METHODOLOGIES FOR RESERVOIR SYSTEMS ANALYSIS: APPLICATION OF OPTIMIZATION AND DEEP LEARNING

A Dissertation Presented

by

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ABSTRACT

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Reservoir systems operations are challenging given that they must function to meet conflicting goals. Using mathematical programming and deep learning techniques, this dissertation presents innovative methodologies to address some of the challenges. The first chapter focuses on development of a mathematical programming framework for assessing sub-daily hydropower hydropeaking operation and flow regime outcomes of a system of five large sequential hydropower facilities on the mainstem Connecticut River under various operation scenarios. A formulation for the pumped-storage Northfield reservoir is presented that uses binary decision variables to properly model the reservoir operations. The results closely match annual historical power values that indicates the model can replicate the operations. The second chapter presents a novel multiple objective optimization methodology for trade-off analysis of river basins. The novelties include a weighting scheme that normalize different objectives having different range of variabilities and formulations for quantification of ecological and flood control objectives as frequencies of meeting desirable conditions. The methodology is applied to the Connecticut River basin. In this chapter, formulations are developed that use binary decision variables to quantify ecological and flood control objectives along with other operational goals. The key trade-offs of the system objectives are identified. The results indicate hydropower revenue objective highly conflict with any other objective than flood control. Moreover, it is concluded that a balanced operation that equally weight different objectives has the potential to improve all the objectives. The third chapter presents a methodology for designing reservoir operation policy using optimization and deep learning. This chapter addresses the challenge of designing of an operation policy for a reservoir with conflicting objectives under uncertainty of hydrological and energy prices data. A deep neural network is developed to infer near-optimal operation policies under different foresight scenarios using the optimization modeling results. The methodology is applied to the Wilder reservoir on the mainstem Connecticut River. A base method is also developed that uses linear regression and is applied to the problem and the associated results are used as a comparison basis. Results indicate that the designed policies using neural networks perform better than the base method used while having foresight for a longer time improves the performance.

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INTRODUCTION

Optimal operation of reservoir systems is challenging due to presence of conflicting system objectives (Castelletti et al., 2013). Reservoir systems benefit human communities directly and indirectly. Direct benefits include supplying domestic water, controlling floods, generation of electricity, facilitating recreational uses and navigation. The indirect benefits include contributing to the sustainability and integrity of watershed communities (R.-S. Chen & Tsai, 2017). How to operate reservoir systems to best balance different objectives and services is a problem that requires advanced analytics to make better-informed decisions.

It is crucial to consider sustainability of watersheds and ecological integrity when designing water resources operation policies (Richter et al., 2003). The benefits of facilitating environmental sustainability are not as tangible as the direct benefits of reservoir systems while they might be more important for human welfare. Developing hydropower plants and operating the systems to maximize the immediate hydropower generation revenues alters the natural flow regime compared to the pre-development regime. The alteration threatens species of the watershed since many of them rely on specific flow regimes in their life stages to survive and thrive. Any alteration might severely affect watershed communities sustainability and change the whole ecosystem (Jager & Smith, 2008). Thus, it is necessary to consider flow regime requirements in water resources management studies along with other objectives of the systems.

Optimal balance of water resources systems objectives has been studied for decades. However, there are still challenges in designing systems operation policies because there exist multiple conflicting objectives, and uncertainties associated with hydrological (Quinn et al., 2018), and energy market variables. This research attempts to address some of the existing challenges by presenting novel methodologies that derive useful information for decision makers and stakeholders. Chapter 1 of this dissertation presents a mathematical programming model developed for evaluating hydropower and flow regime outcomes under different operation scenarios of a reservoir system. Using a mathematical programming optimization model, a modeling tool is presented that mimics status-quo operations on five large sequential hydropower reservoirs on the mainstem Connecticut River. Other versions of the model associated with alternative operation policies are developed and presented to assess the outcomes of the alternative operation scenarios. The results provide new insight regarding implications of execution of different operation scenarios.

Chapter 2 focuses on development of a methodology for trade-off analysis of water resources systems considering conflicting objectives. Moreover, the quantification of different objectives is addressed by presenting new formulations for measuring ecological and flood control targets. The formulations measure the frequency of meeting ecosystem requirements and the frequency of controlling flood conditions. With an approach that compares each objective value to its maximum possible, a modeling framework is presented that quantifies various objectives and develops a subset of the Pareto front by running the algorithm developed for different weighting values of objectives. The methodology is applied to the Connecticut River basin and includes 54 of the largest reservoirs, ecological locations of interests on the mainstem and tributaries, and flood checkpoints. Four different objectives: ecological, flood control, hydropower revenue, and desired storage level are modeled. The results show how objectives interact with each other and provides insight on compromised solutions.

Chapter 3 presents a method for operation policy design of reservoir systems. Existing methods usually suffer from computational issues and lack of optimality guarantee (Giuliani et al., 2016). Designing optimal or near-optimal reservoir operation policies under uncertainty requires quantification of the system objectives and dealing with uncertainties associated with future system conditions. First, an optimization scheme is used to optimize the release schedules. Afterwards, a Deep Learning technique is used to approximate a near-optimal operation policy. For this purpose, a multiple objective optimization methodology is developed for Wilder reservoir using mathematical programming that optimizes the system and develops the trade-offs. Next, Deep Neural Networks are trained to approximate the optimal operation policy. The trade-offs resultant of the release decisions prescribed by the policy designed are developed and compared to those of the optimization model. The comparison provides insight on the performance of the operation policy designed since it is compared with the best possible performance under perfect future insight.

CHAPTER 1

EVALUATION OF ECONOMIC AND FLOW REGIME OUTCOMES OF ALTERNATIVE HYDROPOWER OPERATIONS ON THE CONNECTICUT RIVER MAINSTEM

1.1. Introduction

Surface water reservoirs facilitate hydropower generation along with providing other services including municipal water supply, flood control, and ecological streamflow requirements. Hydropower is a mature technology and an inexpensive energy source with a low CO2 footprint (Bello et al., 2018; Koo, 2017; J. Zhang et al., 2015). The operation of hydropower reservoirs has implications for ecosystems because they significantly alter flow characteristics to follow sub-daily energy market dynamics (Benejam et al., 2014; Jager & Smith, 2008; Kennedy et al., 2016; Pang et al., 2015; Sabo et al., 2017; Winemiller et al., 2016). This kind of operation, called hydropeaking, conflicts with providing the ecological streamflow requirements (Anderson et al., 2014; Ding et al., 2018; Fanaian et al., 2015; Feng et al., 2018; W. Zhang et al., 2016) since they change the flow regime that should be maintained for survival of aquatic communities (Arthington et al., 2009; Davies et al., 2014; R. Li et al., 2015; Tonkin et al., 2018). To mitigate the negative ecological impacts, regulatory constraints are imposed on the hydropower operations that usually result in reductions in the hydropower revenues generated (Jager & Bevelhimer, 2007; Jager & Smith, 2008; McManamay et al., 2016; Rheinheimer et al., 2012). However, it is not often clear if enforcement of these regulations results in fully meeting ecological streamflow requirements (Poff, 2009).

Natural flow regime paradigm has widely been utilized for water flow alterations studies (Archfield et al., 2013; Arthington et al., 2009; Blythe & Schmidt, 2018; Chinnayakanahalli et al., 2011; Kiernan et al., 2012; Lehner et al., 2011; Lytle & Poff, 2004; Maheshwari et al., 1995; Marchetti & Moyle, 2001; Olden & Naiman, 2009; Propst & Gido, 2004; Suen, 2011). According to this paradigm, ecological streamflow requirements are based on the natural patterns of the streamflow quantity and timing (Arthington et al., 2009; Naiman et al., 2002) and any alteration from the natural regime will negatively impact the river ecosystem. The natural flow regime of a river is affected by patterns of climate, geology, topography, soil type, and vegetation and its characteristics are generally defined in terms of magnitude, frequency, duration, timing, and rate of change (Naiman et al., 2008; Poff et al., 1997). Natural regime impacts structure of instream, riparian, and floodplain ecological communities (Bunn & Arthington, 2002; Poff et al., 1997). The scope of natural flow regime however may be required to be broaden given the nonstationary observed in the streamflows (Gibson et al., 2005; Mittal et al., 2016; Papadaki et al., 2016; N. LeRoy Poff, 2017; Wohl et al., 2015). Thus, seeking appropriate methods and indicators that measure flow regimes seems to be necessary for evaluation of reservoir systems operations impacts on the ecosystems (Liermann, 2015; Lytle et al., 2017; Mackay et al., 2014).

