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Turbidity Informed Real-Time Control of a Dry Extended Detention Basin: A Case Study

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ABSTRACT

Dry extended detention basins are static stormwater infrastructure, unable to adapt to shifts in water quality caused by urbanization in their source watersheds or long-term changes in rainfall patterns. As a potential solution to these problems, this research investigated the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor with the goal of more consistently meeting water quality objectives. When rainfall was detected, the basin's valve would close and detain all water until either a maximum allowable detention time was reached, or turbidity values fell below a predetermined threshold. This method was shown to produce highly variable detention times after rainfall events which highlights the advantages an adaptive system has over a traditional static system or one which uses predetermined detention times to meet *water quality objectives. To investigate if turbidity-based controls could operate effectively in the future if the turbidity sensor were to be removed, an advantage for economical resource allocation, several modeling approaches were evaluated to estimate the detention time of the system based on observed basin stage and precipitation data. Two of these models, a logistic regression model and a Long Short-Term Memory (LSTM) model, proved accurate in estimating the necessary detention time of the system. With this system's ability to meet water quality objectives more consistently when real-time water quality data were integrated into the decision framework, this study lays the groundwork for other applications where improved water quality is the goal.*

WATER IMPACT STATEMENT

This study explores the design, application, and analysis of a dry extended detention basin equipped with real-time control (RTC) which integrates real-time water quality data to achieve objectives more consistently. The results highlight how existing technology combined with innovative methodologies can be deployed to improve the quality of effluent from stormwater infrastructure and contribute to the ecological health of receiving waterbodies.

INTRODUCTION

The majority of stormwater infrastructure is static, unable to adapt to land use conversion and a changing climate. This includes stormwater control measures such as dry extended detention basins. Dry extended detention basins are storage facilities which are installed within drainage networks to temporarily store stormwater runoff.[1,2] Their primary purpose is to provide channel and flood protection for the receiving stream or river by attenuating flows to match pre-development conditions.[1,2]

Real-Time Control. Recent studies have begun to investigate the impact of retrofitting such systems with real-time control (RTC) by installing a controllable valve on the outlet to increase or change detention times during rainfall events.[3-9] Typically, these detention times are predetermined, and thus don't account for changing conditions between and during rainfall events such as shifts in water quality. Thus, they are still treated as a "static solution to a dynamic problem".[10] Although there is evidence that utilizing real-time water quality data in the control decisions of stormwater infrastructure is beneficial for meeting water quality objectives, there are limited case studies in literature.[11] Of those studies that have been performed, the primary focus was using this technology to prevent combined sewer overflows or to redirect water to wastewater treatment plants.[12] Additional studies are needed to investigate the impact and efficiency of adaptable stormwater systems which integrate real-time water quality data into the decision framework for stormwater controls.

Impact and Measurement of Turbidity. Turbidity, which can cause water bodies to appear murky or cloudy, is an optical quality of water and a measurement of the scattering and absorption of light. It is elevated primarily by the presence of suspended sediment but also by organic matter and microscopic organisms.[13] Turbidity is considered an indicator of the ecological health of a water body.[13] For example, elevated turbidity levels can result in negative impacts to aquatic life and stream ecology by reducing photosynthetic activity, reducing food availability to fish and aquatic life, degrading aquatic habitats, and directly harming organisms by impairing respiration and digestive processes.[14]

There are numerous standards and techniques for measuring turbidity, but most use a light source and detector to measure the optical scatter of a water sample. This diversity of instrumentation and measurement techniques have resulted in numerous designations for the units of a turbidity measurement. For the purposes of this study, turbidity measurements were reported in Formazin Nephelometric Units (FNU) which corresponds to an instrument that measures turbidity by analyzing the sidescatter (90° to incident beam) from a single illumination beam light source using near infrared wavelengths.[13] Another common turbidity unit is Nephelometric Turbidity Units (NTU) which replaces the near infrared light source of the FNU measurement technique with a white light source.[13] Some instrumentation manufacturers have continued to report turbidity measurements in NTU as a generic turbidity unit though it may not be the correct designation.[13] While frequent calibration of modern instruments is not generally required (unlike sensors for other water quality parameters), maintenance and installation of these sensors can be quite time consuming. Maintenance issues generally arise when sediment or biologic fouling occurs and obscures the sensor. To alleviate this issue, many sensors come equipped with cleaning protocols that physically wipe/remove any obscurities from the sensor's lens, though the addition of this feature makes the sensor considerably more expensive. However, these cleaning protocols are not equipped to handle the sensor being obscured by larger debris (such as vegetation) blocking the sensor's view of the water column; alleviation of these issues would require physical removal of the object(s) from in front of the sensor. Thus, long term deployment of such sensors can require a substantial investment to maintain system function.

Turbidity and Stormwater Controls. To reduce the turbidity of stormwater entering a stream or river, thereby improving the ecological health of the system, stormwater controls such as dry extended detention basins are used. Dry extended detention basins are able to reduce the impact of turbidity primarily through gravitational settling and trapping of suspended particles found in stormwater.[1-5,9,13] By attenuating flows and increasing the hydraulic residence time, these settling and trapping processes have more time to occur which results in removal rates of 40-70% for suspended sediment.[1-5,9] RTC has been able to enhance these processes and substantially improve the removal efficiency of suspended sediment to 70-90% by increasing the hydraulic residence time.[3-5,7,9] However, none of these studies incorporated real-time water quality data to control this hydraulic residence time. This may prove to be a more versatile alternative for targeting specific water quality objectives by adjusting the hydraulic residence time as shifts in water quality occur.

Objectives. Although RTC is increasingly being viewed as a way to bolster the performance of stormwater infrastructure, there are numerous applications yet to be explored. To the authors' knowledge there are no case studies utilizing real-time water quality data in the decision framework of dry extended detention basins, or other stormwater control measures, retrofitted with active controls. Based on the understanding that effluent turbidity levels may improve when detention times within stormwater facilities are increased, RTC may offer an avenue to achieve better outcomes than static systems. Furthermore, integration of real-time turbidity data is a starting point for showing how water quality informed RTC can be leveraged to achieve water quality objectives more consistently. Thus, the results of this study should encourage novel research into other applications of RTC integrated with real-time water quality data. The objectives of this study were to: (1) investigate the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor as a novel methodology for more consistently meeting water quality objectives, and (2) leverage predictive models to alleviate the need for long term deployment of the turbidity sensor, an advantage for economical resource allocation during widespread adoption by reducing the number of necessary sensors and required maintenance.

