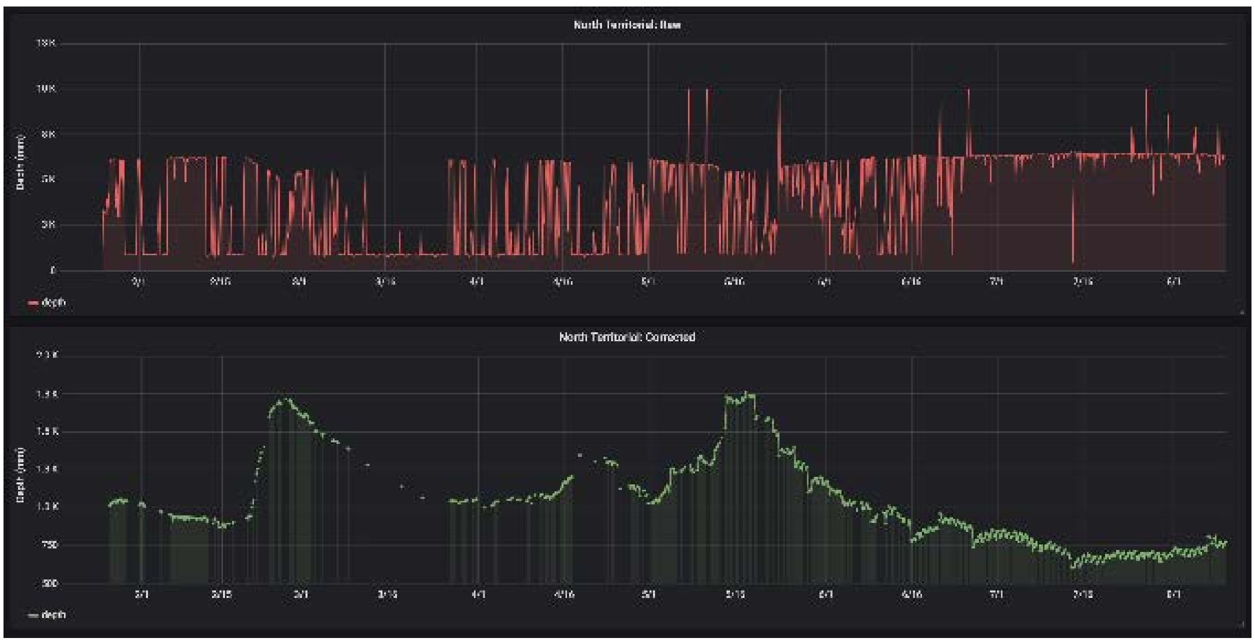


Figure 2. Open-storm's filtering tool extracting corrected flow measurements from noisy sensor readings.

Analysis and Interpretation

This section describes the theory, implementation of this real-time control algorithm, and results in support of our system objectives.

Team members at the University of Michigan have developed a control algorithm for the use in stormwater systems influenced by work done in the field of structural engineering[2]. Essentially market-based control utilizes the concept of a virtual, idealized marketplace where a commodity – or commodities – is bought and sold by system agents to inform control decisions across a stormwater system.

The control algorithm employed here is market-based control, in which decisions are made in a virtual marketplace where a commodity is bought and sold by system agents. In this case, the commodity is volumetric capacity within the sewer system, the buyers of this commodity are upstream storage agents (e.g., pump stations, storage basins, inflatable storage dams), and the sellers are downstream points within the sewer network. The downstream point has an operator-defined setpoint to achieve; the downstream capacity is determined as the current volume above or below this setpoint. Price of the commodity fluctuates through time and is based **only** on the current state of the system: how much capacity is available at an instance and how greatly it is demanded by upstream agents. Water is moved throughout the system via "purchases" of capacity by upstream agents, which dictate how much stored water each upstream agent can release to the downstream agents. Because the system considered here is so large and spatially distributed, we divide the system into sub-markets, each with its own price of capacity, one seller/downstream agent, and potentially several buyers/upstream agents. In this way, each sub-market acts independently of all other markets. An example of a market can be seen to the left. See Appendix for the mathematical formulation of the theory and pseudocode on the implementation of our control during a simulation.