While most current ecological flow requirements are implemented as the minimum flow magnitudes (Arthington et al., 2006), more complex indicators and methodologies have been developed to quantify the degree of flow regime alterations and requirements of ecosystems (Black et al., 2005; Bragg et al., 2005; Carlisle et al., 2009; Döll et al., 2009; Extence et al., 1999; Mathews & Richter, 2007; Olden & Poff, 2003; Richter et al., 1996, 1998; Rougé & Tilmant, 2016; Shiau & Wu, 2008; Tilmant et al., 2010; Z. Yang et al., 2012). Imposing sub-daily regulations reduces flexibility of hydropower operations (Olivares et al., 2015), but it better provides the ecological communities with flow requirements. It should be noted that for the purpose of analysis of hydropeaking operations, metrics and methods that consider flow regime alterations on a sub-daily scale (Bevelhimer et al., 2014) are required (Bejarano et al., 2017; Carolli et al., 2015; Meile et al., 2011; Sauterleute & Charmasson, 2014; Zimmerman et al., 2010). In this regard, Zimmerman et al. (2010) applied a few sub-daily flow metrics to assess alterations observed at different locations throughout the Connecticut River basin. The analysis demonstrated that streamflows downstream of hydropeaking facilities had a significantly higher degree of alteration compared to sections exposed to run-of-river (inflow to the reservoir equals outflow) operations or sections of the river that are not regulated. Thus, the metrics used and the model developed in this study have a sub-daily time scale to more accurately evaluate flow regime outcomes of different operation scenarios.

Optimization techniques have long been applied to reservoir operations. Various optimization techniques including dynamic programming (Cervellera et al., 2006; Macian-Sorribes et al., 2016; Rougé & Tilmant, 2016), the Genetic Algorithms (F.-J. Chang et al., 2005; Wang et al., 2015; Zatarain Salazar et al., 2016), and mathematical programming (Moy et al., 1986; Reis et al., 2005) have been applied to reservoir operation. Recently, optimization schemes have been applied to river systems to optimally balance ecological flow requirements and other system objectives (Barbour et al., 2016; L.-C. Chang et al., 2010; Q. Chen et al., 2012; W. Chen & Olden, 2017; Horne et al., 2017; D. Li et al., 2018; Shiau & Wu, 2013; Tsai et al., 2015; N. Yang et al., 2012; X. Yin et al., 2009, 2010; X. Yin & Yang, 2011). Likewise, in this research, a mathematical optimization model is developed to assess how different operation scenarios might affect the economic and flow regime outcomes at the system outlet.

Based on the Federal Power Act, non-federal hydropower in the United States is regulated by the Federal Energy Regulatory Commission (FERC) (Sensiba & White, 2016). Hydropower facilities are required to obtain operating licenses from FERC. The Connecticut River has five large sequential hydropower reservoirs owned by two distinct entities that are currently undergoing a joint FERC relicensing process. This relicensing procedure has provided an opportunity for The Nature Conservancy (TNC) to seek alternative hydropower operations that minimize negative impacts on the ecology while maintaining the benefits of hydropower generation. To support making better decisions by TNC, an optimization model is developed and presented for the five sequential hydropower plants on the Connecticut River mainstem including Wilder, Bellows Falls, Vernon, Northfield, and Turners Falls reservoirs undergoing a joint relicensing process (Figure 1.1). The optimization modeling mimics the current operations since it maximizes hydropower revenues given energy prices variations. Given that energy prices variations during a day impact hydropower reservoirs operation, a sub-daily time-step is required for the proper evaluation of the hydropeaking operations and flow regime. Thus, the model time-step developed in this research is hourly and takes into account hourly energy prices, inflows and flow regime metrics. Three different operational scenarios are developed and evaluated. The first scenario is called a Baseline scenario in which it is attempted to match the historical operations power generated. Two additional alternative operation scenarios including an IEO scenario in which inflows to reservoirs are enforced to equal outflows during any time step, and a Closed-loop scenario in which the pumped storage Northfield facility is assumed to operate offline (detached form the river) are modeled. The hydropower and sub-daily flow regime outcomes are evaluated under each operation scenario. The outcomes of these modeling efforts provide insight on implications of execution of each operation scenario regarding the flow regime and hydropower revenue and power generated. Having the insight beforehand make stakeholders and parties involved in relicensing process better-informed when choosing an operation scenario.

1.2. Study Area

The system studied is located on the Connecticut River, New England's largest river. There are 38 major sub-basins contributing to the basin with more than 30,000 square kilometers of drainage. The river originates from Canada and ultimately discharges into the Long Island Sound. The basin covers New Hampshire, a small portion of Maine, Vermont, Massachusetts, and Connecticut. There are over 2,700 dams constructed in the basin that contribute to the flow regime alterations across the basin. Many of the dams have hydropower facilities developed during New England's industrial revolution (Clay et al., 2006; Martin & Apse, 2011). Figure 1.1. shows the system schematic including the five hydropeaking and pumped storage facilities and reservoirs. The Northfield facility (NFD) is a pump-storage power plant that is slightly off the river to the east. The other four facilities are large reservoirs located on the mainstem. The facilities are operated by

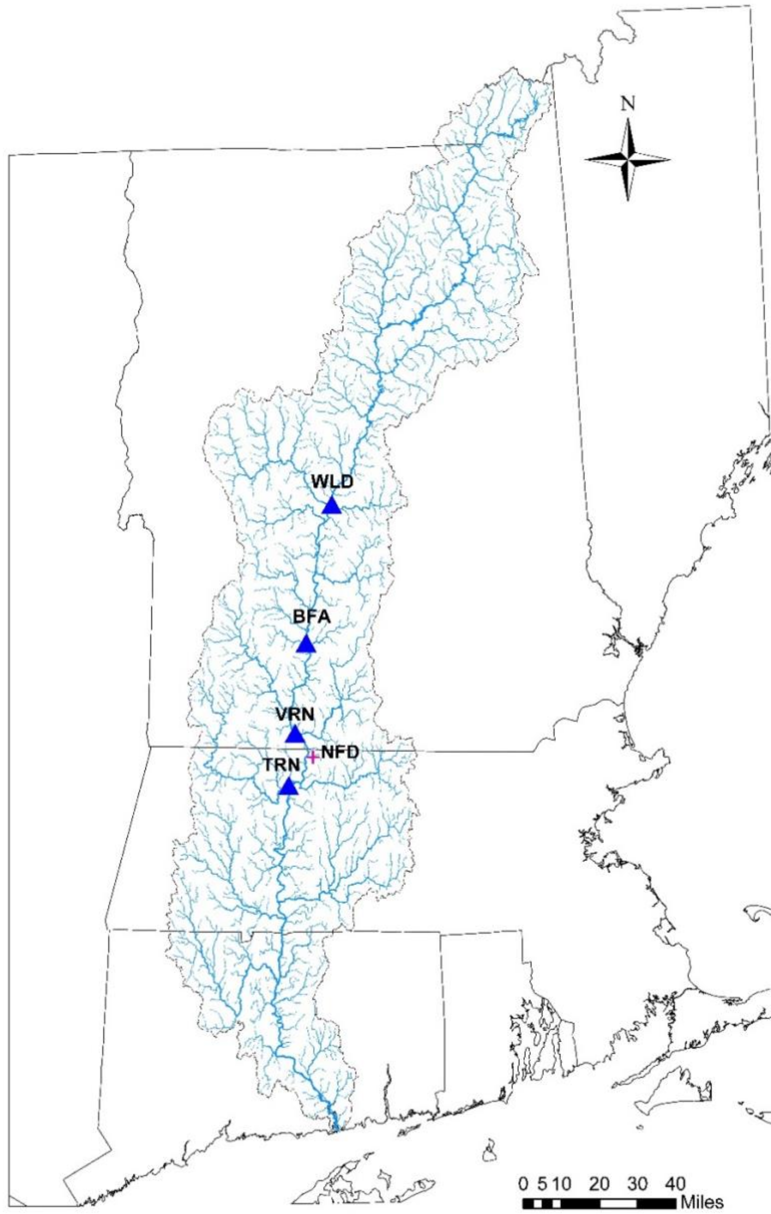

Figure 1.1. System schematic for the Connecticut River hydropower facilities undergoing a joint FERC relicensing process (refer to Table 1.1. for abbreviations)

Table 1.1. Characteristics of the hydropower reservoirs studied

Reservoir (Abbreviation)	Operation type	Operator	Average inflow (m^3/s) (cfs)	Active storage million m^3 (acre-foot)	Estimated refill time (hr)	Power capacity (MW)
Wilder (WLD)	Peaking	TransCanada	181 (11,010)	16.5 (13,350)	25	35.6
Bellows Falls (BFA)	Peaking	TransCanada	297 (10,500)	9.2 (7,480)	8.6	48.6
Vernon (VRN)	Peaking	TransCanada	346 (12,200)	14.7 (11915)	11.8	32.4
Northfield (NFD)	Pumped Storage	FirstLight	N/A	15.2 (12,328)	10	1,119
Turners Falls (TRN)	Peaking	FirstLight	394 (13,900)	10.9 (8861)	7.7	73.4

two companies (TransCanada, and FirstLight) involved in a joint relicensing process. Table 1.1 provides key characteristics of the facilities studied, demonstrating their hydrologic and power capacity data. Northfield pumped-storage facility is one of the largest facilities of this kind in the world with a power capacity of 1119 MW. The other four hydropeaking facilities depicted in Table 1.1 have much lower power capacities. An average refill time is estimated and depicted in Table 1.1 using average inflow values and the reservoir storage capacity values. The refill time values calculated are not significant compared to the average flow values, suggesting these facilities do not have the potential to alter the mainstem flow regime on a time-scale greater than 24-hour. However, the facilities store water and release huge values affecting downstream flow regimes on a sub-daily scale.