MATERIALS AND METHODS

Site Description

A dry extended detention basin in the Conner Creek watershed of Eastern Tennessee was chosen for this study (Fig. 1). The dry extended detention basin collects runoff from the impervious areas (such as roofs and parking lots) and practice fields of a local high school and elementary school. The contributing drainage area is 19.7 ha and the landcover is 86% impervious. The basin can detain approximately 14,760 m^3 of water at a maximum stage of 3.05 m before water overtops the outlet riser of the basin.

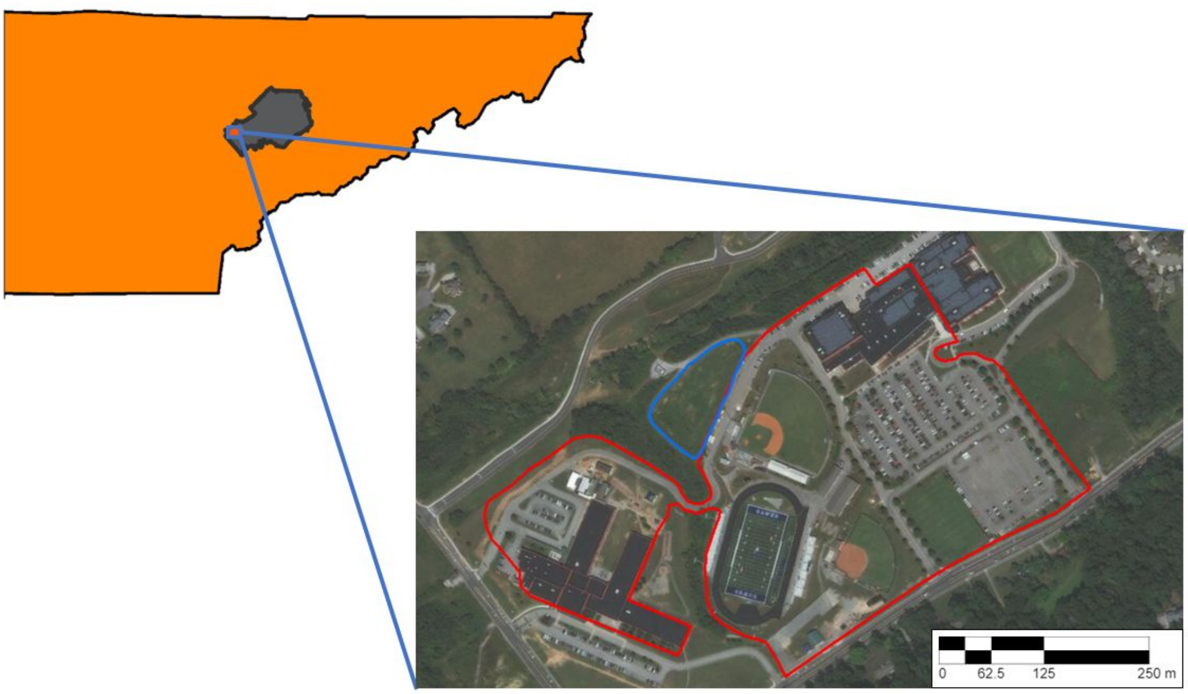

Fig. 1. Study location in the Conner Creek watershed of Eastern Tennessee with the subcatchment of the dry extended detention basin outlined in red and the footprint of the basin outlined in blue.

To convert this static stormwater infrastructure into an adaptable system, the outlet structure (Fig. 2) was retrofitted with a 150 mm (6”) diameter butterfly valve (Valworx 564548) and matching electric actuator (Valworx 561877A), an ultrasonic depth sensor installed above the basin (Grove Ultrasonic Ranger), and a dual sidescatter/backscatter turbidity sensor.[15] A custom control circuit was developed and powered by a Particle Boron LTE development board to which the actuator and sensors were connected. To ensure that all turbidity measurements were reflective of the basin’s effluent conditions, the turbidity sensor was installed directly next to the basin’s outlet. Additionally, a tipping bucket rain gauge was integrated into the system to record rainfall and assist in the control decisions made by the system. While this system allowed for variable control of the valve (could be set anywhere between 100% fully open and 0% fully closed), binary control (fully closed or fully open) was used in this study. To utilize the full capacity of the basin, the bypass orifice (used to attenuate flows not able to be conveyed by the 150 mm low flow orifice) on the outlet riser was sealed with a circular metal plate and gasket to prohibit it from discharging (as seen in the center of the left figure in Fig. 2).

Fig. 2. Dry extended detention basin outlet riser (left) outfitted with controllable valve, water depth sensor, and turbidity sensor and (right) the basin following a rainfall event.

Water Quality Informed RTC Strategy

Turbidity was selected for this study as it is an important parameter for judging stream health, can act as a surrogate for other pollutants, and can be measured reliably with commercially available sensors (unlike other water quality parameters such as Total Suspended Sediment (TSS), bacteria, or nitrate). To investigate how real-time turbidity data may allow improved system performance for water quality, a set of control rules for the system were established. When rainfall was detected, the basin's valve would close and detain all water (Fig. 2) for a minimum of 24 hours following the end of a rainfall event. The valve would remain closed until either a maximum detention time of 72 hours was reached, or turbidity values fell below a predetermined threshold of 25 FNU determined via the turbidity sensor's sidescatter measurements (justification for these thresholds is provided below). A simplified logic diagram (represented using AND and OR logic gate notation) of these control rules can be found below in Fig. 3.