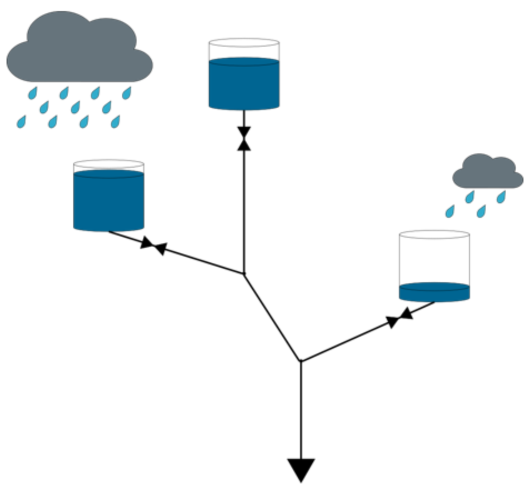


Figure 3. A market is comprised of upstream buyers and a downstream seller. Buyers have storage volume and a control element, allowing them to regulate their outflow. At each timestep, discharge from each buyer is determined within the market.

We use market-based control with an EPA SWMM input file representing a portion of the GLWA combined sewer collection system. Control actions are made during a simulation via PySWMM, a Python language SWMM wrapper. The choice of assets to control was made in consultation with the stormwater operations team and through inspection of the gates, pumps, and valves within the physical system and the model. Simplifications were made in the model when the level of detail was not necessary for control. For each controllable asset there is an associated upstream element – which is either a storage element or a conduit. Upstream storage elements in the model usually represent inline structures or retention basins with significant storage volumes (millions of gallons of storage). In current studies downstream elements are conduits that are either at the confluence of upstream controllable flows or shortly thereafter.

[2] Lynch, J.P., Law, K. Market-based control of linear structural systems. *Earthquake Engineering and Structural Dynamics.* (2002) 31:10. 1855-1877.

Results presented in this submission were generated using parameter values identified using a genetic algorithm on a single storm of one-inch depth and 16-hour duration. Performance of the algorithm for each event was compared with a baseline value, calculated by running the simulation with an unaltered version of the SWMM input file developed by the Authority and its consulting engineers. This model reflects current operating procedure and can be considered current "best practice" by GLWA. During calibration we achieved a 77% reduction in combined sewer overflows using our market-based control algorithm and the best parameters found from the genetic algorithm. These parameters were then used to make control decisions during simulation of 4 new events, whose outputs are discussed here. A summary of results can be found in the table below.

Event Date	Event Type	Event Duration [hours]	Precipitation Depth [inches]	Total CSO Volume [Millions of Gallons]		
				Baseline	With Control	Reduction (%)
4-May-17	**Calibration**	16	1	130	30	77%
11-May-18	**Evaluation**	96	2.8	1666	1906	-14%
2-Jun-18	**Evaluation**	1	0.7	47	46	2%
31-Jul-18	**Evaluation**	8	1.3	1318	1274	3%
31-May-15	**Evaluation**	28	2.0	842	735	13%

Table 1. Comparison of outflow volumes for storm events using the current operation procedure, baseline, versus applying the team's dynamic control algorithm.