Figure 1.2. illustrates the real-time energy prices along with flows observed at the USGS gage 01144500 downstream of Wilder and the reservoir inflows for the first week in

January 2003. As it is evident in Figure 1.2.a. there usually exist two peaks within a day. Historical flows observed downstream of Wilder reservoir at USGS gage 01144500 seem to follow sub-daily energy price variations for the region and they too show two peaks during a day, matched with the energy prices peaks. Comparison of parts a, b of Figure 1.2. reveals Wilder operators schedule releases to make as much revenue as possible by releasing significant volumes through turbines during peak demand hours when the region energy prices are higher. Hydropeaking operations at other reservoirs are expected to be similar given the same energy prices variations for the region.

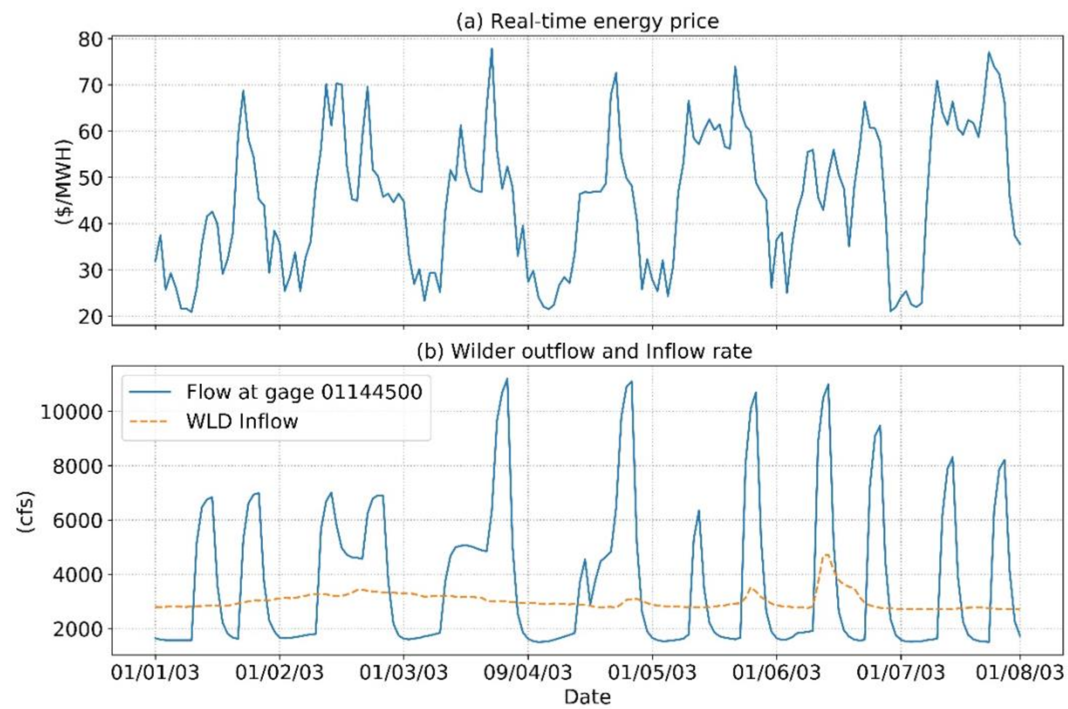

Figure 1.2. Real-time energy prices for western-central mass area, b) Flow at USGS gage 01144500 and inflows observed, for the horizon 01/01/2003 to 01/08/2003

Figure 1.2.b. shows Wilder inflows and flows observed at the gage downstream of the reservoir for the same horizon. Wilder inflows have smoother variations that is impacted

by operation of the upstream hydropeaking facilities. Comparing outflows and inflows of Wilder at Figure 1.2.b., conveys Wilder hydropeaking regulations make the outflows much flashier compared to the inflows to make as much revenue as possible.

1.3. Data

The data used in this research include reservoirs inflows, energy prices, turbine and generator characteristics, reservoirs minimum and maximum storage values, release requirements, and rates of changes for release values. Reservoir inflows are calculated using the Connecticut River Unimpacted Streamflow Estimation (CRUISE) tool developed by the United States Geological Survey (USGS) (Archfield et al., 2012a). This tool provides daily flow data for the horizon 1961-2011 for the reservoirs. Natural daily flows are calculated using the same tool and then simply disaggregated from the daily time-step to hourly time-step. Observed hourly flows upstream of Wilder reservoir were incorporated into the hourly model. Other data required to develop the model are either extracted from reservoirs documents or through contacting operators.

Independent System Operator New England (ISO-NE) provides hourly energy prices. Historical real-time energy price data for the region were downloaded from the ISO-NE website and were incorporated into the model to serve as the signal which would cause the optimizer to mimic the current operations. Since the data is available for 2003-present, the modeled horizon in this study is limited to the 2003-2011 period where available CRUISE and ISO-NE real-time energy prices overlap.

Table 1.2. and Figure 1.3. illustrate historical power generations across the facilities for

years 2003-2011. Because the Northfield Mountain Project was out of operation for much of year 2010, the average calculated for Northfield excludes this year. The Northfield and Turners Falls information for year 2011 are not available. The data in the Table 1.2 are used to calibrate the baseline model aimed at matching the historical power generations.

Table 1.2. Annual historical power generated (in MWH) at the five hydropower facilities for the horizon 2003-2011

Year	WLD	BFA	VRN	NFD	TRN
2003	146,931	220,816	124,956	1,034,432	281,836
2004	146,380	237,628	125,675	1,056,540	301,500
2005	166,302	261,138	111,336	910,072	342,192
2006	191,383	293,816	131,066	1,035,395	412,628
2007	157,940	250,320	113,113	1,100,567	310,868
2008	193,550	282,756	171,514	1,179,584	403,505
2009	185,552	290,576	192,564	972,596	409,215
2010	173,664	264,346	161,782	372,689	343,563
2011	166,430	272,608	170,941	NA	NA
Average	169,792	263,778	144,772	1,041,312	350,663

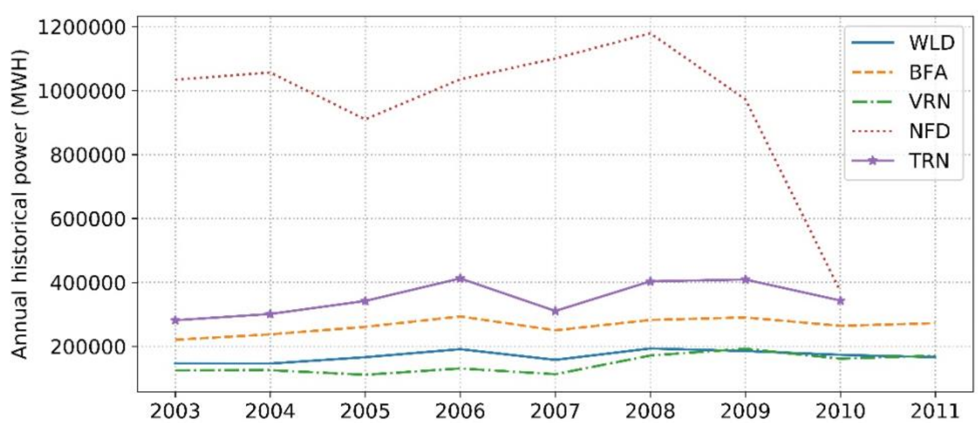

Figure 1.3. Annual historical power generated at the five hydropower facilities for years 2003-2011