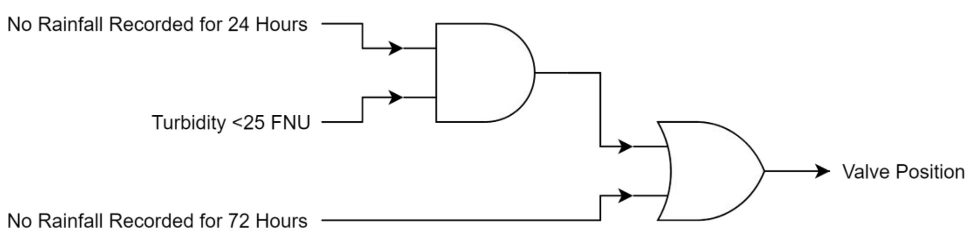

Fig. 3. Simplified logic diagram of control rules in which the valve will be opened if no rainfall has occurred for 24 hours (minimum detention time) and turbidity is below the threshold (25 FNU) or no rainfall has occurred for 72 hours (maximum detention time). Otherwise, the valve is closed.

The sidescatter turbidity measurements from the turbidity sensor were chosen for this study as they have the advantage of being more accurate in clean water compared to backscatter measurements which are useful for measuring higher levels of turbidity (≤4000 TU).[15] The minimum and maximum detention times were adopted from regional design and operation guidance on dry extended detention basins.[1-2] Additionally, since Tennessee does not have any explicit regulations regarding turbidity in surface waters, guidance for the turbidity threshold came from regulations for ponds, reservoirs, and streams from 8 states' water quality standards: Arizona, Hawaii, Iowa, Louisiana, Minnesota, North Carolina, Oklahoma, and Vermont (Table 1).[14] Some states may also regulate TSS in surface waters as an additional way to improve the clarity and quantity of suspended material present in water. However, it is much more difficult to measure TSS continuously than turbidity.

Table 1. State turbidity regulations used as guidance for determining the turbidity threshold used in this study (adapted from [14]).

State	Applicable Numeric Turbidity Criteria
Arizona	25 NTU in lakes for human contact and warm water fisheries 50 NTU in rivers for human contact and warm water fisheries
Hawaii	2-25 NTU for streams
Iowa	25 NTU
Louisiana	25 NTU for freshwater lakes, reservoirs, and oxbows; designated scenic streams and outstanding natural resource waters
Minnesota	25 NTU for fisheries and recreational waters with a Class B or C designation
North Carolina	25 NTU in lakes and reservoirs 50 NTU in streams
Oklahoma	25 NTU in lakes 50 NTU for other surface waters
Vermont	25 NTU for class B warm water fish habitats

To ensure that a series of insignificant rainfall events did not detain water within the basin indefinitely, additional advanced control rules were added. These rules would require that the initial rainfall or any additional rainfall (≥6 hours post the end of initial rainfall) must meet a minimum threshold (2.54 mm) equal to the initial abstraction of the watershed within a 6-hour duration for the rainfall to be included in control decisions. For example, if 12 hours after the end of initial rainfall a secondary storm passed through the watershed and rained 5 mm within 3 hours, the system would recognize this as the new end of rainfall, thus resetting the countdown for the 24-hour minimum detention time. If that rainfall threshold was not met, or was not met within the time limit (6 hours), the countdown to the minimum detention time would remain unchanged. Safety precautions were also included in these additional control rules to prevent overtopping of the outlet riser. If the water depth of the basin exceeded 2.51 m (~80% of maximum water depth; ~75% of maximum volume) the valve would open and release water until the water depth fell below 2.44 m. This control rule was designed to override all others and was only enacted by the system once during the study when cumulative rainfall exceeded 130 mm.

With the dry extended detention basin properly retrofitted with real-time turbidity measurements and controllable infrastructure, the data collection period of this study was allowed to commence. The system autonomously reacted to changing hydrologic and water quality conditions over a 5-month period (October 19th, 2019 – March 18th, 2020) during which the system was continuously online excluding a 39-day period (December 5th, 2019 - January 13th, 2020) when the turbidity sensor was uninstalled (for reasons explained in subsequent sections). Routine maintenance occurred weekly to check the turbidity sensor for large debris (such as vegetation that cannot be removed by the sensor's cleaning protocols which would result in obscured measurements) to ensure that basin control decisions were informed by accurate turbidity measurements. Additional maintenance activities included confirming that the valve was free of debris and that the stage sensor was reporting accurate measurements. If this system were to be installed by a municipality, maintenance frequency could likely be reduced to once every 2-3 weeks dependent on site-specific conditions.

Simulating an Uncontrolled System

While performance metrics and water quality data for an uncontrolled baseline were not collected in this study, a comparison in performance between this adaptive RTC strategy and an uncontrolled basin can be inferred by comparing their hydraulic residence times. Multiple studies have observed a positive relationship between water quality and hydraulic residence time in which an increase in the latter leads to an improvement in the former.[3-5,7,9,16] This observed relationship occurs because sediment settling and nutrient uptake mechanisms have more time to process. For example, Gaborit et al. and Muschalla et al., during their simulations of a dry extended detention basin, observed substantial improvements in TSS removal efficiency (60%-90%) when RTC was utilized as compared to an uncontrolled baseline (~40%).[3-4,9] However, the baseline uncontrolled in these studies may have been underperforming as these systems generally remove approximately 66% of TSS.[17] Field studies by Gilpin and Barrett, Jacopin et al., and Middleton and Barrett validate these observations with RTC strategies which extend hydraulic residence times being shown to achieve TSS removal efficiencies of 70-90%.[5-7]

Simulations using the Personal Computer Stormwater Management Model (PCSWMM) and collected rainfall data were used to determine the hydraulic residence times (total time that water was detained within the basin) for each event in an uncontrolled scenario (both the bypass orifice and valve of the basin are left open).[18] This PCSWMM model of the study site was created using available data for the basin's drainage network (provided by construction/planning documents and Knoxville GIS) and soil infiltration properties (provided by the Natural Resources Conservation Service's Web Soil Survey).[19] PCSWMM's Sensitivity-based Radio Tuning Calibration (SRTC) tool was then used to calibrate this model using a one-month period of observed basin stage and rainfall (7 rainfall events for a cumulative total of 227.33 mm) during which no manipulation of the basin's valve occurred.[20] This model achieved a Nash-Sutcliffe Efficiency of 0.82 for the calibration period. The model's performance was then validated with an additional five rainfall events (including a mix of those which utilized RTC and those which did not) and achieved Nash-Sutcliffe Efficiencies as high as 0.82 for uncontrolled scenarios and 0.98 for scenarios which utilized RTC (controlled by preset RTC rules) ensuring that the model would produce accurate results.