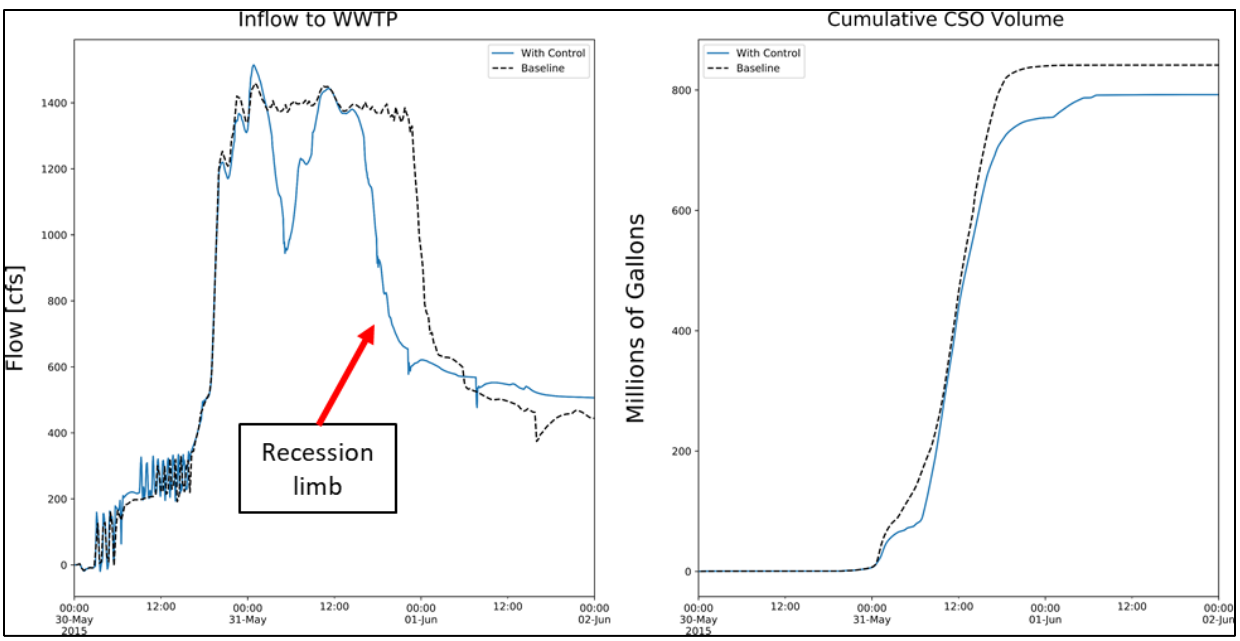


Figure 4. Timeseries results for the May 30, 2015 storm event. Dynamic control resulted in a reduction of ~100 Million Gallons of combined sewer overflow as compared to baseline.

Figure 4 demonstrates the impact of our control approach on the inflow to the wastewater treatment plant and the volume of combined sewer overflows over the course of a storm event compared to the baseline scenario. During this event, there is a reduction in CSO volume of approximately 100 million gallons, around 13% compared to the baseline case. Additionally, focusing on the inflow to the treatment plant, the recession limb trails off more quickly and maintains a constant value of approximately 500 cfs at the end of the storm event, indicating that we can quickly stabilize to an inflow setpoint. Similar results were observed for other storm events, with the exception of the 11-May-18 storm event listed in Table 1. We hypothesize that this is due to the identification of parameters via a genetic algorithm trained on a single-storm event of certain characteristics. Note that the duration and total precipitation depth for these events are very different and thus the parameters identified by the genetic algorithm do not likely to be optimal for rain events of this nature. See the Appendix for performance of the control algorithm for the 11-May-18 remaining storm events.

Moreover these results were achieved simply by using the storage capacity already present in the system, meaning no major capital investments from the stormwater authority would be required to have a significant impact on both CSO volume reduction and equalization of inflows to the treatment plant.

Communication and Use

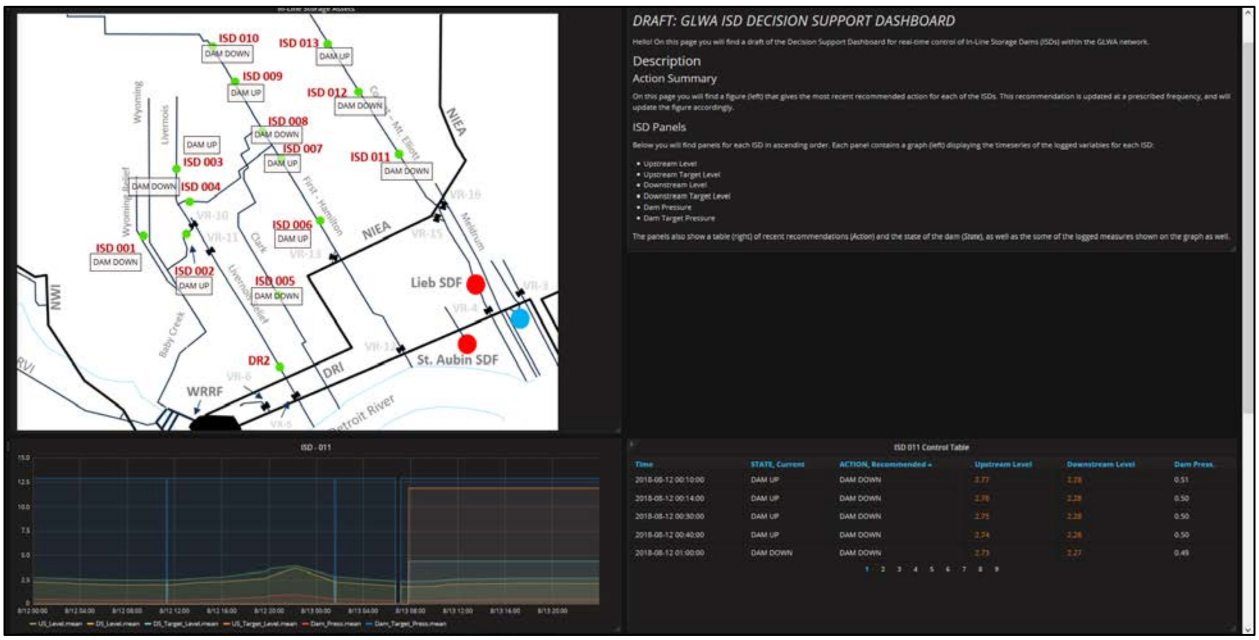


Figure 5. GLWA in-line storage dam dashboard provides real-time recommendation of control actions.