1.4. Model Formulation Experiment

To compare different alternative operation scenarios results with the current operations, it is required to first develop a model that closely mimics the current operations. Afterwards, models associated with alternative operation scenarios are developed. Given, the reservoirs are operated to maximize hydropower generation revenues by storing water during non-peak hours and releasing significant water during peak hours, an optimization model would be capable of closely resembling this kind of operation with an objective function of maximizing total revenues. Revenues made are a function of power generated and energy prices. Power generated at each facility is a function of turbine and generator efficiency, specific weight of water, flow rate, and water head over turbines as follows:

$$P = \eta \times \gamma \times Q \times head \tag{1.1}$$

where P denotes hydropower generated, η denotes turbine efficiency, γ is specific weight of water, Q is the flow rate, and $head$ is the water head over turbines. If water head variations are not significant, it can be assumed that the water head is constant. For the facilities studied, this assumption is reasonable given hydraulic head variations are small compared to average heads. This assumption makes the power term in the equation 1.1 a linear function of water discharge. Since mathematical programming models consider flow value passed through turbines in a time-step (like an hourly time-step), one can use flow passed through turbines instead of discharge rate in the equation 1.1. As a result, power generated in each hour h for facility f is dependent of water volume released through the turbine during the hour as follows:

$$P_{f,h} = R_{f,h} \times C_f \tag{1.2}$$

where $P_{f,h}$ is the power generated during hour h for facility f, $R_{f,h}$ denotes the turbine release for facility f during hour h, and C_f denotes the conversion factor relating turbine release to power generated at facility h. In this research, a model is developed that maximizes total hydropower revenues for the five sequential facilities. Revenue made at each hour of operation is product of power made and the energy price during the time-step. Thus, the objective function can be written as:

$$Max\ Z = \sum_{f=1}^{F}\sum_{h=1}^{H} P_{f,h} \times E_h \tag{1.3}$$

where Z denotes the objective function of the programming model; and E_h is the real-time energy price at the time-step (hour h). The objective function in (1.3) is subject to some constraints that either represent operation requirements or the system operation limitations including minimum and maximum flow rates, generator capacities, minimum and maximum reservoir storage capacities, rates of changes in releases, and mass balances of the reservoirs.

The objective and constraints are linear but binary variables are used in some constraints resulting in a mixed-binary mathematical programming model. The motivation for introducing binary variables is to properly model Northfield pumped-storage facility operations. The Northfield facility usually pumps water from the river up to the reservoir during non-peak hours and then release the water during peak hours when energy prices are higher. Since, water is not pumped and released at the same time, binary variables are introduced to the mass balance of the reservoir as follows:

$$S_{h+1} = S_h + I_h - R_h, \forall\, h = 1, \ldots, H \tag{1.4}$$

$$I_h \ <= \ b_h \times L, \forall \ h = 1, \dots, H \tag{1.5}$$

$$R_h \ <= \ (1 \ - \ b_h) \times L, \forall \ h = 1, \dots, H \tag{1.6}$$

where S_h denotes storage value at the beginning of hour h, I_h denotes the water volume pumped up to the Northfield reservoir during hour h, R_h is the water volume released down during hour h, H is the number of hours modeled, b_h is a binary (zero-one) variable, and L is an arbitrary large value. The purpose of introducing binary variables and these constraints is to enforce the optimizer does not assign values to the water pumped and water released for the same hour. For a given hour h, if binary variable b_h takes value of one, then based on Constraint 1.3, I_h will be enforced to be less than the large value L and R_h will take value of zero since it must be non-negative. If b_h takes value zero, then I_h will be zero and R_h can take a positive value less than L. It should be noted L value has to be chosen large enough so that it does not limit operations when I_h, R_h take positive values.

1.5. Operational Scenarios

Three different operation scenarios are modeled in this study. The first scenario is called a baseline scenario in which it is tried to match the power generations outcomes with the historical power generations across all the facilities. The outcomes of the baseline model are compared with the data presented in Table 1.2. Two other alternative scenarios include an IEO scenario and a Closed-loop scenario explained in the following.

IEO, standing for inflow equals outflow, represents an operation scenario in which the four reservoirs on the mainstem are enforced to release flows equal to inflows while the

Northfield facility can still hydropeak. The reason why TNC desired to study outcomes of this scenario was that they expected this scenario to have a potential to improve the flow regime characteristics because the four sequential reservoirs would not regulate flows in this case. Under the IEO scenario, Northfield pumped-storage facility is assumed to hydropeak meaning it can pump water up from its lower reservoir, Turners Falls, and release water down during peak demand hours to the same reservoir. Turners Falls reservoir would be able to control significant flow alterations resultant of Northfield operations. This scenario is modeled by introducing constraints that enforce the outflows equal inflows at any time-step for the four reservoirs on the mainstem.

Another scenario modeled is called Closed-loop under which it is assumed another reservoir as big as Northfield reservoir is constructed at the same elevation as the river. The hypothetical reservoir is used as the downstream reservoir for the Northfield operations. Under this scenario, there would be no linkage between the hypothetical pumped-storage system and the Connecticut River. The motivation for developing this scenario for TNC was to investigate flow regime and economic outcome if Northfield operations are completely detached from the remainder of the system. It was expected such a scenario significantly alleviate flow regime alterations. A version of the model that considers operations associated with this scenario is developed assuming a reservoir as big as Northfield is available with the same turbine efficiency and pumping and release capacities used in the baseline model.

1.6. Results and Analysis

The models are developed in GUROBI (GUROBI Optimization Inc, 2018) solver environment. For the Baseline model, 5 reservoirs are modeled over 9 years with an hourly time-step. Release and storage values are decision variables in each reservoir operation (Eq. 1.4) while there are constraints on minimum and maximum of these variables in each time-step. There is a binary variable for each time-step associated with Northfield reservoir operation (Eq. 1.6) As a result, there are 2,995,913 constraints, 78,840 integer (binary) variables, and 2,680,565 continuous decision variables for the entire analysis horizon. The run-time is less than an hour on the machine used (Intel Xeon Processor E5-2630 v4 25M Cache, 2.20 GHz, 16 GB RAM) with an optimality gap of 1% (it means the optimal solution is within 1% of the solution). Three model versions associated with the Baseline, IEO, and Closed-loop operation scenarios are developed and solved. In the following sections the key results are presented and analyzed.

1.6.1. Hydropeaking Operation

The Baseline model was developed aimed at closely mimicking historic hydropeaking operations in the five sequential hydropower facilities on the mainstem. To calibrate the baseline version, maximum allowed ramping rates (rates of changes in release values) were adjusted in a way that results in modeled hydropower outcomes comparable to those of historical power generations across the facilities. Since the objective function in the model is set as maximization of total hydropower revenue made at the facilities, the modeled operations follow energy prices variations. Thus, the reservoirs hydropeak, meaning they store water during non-peak hours and release the water during hours with high energy prices. A sample of the hydropeaking operations for the five reservoirs, along with the real-time energy prices variation for a one-week horizon are illustrated in Figure 1.4. Figure 1.4.a illustrates the hourly energy prices in $/MWH for the horizon. Figure 1.4.b illustrates modeled outflows of the four hydropeaking reservoirs WLD, BFA, VRN, and TRN on the mainstem. It is observed that the optimized outflows for all the four reservoirs usually vary accordingly since energy prices are the same for all the facilities modeled in this study.

From Figure 1.4. one can conclude that the lower the reservoir, the higher release rate. This is because the water released from the upstream reservoirs end up in the lower reservoirs. Among the four reservoirs, TRN has the highest outflow rates since it is the lower-most reservoir on the Connecticut River mainstem. Figure 1.4.c. presents the Northfield pumped-storage facility outflow and intake rates for the same horizon. Northfield releases during peak hours and pumps water up during non-peak hours. Maximum releases coordinate with the other four reservoirs hydropeaking timing. The release and pumping rate changes are limited by the ramping rates applied. It is evident that Northfield release and pumping does not happen at the same time indicating the introduction of binary variables in the mass balance equation of the facility is working properly since it does not allow the optimizer to allocate positive values to release and pumping at the same time.