Modeling Analysis

Following the data collection period of this study, several modeling approaches were examined to determine if they could accurately estimate the detention time of the system necessary to meet the turbidity threshold (within the minimum and maximum detention times of this study). The purpose of this modeling investigation was to determine if the system could operate effectively in the future if the turbidity sensor were to be removed. This would allow organizations implementing this system to save on maintenance and overhead costs associated with keeping the turbidity sensor clean and functional while also reducing the quantity of turbidity sensors required for the operation of multiple systems. The models evaluated consisted of a diverse selection of traditional statistical models and machine learning techniques. Available predictors for these models consisted of data that could be derived without the need of a turbidity sensor and included: initial water depth (m), maximum water depth during the initial 24 hours after a rainfall event (m), cumulative rainfall (mm), rainfall duration (h), maximum 5-minute rainfall intensity (mm/h), antecedent dry time (h), and time between storms (h). Each of the developed models predicted the detention time (h) required to meet the turbidity threshold within the minimum and maximum detention time constraints outlined previously. The mean absolute error (MAE) of each unique model's predictions were used to compare model performance.

The traditional statistical models ranged from simple to complex and included logistic, linear, multiple, and polynomial regression models and were chosen to represent a diverse selection of regression models. The logistic regression model was created by analyzing predictors iteratively for potential sigmoidal relationships. Once predictors displaying sigmoidal relationships were identified, each was analyzed using a diverse set of starting functions. The model with the lowest RMSE (root mean square error) value was selected as the optimal logistic regression model. The linear regression model was created by testing all possible subsets of predictors and selecting the model with the lowest RMSE. Similarly, the multiple regression model was created by testing all possible subsets of predictors and selecting a model with the lowest RMSE while also ensuring that the chosen model was free of multicollinearity. The polynomial regression model was derived using the same process as that of the multiple regression model with the addition of squared predictors. Each of these models were then validated using 10-fold cross-validation in which data were segmented into 10 equal parts and in each iteration, nine segments (90% of the data) were used for training and the remaining segment (respectively, 10%) was used for validation. The MAE of this validation procedure for each model was then used for model comparison.

A random forest model was the first machine learning technique that was explored as a viable option for predicting the detention time of the system. Random forest models consist of a number of randomly generated decision trees, grouped together as a "forest", which ask binary questions of predictors in order to arrive at a conclusion.[21] The random forest model developed in this study consisted of 500 trees in its "forest" using a variety of predictors as the model's independent variables. The number of trees used in the creation of this random forest model was fixed at 500 due to restrictions with the software package. Despite the number of trees being fixed, this package was selected as it exposed additional tuning parameters absent in other packages (that were observed to be more beneficial during the model's creation). These additional tuning parameters included the number of randomly selected parameters at each node, target node size, and enacted splitting rule. The optimal random forest model was chosen by assessing the importance of each available predictor, altering the tuning parameters (number of randomly selected parameters, target node size, and splitting rule) using a tuning grid to assess all available combinations, and assessing model performance. The combination which resulted in the lowest RMSE for 10-fold cross-validation was chosen. The final random forest model's MAE value was then used for model comparison and discussion.

Finally, a more advanced machine learning model was created and analyzed to determine if additional complexity would result in improved model performance. This model consisted of a long short-term memory (LSTM) network, which is a type of recurrent neural network (RNN) used primarily for time series prediction that has the ability to learn from short-term and long-term trends in data to predict an output.[22] This ability to learn from both long and short-term data trends makes it an ideal candidate for modeling scenarios that may be temporally dependent, such as this study. Since LSTM models use time series data (as opposed to tabular data) as their input to predict an output at each modeled time step, the LSTM model developed for this study used observed basin stage (m) and rainfall (mm) time series data at 15-minute time steps to predict turbidity as a binary output (1 for turbidity < 25 FNU, 0 for turbidity ≥ 25 FNU). To simulate real world conditions, the output data (turbidity) was shifted 12 hours so that any prediction made by the LSTM model was always 12 hours in the future (i.e. basin stage and rainfall at any time t would predict turbidity at time t + 12 hours). In a production setting, this would allow enough time for the model to iterate every few hours (as the computational time for this model is significantly higher than others developed within this study) with updated time series data and form a prediction before a control decision would actually need to be made. This time shift would not be necessary for other models within this study as they are able to form a decision with data collected during and immediately following rainfall.

The LSTM model used a 10-fold cross-validation process in which time series data were segmented into 10 equal parts and in each iteration, nine segments (90% of the time series data) were used for training and the remaining segment (respectively, 10%) was used for validation. As a reminder, for the other models explored within this study, the split between training and validation was based on the total number of events. The predicted turbidity at each 15-minute time step from each of these validation iterations were then combined and fed through the control rules outlined above to determine the valve position of the dry extended detention basin (1 for open, 0 for closed). From the predicted valve position and observed rainfall, predicted detention time for each event was established, and the model's MAE was determined (necessary for model comparison and discussion).

RESULTS AND DISCUSSION

Observed Performance of System

A total of 21 events were collected from October 19th, 2019, through March 18th, 2020, with an event being defined as the time between when rainfall is initially detected at the site and when the system makes the control decision to release water from the dry extended detention basin. No events were recorded between December 5th, 2019, and January 13th, 2020, as the turbidity sensor was uninstalled due to ambient temperatures routinely falling below its operating temperature range.[15] A summary of each of these events can be found below in Table 2. Events 3 and 12 were removed from any further analysis in this study as they were deemed not representative. Specifically, event 3 was removed as debris covered the outlet and obscured the turbidity sensor's measurements, while event 12 was removed due to the extremely high rainfall (134.87 mm) that occurred and flooded the basin/watershed. The control rules were limited in their ability to affect turbidity in a manner consistent with the other events under these extreme circumstances.