This control algorithm is light-weight enough to be implemented in real-time, providing operators with recommendations of system-wide control actions during the course of a storm event. This is presented in a decision support dashboard shown in Figure 5 and can be interactively experienced in the link in the GitHub Repository. In conversation with GLWA stormwater operators, they indicated a need for a dashboard that provides easy visualization of control recommendations in the context of the overall system. Hence we developed our dashboard with the ability to assimilate data from a variety of sources, including real-time sensor feeds and simulation model outputs along with the recommendations from our control algorithm.

The Solution

The main takeaways from this work include the following.

- With minimal capital investment, our team has been able to demonstrate a reduction in CSO volumes by increasing the utilization of sewer storage capacity informed by our control algorithm. Over time, this could result in significant financial savings through avoided unpermitted discharges and the associated monetary penalties.

- The utility will be able to avoid considerable financial investment in construction of new storage infrastructure (e.g., CSO basins, tunnel networks) by better utilizing existing storage capacity.
- Our dashboard provides a one-stop visualization tool, displaying control recommendations in the context of the real-time state of the sewer network.
- All of the tools developed in this work are available to the public and thus can be adopted by other utilities with minimal experience in real-time control as our control approach only requires sensor feeds of system states and remotely-controllable storage assets. The tools provided make this accessible to anyone.
- The procedure we implemented was relatively simple (a single storm event to train the genetic algorithm) and illustrates even greater potential by increasing the number of training storms to parameterize the control algorithm. This can be further extended to incorporate water quality objectives (e.g., pollutant loads influent to the treatment plant).

APPENDIX

Market-Based Control Theory

Each buyer/upstream agent has a particular wealth with which to "purchase" capacity which is based on its current volume normalized to its maximum volume capacity; thus, if a storage agent is close to using all of its available volume, it possesses more wealth to "purchase" more capacity from downstream, that is release more water to avoid flooding locally. The wealth for upstream agent i is computed via

$$P_{wealth,i} = uparam_i \times V_{up,i}$$

where $uparam_i$ is a weighting parameter describing priority toward mitigating local upstream flooding, $V_{up,i}$ is the normalized volume of upstream agent i.

The sum of wealth within each sub-market is computed via

$$G_{wealth} = P_{wealth} * groupM^T$$

where *groupM* is a binary matrix denoting the sub-market that each upstream agent belongs to.

Each seller/downstream agent determines the cost it places on the commodity based on its current volume about the desired setpoint. The cost of downstream agent j is computed as

$$D_{cost,j} = \left(V_{down,j} - setpt_j\right) \times dparam_j$$

where $V_{down,j}$ is the normalized volume of downstream agent j, $setpt_j$ is the operator-defined normalized volumetric setpoint of agent j, and *dparam* is a weighting parameter describing priority toward achieving the setpoint.

The price of volumetric capacity within sub-market j is computed via

$$p_j = \frac{G_{wealth,j} + D_{cost,j}}{n_j + 1}$$

where n_j is the number of buyers/upstream agents in sub-market j. It is crucial to note that this results in a pareto optimal distribution of capacity for each sub-market, meaning that any benefit to one agent would result in a detriment of other agents.

The purchasing power of each upstream agent i in sub-market j is computed via

$$P_{power,i} = \max\left(P_{wealth,i} - p_j, 0\right)$$

The available volumetric capacity in sub-market j is computed as

$$V_{available,j} = (1 - V_{down,j}) \times V_{max,j}$$

where $V_{max,j}$ is the maximum possible volume at downstream agent j.

Thus, the available flow capacity in sub-market j is

$$Q_{available,j} = \frac{V_{available,j}}{T}$$

where T is the length of time between control actions. (In most cases, the simulation timestep is used.)

Finally, the flow to be released from buyer/upstream agent *i* is computed as

$$Q_{goal,i} = Q_{available,j} \times P_{power,i}$$

<u>Implementation</u>

The following pseudocode outlines the steps to implement our controller with a simulation:

```
# Pseudo Code for Implementation of Market-Based Control

      Initialize Downstream and Upstream Variables
      Initialize Operator Defined Parameters Uparam, Dparam, and Setpoints

      For each timestep in simulation:
            Measure and Normalize Volume of Each Asset

            Calculate Wealth for each Upstream Asset (Pwealth)
            Calculate Total Wealth for each group (Gwealth)

            Calculate Downstream Cost for each market (Dcost)

            Solve for Pareto Price for each Group/Market (P)

            Calculate Purchasing Power of Each Upstream Point (Ppower)

            Calculate Available Volume Downstream (Qavailable)
            Calculate Flow goal for each Control Asset (Qgoal)

            Given Qgoal, find target setting for each control point
            Set control asset to target setting
```

Performance of 11-May-18 Storm Event