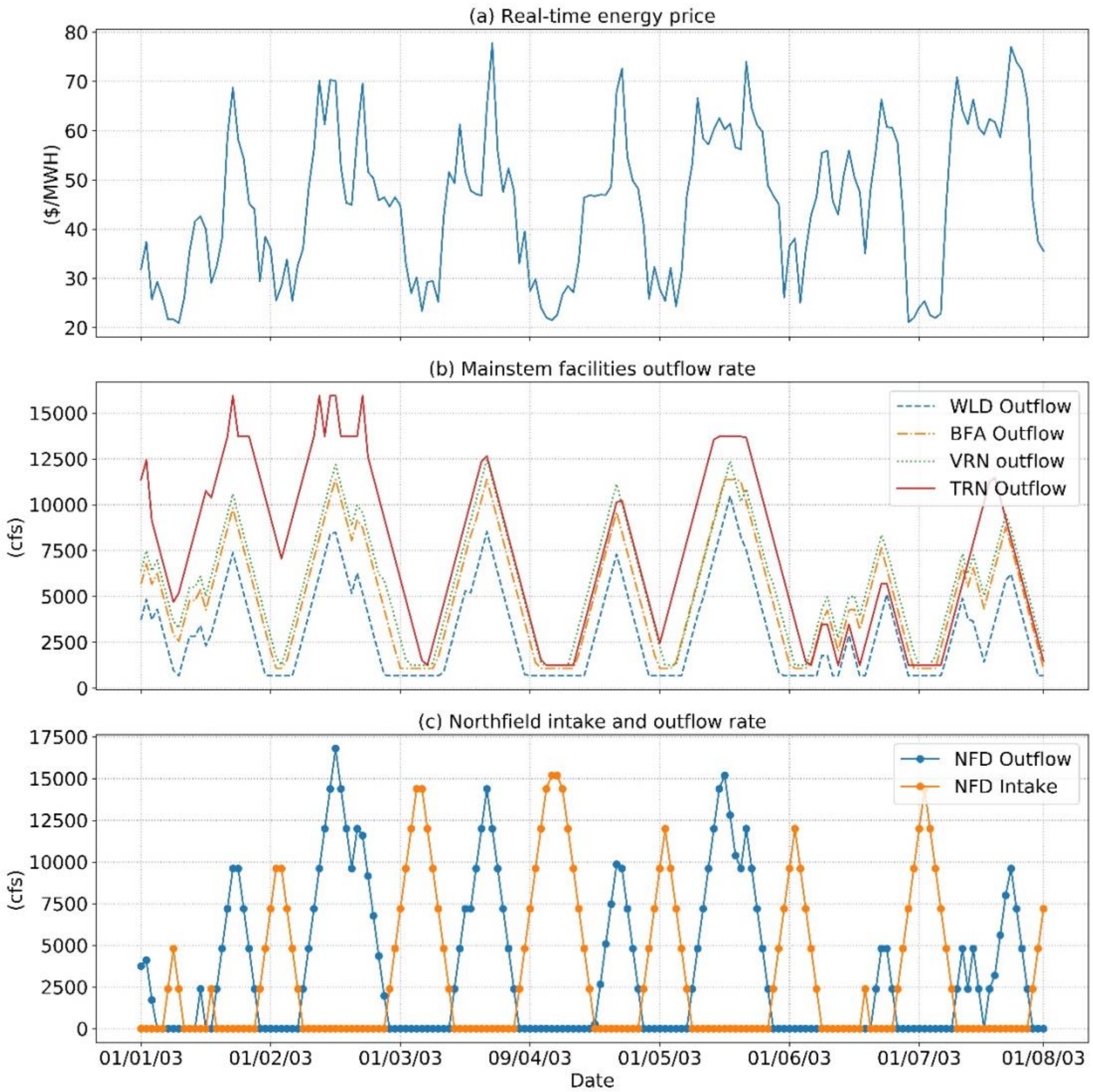

Figure 1.4. a) Real-time energy prices; b) Mainstem facilities outflow rate; c) Northfield outflow and intake rate for the horizon 01/01/03 to 01/08/03 and the Baseline operation scenario

1.6.2. Power Generation Outcomes

Average annual historical power generations along with the hydropower outcomes for the three operation scenarios modeled for years 2003-2011 are depicted in Table 1.3., illustrated in Figure 1.5. The power made at each facility depends on several factors including operation type, turbine efficiency and capacity, storage size, and the amount and timing of inflows. As illustrated in Figure 1.5., the power outcomes of the Baseline model closely match the historical power generations for each facility. This indicates the baseline model is accurately modeling the status-que operations in terms of power generations. As depicted in Table 1.3., the total historic power generation across the facilities is 1,970,318 MWH while the total for the Baseline model is 1,965,612 MWH, showing a 0.2 % difference. All facilities except for Northfield have generated very close hydropower under different operation scenarios. The hydropower generated for a specific facility is dependent on the total water volume released through turbines (not the water spilled out). It seems the total water released through the turbines for the four hydropeaking facilities on the mainstem is the same under Baseline and Closed-loop operation scenarios. Moreover, it seems under IEO scenario more spilling happens resulting in slightly lower power generation. The reason is because sometimes the inflow rates are higher than the turbine capacities. The ability of the reservoirs to regulate inflows under Baseline and Closed-loop scenarios facilitates regulating inflows when they are higher than turbine capacities. The turbine capacity limitation has resulted in a slight power generation reduction on the mainstem facilities under IEO scenario compared to the Baseline and Closed-loop scenarios.

Table 1.3. Average Annual hydropower generation (in MWH) under historic operation and the three modeled operation scenarios for the five facilities on the Connecticut River for years 2003-2011

Operation Scenario	Wilder	Bellows Falls	Vernon	Northfield	Turners Falls	**Total**
Historic	169,792	263,778	144,772	1,041,312	350,663	1,970,318
Baseline	161,816	248,066	149,182	1,027,713	378,835	1,965,612
IEO	156,657	239,436	143,242	945,645	365,455	1,850,434
Closed-loop	161,814	248,043	149,170	1,700,649	380,346	2,640,022

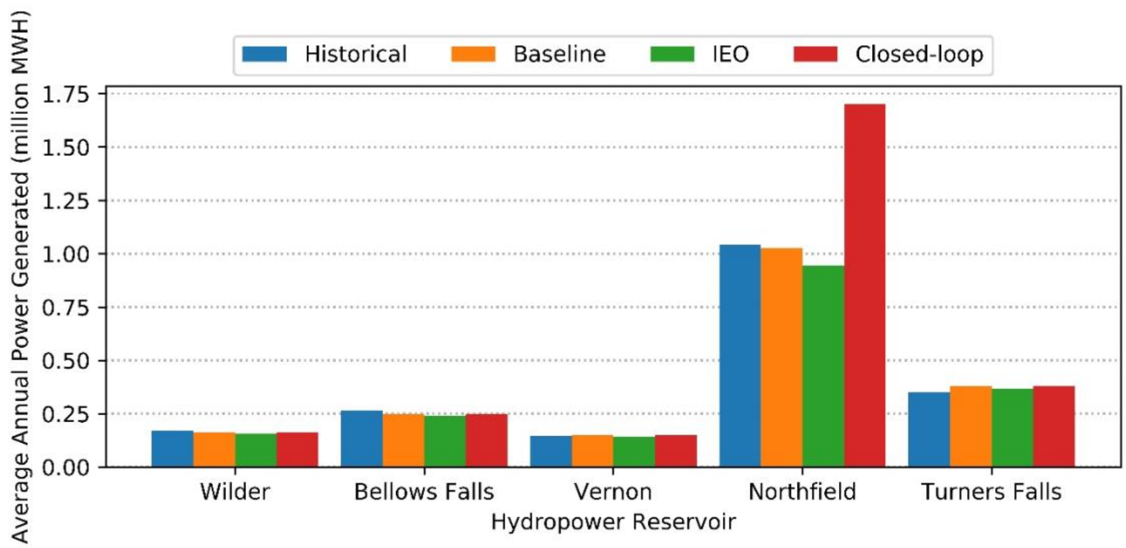

Figure 1.5. Historical and modeled average annual power generation of the five hydropower facilities for years 2003-2011

Northfield has generated around 8% less power under IEO scenario, and 65% more in the Closed-loop scenario compared to the Baseline scenario. The reason for the 8% reduction under IEO scenario seems to be the inability of the Northfield facility to rely on the upstream reservoir (Vernon) releases as the intake since the Vernon reservoir releases cannot be stored at Turners Falls reservoir to be used for Northfield pumping. The reason for the significant 65% increase under Closed-loop scenario is because Northfield and the hypothetical lower reservoirs would be able to operate at their full capacity with water being always available for pumping or release.

1.6.3. Hydropower Revenue Outcomes

The average annual economic outcomes under each operation scenario is presented in Table 1.4 and Figure 1.6. The revenue calculated is a multiplication of the energy made (Eq. 1.2) and the energy price during each time-step. Historical revenue data are not available to be used for comparison. The results associated with the Baseline, IEO, and Closed-loop scenarios are presented for years 2003-2011. The revenue modeled at the facilities depend on power generated and the energy prices. Northfield and Turners Falls make higher revenues due to the larger size of the facilities and passing higher inflows through the turbines.