Overall, 63% of events (12 of 19) met the 25 FNU turbidity threshold for water release before the maximum detention time, and the median turbidity value for all events in the study at release was 24.7 FNU. Although the turbidity threshold was not met for 37% (7 of 19) of events, events in this category still saw a median decrease of 7.9 FNU (22% reduction) during the 24 to 72 hours following the end of the rainfall event with a median turbidity value of 35.0 FNU at release. The majority of events resulted in turbidity trends comparable to that of Fig. . Specifically, turbidity initially increases during and following rainfall before steadily decreasing over the next few days. Though similar trends in turbidity occurred, overall detention times were highly variable due to differences in initial turbidity magnitudes, the rate at which readings fell (settling rate of suspended particles), or resuspension of sediment due to biologic activity. These observations highlight one of the many advantages an adaptive RTC strategy (that incorporates real-time water quality data) has over other control strategies as it is able to adapt to these diverse conditions.

Table 2. Summary of events collected in study.

Event	Start Time	Rainfall Duration (h)	Rainfall (mm)	Initial Water Depth (m)	Maximum* Water Depth (m)	Maximum* Turbidity (FNU)	Turbidity at Release (FNU)	Detention Time (h)
1	10/19/2019 17:35	9.4	7	0.51	0.62	40.5	24.8	24
2	10/21/2019 20:35	8.4	27	0.00	1.16	100.2	58.7	72
3	10/25/2019 16:40	33.0	46	0.81	1.71	74.5	495.1	72
4	10/30/2019 08:40	30.1	48	1.29	2.12	615.0	24.0	47
5	11/07/2019 10:30	10.0	10	0.82	0.96	28.0	9.7	24
6	11/22/2019 06:45	32.9	54	0.00	1.86	148.4	32.9	72
7	11/26/2019 22:55	9.7	21	1.06	1.52	324.7	24.7	31
8	11/30/2019 14:30	15.9	55	0.00	2.02	100.6	35.0	72
9	01/14/2020 01:10	112.9	42	0.00	1.52	148.6	28.5	72
10	01/23/2020 21:55	15.8	30	0.00	1.23	39.9	24.9	52
11	01/27/2020 04:05	6.5	3	0.84	0.92	82.4	24.1	24
12	02/04/2020 06:00	56.5	135	0.00	3.23	100.7	27.6	72
13	02/10/2020 03:55	30.3	50	1.09	2.17	25.1	20.8	24
14	02/12/2020 13:00	20.6	31	1.81	2.37	58.5	28.4	72
15	02/18/2020 05:30	17.3	23	0.00	1.12	412.1	24.5	34
16	02/20/2020 09:15	6.6	7	1.10	1.25	34.4	19.2	24
17	02/24/2020 06:50	58.3	23	0.00	1.12	71.0	35.4	72
18	03/02/2020 06:50	26.7	40	0.00	1.59	143.4	84.6	72
19	03/10/2020 05:35	14.9	11	0.00	0.63	187.3	22.3	24
20	03/13/2020 00:20	53.8	14	0.00	0.78	238.9	19.9	25
21	03/16/2020 23:40	12.4	11	0.70	1.09	32.2	19.8	24
Median for All Events		15.9	23	0.00	1.23	100.2	24.7	25
St. Dev for All Events		25.1	17	0.57	0.52	150.6	16.1	16

Note: Median and St. Dev do not include Events 3 and 12 as they were removed from any analysis.

***Maximum during time period between when rainfall begins and 24 hours following the end of rainfall.**

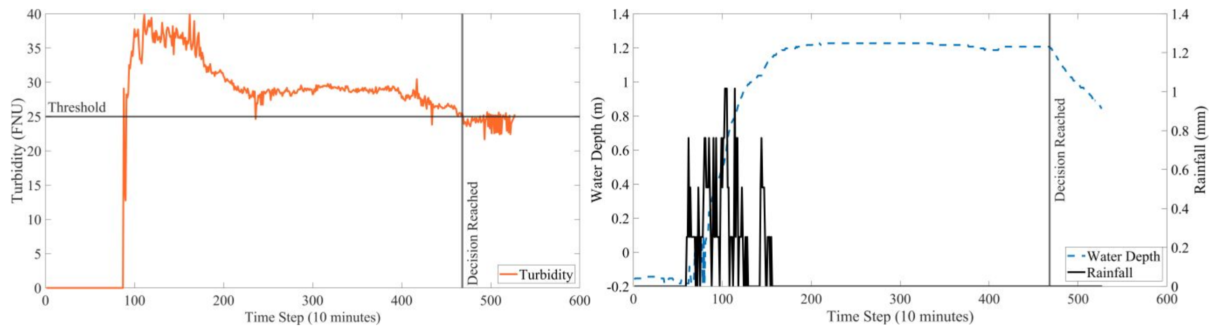

Fig. 4. Turbidity measurements (left) and dry extended detention basin hydrograph (right) for event 10.

Comparison to an Uncontrolled Basin

Table 3 (below) displays the results of the modeling investigation for the uncontrolled scenario with the maximum uncontrolled residence time (beginning of rainfall until the basin is drained), the minimum residence time of the system using RTC (beginning of rainfall until when the valve was opened), and the minimum increase in residence time between the uncontrolled and RTC equipped basin. Equipping the basin with water quality informed RTC led to a median minimum increase in the hydraulic residence time of 82%. From this notable increase in hydraulic residence time, it can be inferred that the water quality informed RTC strategy can provide substantial improvements in water quality when compared to existing/baseline conditions.

Table 3. Comparison of hydraulic residence times between water quality informed RTC and uncontrolled scenarios.

Event	Uncontrolled Residence Time (h)	RTC Residence Time (h)	Increase in Residence Time (%)
1	18.6	33.8	82
2	31.8	80.6	154
4	50.7	76.6	51
5	24.5	34.4	41
6	56.8*	105.1	85
7	29.4	40.2	37
8	43.8	88.1	100
9	73.5*	185.1	152
10	31.6	68.2	116
11	18.4	30.8	67
13	52.9	54.4	3
14	38.8	92.8	139
15	34.5	51.0	48
16	21.1	30.8	46
17	48.5*	130.5	169
18	47.3	98.9	109
19	26.4	39.1	48
20	42.0*	78.7	87
21	26.0	36.7	41
Median for All Events	34.5	68.2	82
St. Dev for All Events	14.4	39.2	46

Note: Uncontrolled residence times denoted by an * are the cumulative residence times for instances where the basin fully drained during an event and was refilled by later rainfall.