Under IEO scenario, the revenue made at the facilities for Wilder, Bellows Falls, Vernon, Northfield, and Turners Falls is respectively around 10%, 8%, 9%, 11%, and 17% reduced compare to the Baseline scenario results. These reductions identify the loss associating with implementing the IEO scenario compared to the Baseline operation scenario. The highest reduction is observed in Northfield and Turners Falls power plants. Under the IEO scenario, Northfield will just rely on the Turners Falls storage capacity for its pumping since the Vernon releases would not be available for Northfield operations, resulting in a 11% reduction in the revenue made at this facility. Turners Falls experiences a 17% reduction under IEO compared to the Baseline, which is because under this scenario the reservoir just releases the volume released from Vernon and would not be able to release Northfield releases when Northfield dispatches huge volumes of water during peak energy prices hours to the Turners Falls reservoir. The total revenue calculated for the system under IEO scenario is 12% less than the revenue associated with the Baseline scenario. Under Closed-loop scenario, reservoirs Wilder, Bellows Falls, and Vernon have resulted in revenues very close to that of Bassline scenario while Northfield revenue is 80% increased and Turners Falls revenue is 10% decreased. The reason for the increase in Northfield revenue is obviously due to utilization of the hypothetical reservoir full capacity under the scenario. The reason for the 10% decrease in Turners Falls revenues seems to be the inability of the reservoir to release Northfield release under Closed-loop scenario since in this scenario the Northfield is releasing into the lower hypothetical reservoir. The total revenue generated under Closed-loop scenario is 22% more compared to the Baseline scenario.

Table 1.4. Average Annual hydropower revenue (in million $) under the three modeled operation scenarios for the five facilities on the Connecticut River for years 2003-2011

Operation Scenario	Wilder	Bellows Falls	Vernon	Northfield	Turners Falls	**Total**
Baseline	10.2	15.1	9.0	26.9	25.4	86.7
IEO	9.2	13.9	8.2	23.9	21.1	76.3
Closed-loop	10.2	15.1	9.1	48.6	23.0	106.1

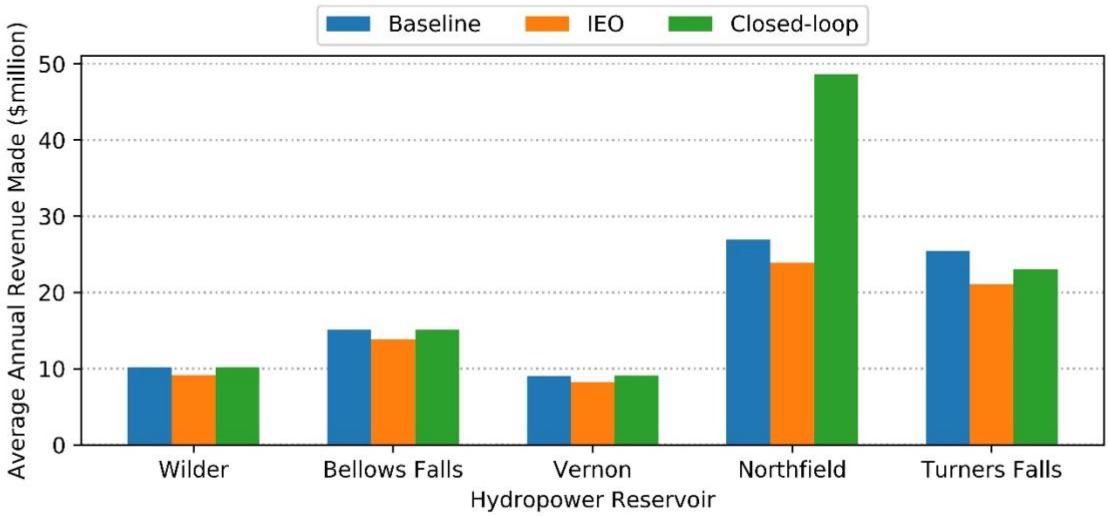

Figure 1.6. Modeled average annual revenue results of the five hydropower facilities for years 2003-2011

1.6.4. Flow Regime Outcomes

The alternative operation scenarios, IEO and Closed-loop are expected to improve flow regimes for ecological goals. Figure 1.7 shows a sample of hydrograph at the system outlet (Turners Falls outlet) for a one-week horizon, illustrating the differences in flow regime between the operation scenarios. Under Baseline and Closed-loop scenarios, the reservoir releases indicate hydropeaking operation while under IEO scenario, releases variations are smooth. Although the flows under IEO scenario are not completely unregulated, since the variations are affected by the system upstream regulations, this figure shows that implementing the IEO scenario has the potential to significantly decrease hydropeaking effects that might be beneficial to the watershed communities. The flows under the Closed-loop scenario illustrate slightly less flashiness compared to the Baseline scenario which could be because under this alternative scenario Northfield hydropeaking operations are not intensifying fluctuations at the system outlet.

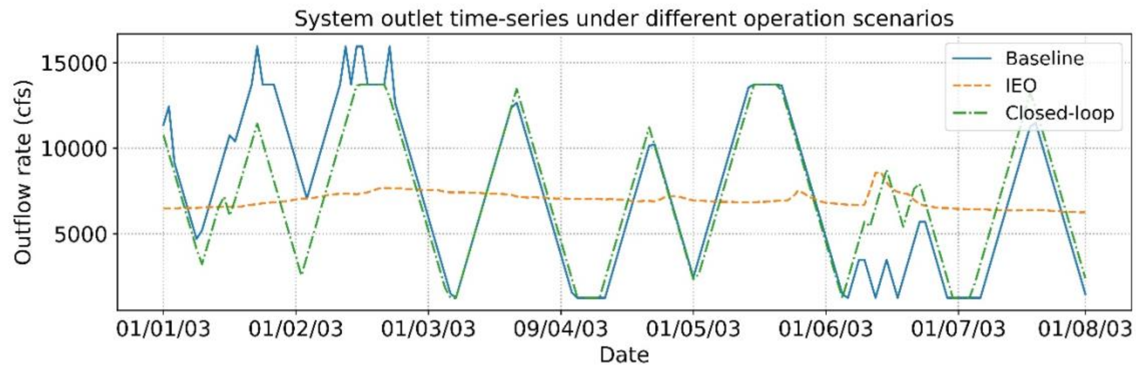

Figure 1.7. System outlet time-series for the horizon 01/01/03-01/08/03 under different operation scenarios

Three flow statistics, Richard-Baker flashiness index, average daily peak flow rate, and average daily flow rate were of interest of TNC to be investigated. The metrics are measured to quantify the sub-daily flow regime characteristics under the different modeled operation scenarios: Baseline, IEO, and Closed-loop. The metrics are calculated for different seasons to investigate the sub-daily flow metric. Richard-Baker flashiness (RBF) index measures the rate of flow changes at a sub-daily time scale. It calculates the relative rate of change in flow values across a day by calculating the summation of average changes in flows during a day and dividing it by the summation of flow values during the day (Zimmerman et al., 2010). The metric is formulated as:

$$RBF = \frac{\sum_{t=1}^{N} 0.5(|F_{t+1} - F_t| + |F_t - F_{t-1}|)}{\sum_{t=1}^{N} F_t} \tag{1.7}$$

where F_t denotes the flow value associated with time t; and N denotes the number of steps which is 24 in this study.

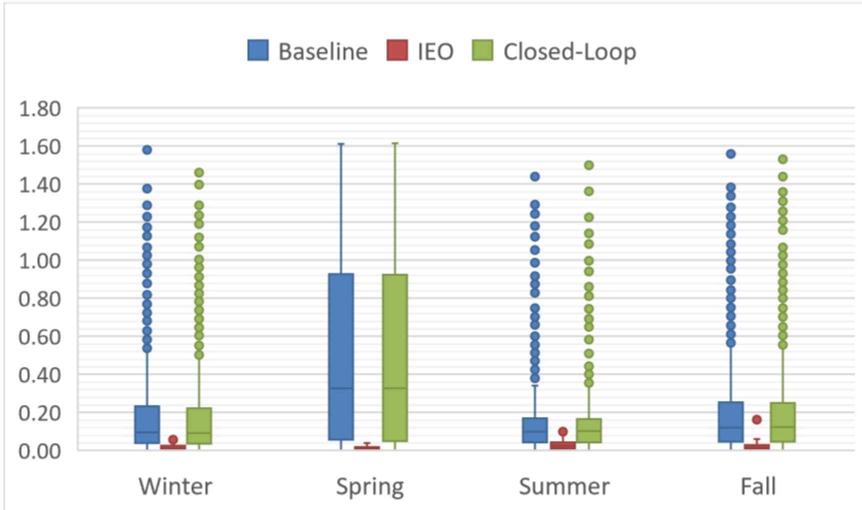

Figure 1.8. Richard-Baker flashiness index by season under the three modeled operation scenarios at the system outlet (Turners Falls releases)

RBF index is calculated for the system outlet (at Turners Falls reservoir outlet) and the box plots of the values calculated are presented in Figure 1.8 for different operation scenarios to investigate how implementation of different scenarios might affect flow regime at downstream of the system. As it is evident in the figure, the IEO scenario has significantly reduced the range of variations while the Closed-loop operation scenario has very slightly reduced the range compared to the Baseline operation scenario. The slight improvement in the Closed-loop scenario is due to the detachment of the Northfield facility huge releases during high energy prices that must be released out from the downstream reservoir, Turners Falls. The flashiness metric has higher median and ranges of variations during Spring for Baseline and Closed-loop scenarios which could be due to high inflows during the season. The metric median for the Baseline and Closed-loop scenarios are roughly 0.08, 0.32, 0.1, and 0.11 respectively for Winer, Spring, Summer, and Fall. The median flashiness associated with IEO scenario are very close in every season and around 0.04.