Comparison to Predetermined Detention Time RTC Strategy

To determine if the turbidity threshold would have been met by a system using a predetermined detention time (simpler RTC strategy), the turbidity values of each event at a variety of pre-determined detention times (12, 24, 48, and 72 hours) were extracted from the observed data set. In instances where the predetermined detention time was longer than the water quality informed detention time, the turbidity value at release from the water quality informed system was used. This conservative assumption was allowed because the majority of events experienced declining trends in turbidity with increased detention time (as previously explored).

Analysis of the efficiency of using predetermined detention times and how this strategy compared to the water quality informed RTC strategy can be found below in Table 4. A substantially higher number of events were observed to meet the turbidity threshold for the water quality informed RTC (63%; 12 of 19 events) in comparison to predetermined detention times of 12 (21%; 4 of 19 events), 24 (42%; 8 of 19 events), and 48 (58%; 11 of 19 events) hours. While no considerable increase in the number of events which would have met the turbidity threshold occurred between the 48 and 72 hour predetermined detention times, there was a substantial reduction in turbidity between these two detention times. Events that fell into this category (events 2, 6, 8, 9, 14, 17, and 18) experienced a median decrease of 5.48 FNU (~10%) during that additional 24 hours. In short, a system utilizing predetermined detention times would need to use the maximum detention time of 72 hours to match the efficiency of the water quality informed RTC strategy. While this is feasible to implement, a system utilizing a predetermined detention time strategy would not provide the added hydrologic benefits such as not detaining water longer than necessary and therefore ensuring capacity in the system for any subsequent rainfall. Hence, it can be concluded that the water quality informed RTC strategy shows greater potential and versatility as an alternative for meeting water quality objectives.

Table 4. Analysis of results investigating if the turbidity threshold would be met using predetermined detention times (red indicates turbidity ≥25 FNU at release; green indicates turbidity <25 FNU at release).

Event	RTC Detention Time (h)	Turbidity at Release (FNU)	Turbidity (FNU) at Release if Predetermined Detention Time Used * 12 Hours	24 Hours	48 Hours	72 Hours
1	24	24.8	**28.4**	**25.6**	**24.8****	**24.8****
2	72	58.7	**51.1**	**98.5**	**64.2**	**58.7**
4	47	24.0	**39.4**	**34.6**	**24.0**	**24.0****
5	24	9.7	**15.6**	**9.9**	**9.7****	**9.7****
6	72	32.9	**44.9**	**66.3**	**49.9**	**32.9**
7	31	24.7	**35.9**	**34.5**	**24.7****	**24.7****
8	72	35.0	**55.3**	**38.6**	**34.3**	**35.0**
9	72	28.5	**39.7**	**36.4**	**31.6**	**28.5**
10	52	24.9	**29.1**	**29.2**	**26.2**	**24.9****
11	24	24.1	**27.6**	**26.1**	**24.1****	**24.1****
13	24	20.8	**21.5**	**20.7**	**20.8****	**20.8****
14	72	28.4	**52.8**	**34.1**	**30.2**	**28.4**
15	34	24.5	**101.0**	**30.1**	**24.5****	**24.5****
16	24	19.2	**25.4**	**19.2**	**19.2****	**19.2****
17	72	35.4	**49.8**	**40.3**	**47.1**	**35.4**
18	72	84.6	**91.0**	**113.3**	**95.8**	**84.6**
19	24	22.3	**57.9**	**22.3**	**22.3****	**22.3****
20	25	19.9	**31.8**	**19.9**	**19.9****	**19.9****
21	24	19.8	**12.8**	**19.8**	**19.8****	**19.8****
Efficiency of Predetermined Detention Time			**21%**	**42%**	**58%**	**63%**

*** Turbidity threshold was initially met within ±2 hours of predetermined detention time.**

****Turbidity (FNU) at release used. Actual turbidity value at this predetermined detention time would likely be lower due to observed reduction in turbidity as detention time increased.**

Modeling Results

Regression Models. As noted above, a variety of models were developed using predictors that could be derived independently of the turbidity sensor. The form of each of these models, including coefficients and independent variables, can be found below in Table 5. Variables of significant value for explaining the data and predicting *DT* (detention time in h) included

Rainfall (cumulative rainfall in mm), D_0 (basin's initial water depth in m), and D_M (basin's maximum water depth during the initial 24 hours following a rainfall event in m). Cumulative rainfall as an important predictor was expected as it is directly responsible for higher rates of runoff that carry sediment/pollutants and contribute to higher levels of turbidity.[14,16,23] Maximum water depth as a predictor appears to represent hydrologic processes similar to rainfall, as determined by the high multicollinearity observed between this predictor and rainfall. Initial water depth also appears to play a vital role in how quickly the turbidity threshold is reached primarily through its impact on resuspension processes. Through investigation of the observed data it is hypothesized that when the basin still contains a portion of the previous event when a new event begins, the erosive energy of the incoming water is diminished, thus reducing resuspension of trapped particles in the basin. This would allow the dry extended detention basin to mimic the function of a wet pond (stormwater control measure which contains a permanent pool) which has been documented to have increased removal rates of suspended particles.[1-2]

Table 5. Analyzed regression models and their form.

Model	Form
Logistic Regression	$DT = 25.038 + 37.851/(1 + e^{-17.704(Rainfall) - 22.663})$
Linear Regression	$DT = 22.497 + 0.859(Rainfall)$
Multiple Regression	$DT = 12.335 - 24.943(D_0) + 33.015(D_M)$
Polynomial Regression	$DT = 26.877 - 62.695(D_0) + 30.378(D_0^2) + 23.425(D_M)$

Random Forest Model. The random forest model consisted of 500 trees in its "forest" (for reasons previously discussed) and used cumulative rainfall (mm) and initial water depth (m) of the basin as the model's independent variables. The model also applied the following tuning parameters: using both parameters at each node, using a target node size of 1, and enacting an "extratrees" splitting rule. An example of a decision tree that may appear in this random forest model can be found below in Fig. . Similar to the regression models, it appears that predictors which describe the resuspension (initial depth) and hydrologic (rainfall) processes of the basin are those which most substantially impact the required detention time to meet the turbidity threshold.

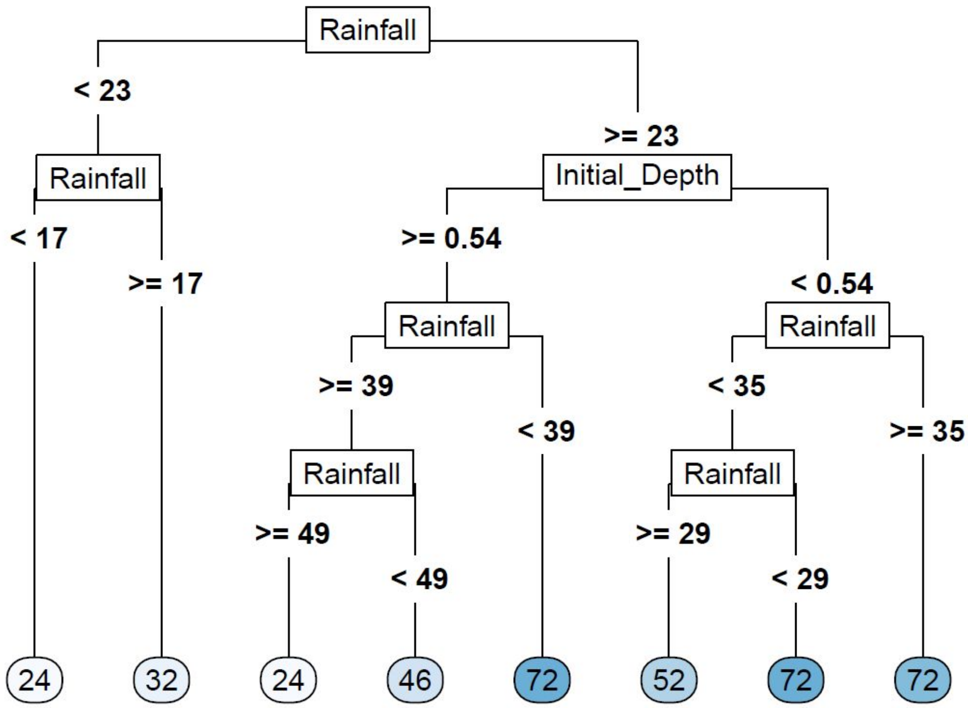

Fig. 5. Example decision tree that may appear in the random forest model.

Long Short-Term Memory Model. Overall, the LSTM model performed well (Fig.). The MAE for this model using 17 of the 19 available events and 10-fold cross-validation was 5.16 hours with a median absolute error of less than half an hour. The model was unable to reach a prediction for the detention times for events 13 and 15 due to the short period of time between when the system actually made the decision to open and when a new rainfall event began (~2.5 and ~0.75 hours, respectively). It should be noted that LSTM models are variable and dependent on layers added to the model. Thus, it is possible that a different, yet to be determined combination could outperform the current iteration. However, the LSTM model analyzed in this study was the optimal model derived from 50 iterations testing different layers/layer types and tuning parameters.

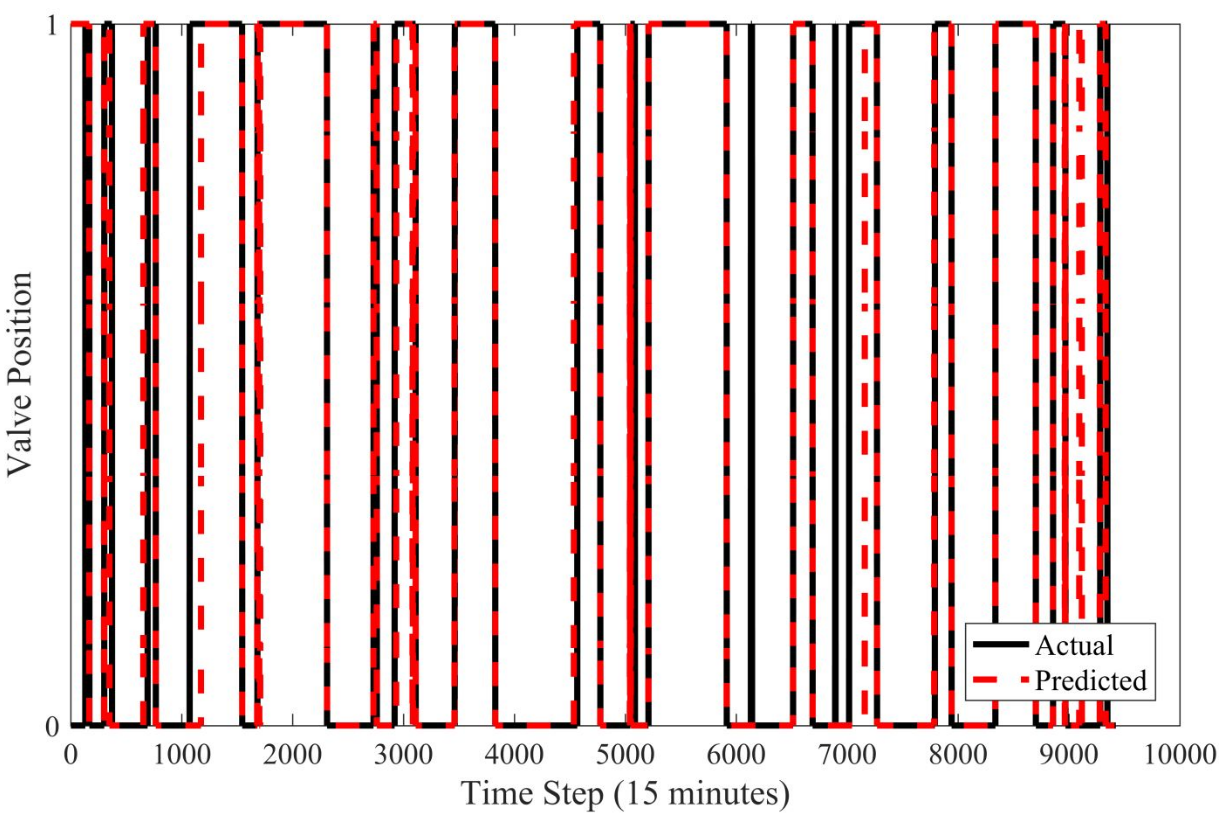

Fig. 6. LSTM modeling results (1 represents fully open; 0 represents fully closed).