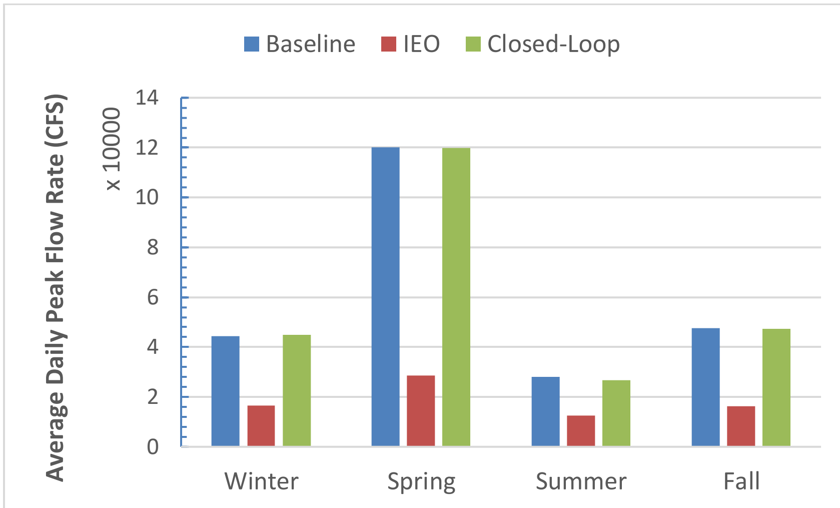

Figure 1.9. Average daily peak flow rate (cfs) for different seasons under the three operation scenarios modeled at the system outlet (Turners Falls releases)

The average daily peak flow rate is calculated for the system outlet for different seasons under the studied operation scenarios and are presented in Figure 1.9. Compared to the Baseline scenario, the results for IEO scenario are much smaller in every season, showing a significant improvement in the magnitude component of the river's flow regime, while the Closed-loop scenario results are just very slightly lower. The results for the IEO scenario are at least twice smaller in every season compared to the two other scenarios. Like the flashiness metric evaluation, this metric has higher values during Spring (around 120,000 cfs for Baseline and Closed-loop scenarios and 30,000 cfs for IEO scenario) under every operation scenario while the results for the other seasons are not significantly different under a given operation scenario.

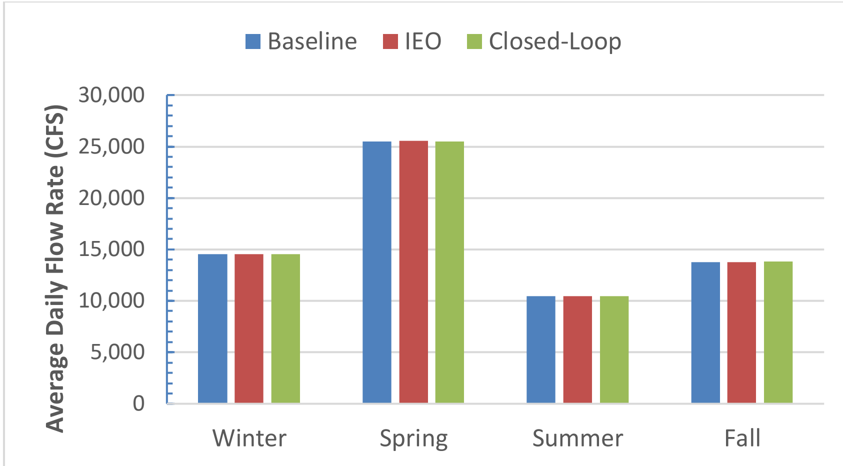

Figure 1.10. Average daily flow rate (in cubic feet per second) for seasons under the three modeled operation scenarios at the system outlet (Turners Falls releases)

The average daily flow rate metric is calculated for all the seasons under the operation scenarios studied and are illustrated in Figure 1.10. As it is evident in this graph, the results for different operation scenarios are very close. This is because the storage capacity at the mainstem reservoirs is not significant compared to the average daily flows and as a result the facilities lack the potential to change average flows on a daily or a larger time-scale. This result further supports the idea that the hydropeaking operations should be studied on a sub-daily time scale.

1.7. Conclusions

Hydropower reservoir operations on the Connecticut River mainstem have altered flow regime on a sub-daily time-scale because the operations follow sub-daily energy market dynamics resulting in implications for the watershed ecology. In this research, a mathematical programming model was developed in GUROBI optimizer environment as an alternative operation scenario assessment tool to evaluate power, revenue, and flow regime outcomes of different operation scenarios. The Baseline model closely matched historical power generations of the five large sequential reservoirs in the system studied and resulted in hydropeaking operation comparable to real-world hydropeaking operations. Two alternative operation scenarios, the IEO scenario in which releases equal inflows, and the Closed-loop scenario in which the Northfield pumped-storage facility is detached from the river, were also evaluated.

Based on the modeling results, it was estimated implementation of the IEO scenario significantly improves the flow regime outcomes while it degrades the total revenue by 12% compared to the Baseline scenario. The Closed-loop scenario improves the flow regime very slightly and enhances power and revenue generated at the system by respectively by 34% and 22% compared to the Baseline model. In terms of power generations, different facilities except for Northfield showed very close outcome under every operation scenario. Under the IEO and Closed-loop operation scenarios, Northfield resulted in an 8% decrease and a 65% increase respectively compared to the Baseline operation scenario. In terms of revenue outcomes, the IEO scenario resulted in 8-17% reduction in revenues across the facilities. Under the Closed-loop scenario, the same revenue is generated for different facilities except for an 80% increase in Northfield and a 10% increase in Turners Falls compared to the Baseline model.

After assessing flow regime metrics, it is concluded the IEO operation scenario results in the least flow alterations since it has smoother release variations at the system outlet and significantly decreases RBF index median and range of variations, and average daily peak flow rate. Closed-loop operation scenario flow regime outcomes closely resembled the Baseline operation scenario. All the three operation scenarios resulted in very close average daily flow rates confirming the hydropeaking operations on the Connecticut River do not change average flow rates on a time-scale greater than a daily time-scale.

CHAPTER 2

A MULTIOBJECTIVE OPTIMIZATION METHODOLOGY FOR RIVER BASIN TRADE-OFF ANALYSIS

2.1. Introduction

Water reservoirs meet different objectives including water supply, electricity generation, flood control, recreation, navigation, and ecological. Regulation of complex reservoir systems to best meet the objectives is challenging because the objectives are not commensurate and are often conflicting (Ahmadi et al., 2014; L.-C. Chang & Chang, 2009; Foued & Sameh, 2001; Reddy & Nagesh Kumar, 2006, 2007; T. Yang et al., 2015). Mathematical modeling can quantify the interactions between the objectives by evaluating future conditions of water systems based on different operation strategies. Various optimization methods have been presented for reservoir systems operation, each with specific limitations and advantages (Biglarbeigi et al., 2018; Giuliani et al., 2016; Labadie, 2004; Mason et al., 2018; Rani & Moreira, 2010; Yeh, 1985; Zatarain Salazar et al., 2016). The applicability of the methods described in the literature depends on factors including time and financial resources, data availability, stakeholder goals, and the modelers experience. Optimization modeling is often done when it is difficult to evaluate all the alternatives using a simulation model. In some cases, analysts develop an optimization model to eliminate less favorable alternatives concerning the objectives of interest and then evaluate the remaining alternatives using a detailed simulation model.