Model Comparison. The fit statistics for the full models and the results of validation using 10-fold cross-validation can be found below in Table 6. The LSTM model outperformed all other models with a significantly lower MAE using 10-fold cross validation. This MAE equates to the model predicting detention times with an error of ±5.16 hours (10-fold cross-validation). Therefore, if the model were implemented as the primary control of the system, one could possibly counteract performance error by instructing the system to increase the predicted detention time by the MAE to ensure that the turbidity threshold is always met (for detention times ≤72 hours) or that comparable performance to the water quality informed RTC is achieved (for detention times >72 hours). This conservative adjustment allows for more time for the turbidity of the basin to decline (as was observed in this study) and either meet or fall below the turbidity threshold.

Table 6. Model fit statistics and validation using 10-fold cross-validation.

	Full Model			10-Fold Cross-Validation
Model	**MAE (h)**	**R^2**	**Adjusted R^2**	**MAE (h)**
Logistic Regression	7.56	0.72	0.70	8.49
Linear Regression	12.37	0.44	0.41	13.52
Multiple Regression	10.17	0.60	0.55	11.96
Polynomial Regression	8.77	0.71	0.66	12.44
Random Forest	N/A	0.51 [1]	N/A	10.04
LSTM Network	N/A	N/A	N/A	5.16 [2]

[1] OOB Error
[2] Time series data

Future Work and Limitations

While the water quality informed RTC strategy successfully improved the ability of a dry extended detention basin to meet water quality objectives, future work is necessary to investigate the impact of this system more broadly beyond the scope of this study site. It is recommended that this RTC strategy be implemented on dry extended detention basins across a diverse selection of regions, designs, and watershed characteristics as site specific features may play a significant role in the hydrologic and settling processes that affect turbidity. For example, if the soil of a basin's watershed consists of more fine particles than those herein, then it can be expected that initial turbidity magnitudes may increase while overall system performance decreases due to additional suspended particles. Conversely, soils with larger particles may lead to an improved ability of this system to meet turbidity objectives. Changes in the design of the basin (such as differences in orifice diameter or basin capacity) may also substantially affect the ability of the system to meet water quality objectives due to their influence on hydrologic processes. Finally, the chosen turbidity threshold for this study may not be what is required by local regulations. Assuming similar pond function as observed herein (initial turbidity magnitudes and rate at which turbidity readings fall), then systems which utilize a higher turbidity threshold (based on local guidance) will experience shorter detention times, while systems which use a lower turbidity threshold will experience much longer detention times.

CONCLUSIONS

The purpose of this study was to investigate the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor. Such an assembly was theorized to be an advancement over static, uncontrolled systems by allowing additional detention time during which settling of particles could occur. The results showed highly variable detention times with 42% of storms reaching the turbidity threshold approximately 24 hours after the end of a rainfall event (minimum detention time) and 37% of events reaching the maximum detention time of 72 hours without reaching the required turbidity threshold. These highly variable detention times were the direct result of differences in initial turbidity magnitudes and the rate at which levels fell based on rainfall amounts and initial basin water depth conditions (as indicated by which variables were identified as consistently important during the modeling investigation). Overall, 63% of events met the 25 FNU turbidity threshold for water release before the maximum detention time, and the median turbidity value for all events in the study at release was 24.7 FNU.

Comparing the water quality informed RTC strategy to other forms of basin operation, the results showed a median minimum increase of 82% in hydraulic residence time (which would result in improved sediment settling efficiencies) when compared with the uncontrolled scenario using static infrastructure. Further, it was concluded that a system utilizing predetermined detention times would need to use the maximum detention time of 72 hours to match the efficiency of the water quality informed RTC strategy. While this is feasible to implement, it does not provide the numerous hydrologic benefits or adaptability of the water quality informed RTC. These combined results support the conclusion that the adaptive system integrated with real-time water quality data was effective in meeting water quality objectives that may not have been met with traditional systems, or those that rely on a predetermined detention time.

Several modeling approaches were investigated to determine if they could accurately estimate the detention time of the system (thereby negating the need for continued deployment of a turbidity sensor). The best performing models consisted of a logistic regression model using cumulative rainfall (mm) to predict detention time as well as a more advanced LSTM model which analyzed the time series data for rainfall and water depth of the basin to predict if turbidity was above or below the predetermined threshold (from which predicted detention time was determined). While the LSTM model outperformed the logistic regression model (MAE of 5.16 and 8.49 hours, respectively), the complexity and computational expense of generating a decision from the LSTM model may lead future users to abandon this for the simplicity of the logistic regression model. Overall, the results from this modeling investigation conclude that either the LSTM model or logistic regression model estimations for the detention time of the basin are comparable to those detention times determined using real-time water quality data. This indicates that after a period of data collection using a turbidity sensor, the sensor may be removed in favor of the basin being controlled by its site-specific model. This would assist municipalities in the widespread adoption of this technology as it would reduce the number of sensors necessary for multiple basins (economic resource allocation) as well as reduce the time and cost of sensor maintenance.

Future work is necessary to investigate this system on a diverse selection of dry extended detention basins (varying watershed and design characteristics) in order to corroborate the conclusions of this study and ensure that this system is broadly applicable. However, the results of this study, both field and modeling in origination, should assist future studies investigating the use of water quality data to make real-time control decisions for stormwater infrastructure. Numerous opportunities remain to implement similar strategies for different stormwater controls and across an array of pollutants of concern.

Data Availability Statement. Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Notation. The following symbols are used in this paper:

D_0 = initial water depth (m) of the dry extended detention basin;

D_M = maximum water depth (m) of the dry extended detention basin during the first 24 hours following the end of rainfall;

DT = Detention time (h);

$Rainfall$ = Cumulative rainfall of event (mm);

TU = Turbidity units;

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