Multiobjective approaches are applied to water resources systems problems when there exist conflicts between the objectives of system (Aboutalebi et al., 2015; Bai, Chang, et al., 2015; Bai, Wu, et al., 2015; Ehteram et al., 2017; Y. Li et al., 2017; Liu et al., 2017; Luo, Chen, et al., 2015; Luo, Qi, et al., 2015; Madani & Hooshyar, 2014; Tsoukalas & Makropoulos, 2015). Multiple objective frameworks illustrate the trade-offs between different objectives and indicate how the system might be operated to improve some objectives without significantly sacrificing other objectives (Cohon & Marks, 1975). Pareto frontier can be developed using these methods that reveals the non-dominated set of solutions (Reed et al., 2013). More recently, different optimization techniques have been used for developing trade-offs in water systems including nature-inspired algorithms (Afshar & Hajiabadi, 2018; Niu et al., 2018; Seifollahi-Aghmiuni & Bozorg Haddad, 2018; Srinivasan & Kumar, 2018) (in which optimization algorithms are developed mimicking the natural phenomena), mathematical programming (linear, mixed-integer, mixed-binary, or nonlinear programming) (Adams et al., 2017; Han et al., 2011), dynamic programming (Delipetrev et al., 2016; Zhao & Zhao, 2014) , and reinforcement learning (Castelletti et al., 2013). The technique chosen depends on the problem characteristics, accuracy required, and computational resources available. Application of nature-inspired algorithms has been limited to simple systems like those of dynamic programming and reinforcement learning. Mathematical programming methods however have successfully been applied to large and complex reservoir systems (Jenkins et al., 2004; Steinschneider et al., 2014). Regardless of the optimization technique selected, objectives must be clearly quantified to allow for a proper evaluation of the objectives performance.

In recent decades, impacts of reservoir operation on sustainability of watersheds communities, and the need for providing complex ecological flow requirements have been studied (Arthington et al., 2006; Bain et al., 1988; Gerten et al., 2013; N. LeRoy Poff, 2009; Brian D Richter & Thomas, 2007; Saito et al., 2001; Sale et al., 1982; Shafroth et al., 2009; Symphorian et al., 2003; Tennant, 1976; X.-A. Yin et al., 2011). Although the implications of each reservoir is unique (McCartney, 2009), all reservoirs affect sustainability of watersheds to some degree by altering the flow regime in terms of magnitude, frequency, duration, timing and rate of changes (Poff et al., 1997). Biologists and ecologists have identified negative ecological impacts of flow alteration by daily and sub-daily reservoir regulations (Magilligan & Nislow, 2001). As Acreman et al. (2014) write "*Environmental flows may be achieved in a number of different ways, most of which are based on either (1) limiting alterations from the natural flow baseline to maintain biodiversity and ecological integrity or (2) designing flow regimes to achieve specific ecological and ecosystem service outcomes. We argue that the former practice is more applicable to natural and semi-natural rivers where the primary objective and opportunity is ecological conservation. The latter "designer" approach is better suited to modified and managed rivers where return to natural conditions is no longer feasible and the objective is to maximize natural capital as well as support economic growth, recreation, or cultural history (466),"* the common hypothesis is that flows will benefit ecosystems the best if they are closest to their natural state (Van Looy et al., 2014; Naiman et al., 2002), but if it is not possible to restore river flows, flows should be designed in a way that meet ecological metrics. In this regard, research has been done on measuring flow alterations to determine the best management practices for riverine ecosystems health (Petts, 2009; N. LeRoyy Poff et al., 2010; Shiau & Wu, 2010; Vogel et al., 2007). Researchers have sought to: 1) identify natural flows; 2) develop measures to quantify the degree of alteration compared to natural flows (Gao et al., 2009; Weiskel et al., 2010), and 3) seek alternative operational strategies that minimize the degree of alteration.

Steinschneider et al. (2014) sought to improve ecological performance of the Connecticut River basin by developing a linear program and examining the effects of various operation scenarios regarding ecological objectives and other goals. They penalized river flow deviations from natural flows in a piece-wise linear form to minimize the total amount of deviations. In another study for the same system, Julian et al. (2015) presented a decision support system combining hydrologic, ecological models with a simulation model developed in HEC-ResSim (Klipsch & Hurst, 2013). They quantified ecological goals using hydroperiods, defined as the number of days per year the flood plain is flooded. The modeling effort converts changes in operations to socio-economic and environmental alterations and describes how the flow regime might link to the specific species health.

This research focuses on identifying the trade-offs of the Connecticut River system by applying a new multiple objective optimization methodology to the system. The methodology focuses on maximizing frequency of meeting ecological flow requirements rather than minimizing deviations from desired bounds performed by Steinschneider et al. (2014). The reason for following this approach is because it is assumed once the flows violate certain boundaries, it would not matter for the watershed communities how beyond the boundaries the flows are. Likewise Richter et al. (2003) emphasize on measuring frequency of meeting ecosystem flow requirements when studying water resources development projects effects. It is assumed frequency is the measure that should be quantified when analyzing ecological flow requirements. As another objective, the frequency of controlling flood conditions is quantified rather than deviations from flood warning levels modeled by Steinschneider et al. (2014). New formulations are developed to quantify the reliability of meeting environmental flows within desirable bounds and the reliability of not violating flood warning levels. Next, an algorithm is designed and developed for the basin that enables solving a mathematical programming model for each year that carries over the end-of-year results into the next year. The reliabilities are optimized for the Connecticut River as objective functions for each year of the analysis in conjunction with other operational objectives. Binary variables are used in the formulations resulting a mixed-binary linear program that was solved with solver GUROBI (GUROBI Optimization Inc, 2018). The trade-offs between the objectives are developed and the associated results at different econodes, flood checkpoints, hydropower facilities, and reservoirs are analyzed.

2.2. System Description

The Connecticut River is the largest river in New England (Figure 2.1). There are more than 2700 dams (Graf, 1999) in the watershed. The river originates in Canada-New Hampshire border and flows to the Atlantic Ocean at Long Island Sound. The mainstem is 410 river miles and covers parts of New Hampshire, Maine, Vermont, Massachusetts, and Connecticut totaling a 30,000 km^2 drainage area. The reservoirs in the basin are used for different purposes including hydropower, recreation, flood control, and water supply. The vast majority of the reservoirs are low head while a number of them are considered large reservoirs ("CorpsMap: The National Inventory of Dams (NID)," 2018).

The significant alteration of flows due to reservoirs operation has significantly changed the natural flow regime across the basin. These changes impact the viability of various flood plain species during different life stages (Marks et al., 2014). The reservoirs have different owners and operators while the USACE operates fourteen large reservoirs on major tributaries, the largest number among different owners. Thirteen reservoirs of the fourteen are solely operated for flood control while one is conjunctively used for flood control and power generation. The largest water supply reservoirs are Quabbin, Barkhamsted, and Cobble Mountain that supply municipal water demands of Boston, Massachusetts, Hartford, Connecticut, and Springfield, Massachusetts, respectively. Cobble Mountain is a dual-purpose reservoir, used for electricity generation as well. Other reservoirs are used for either hydropower, recreation or just for storing water.

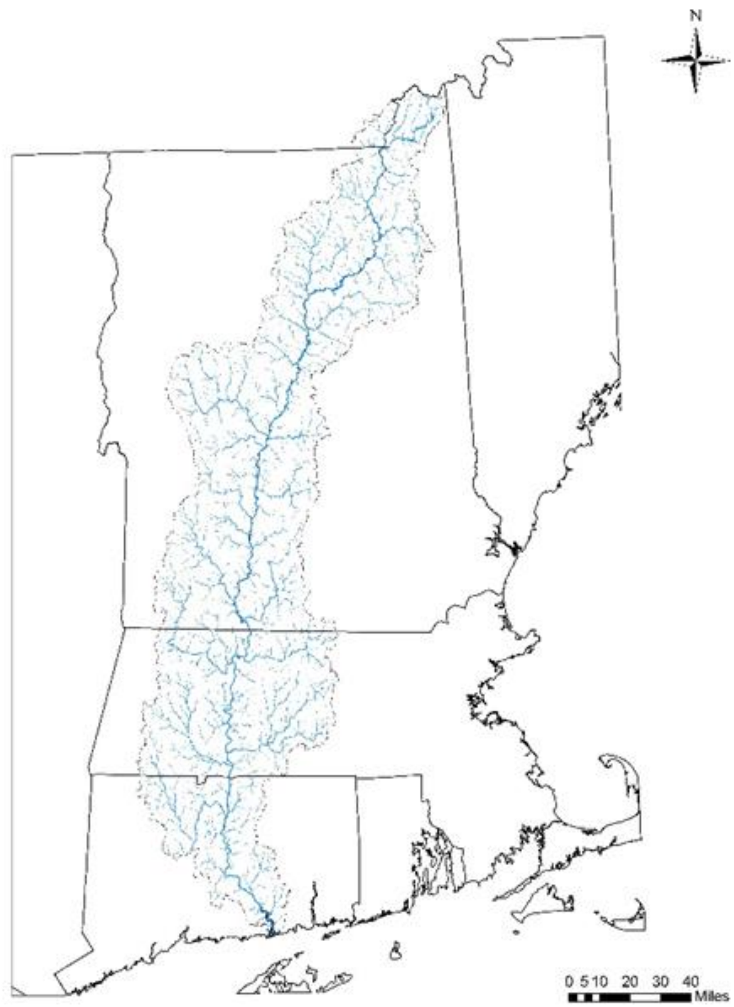

Figure 2.1. The Connecticut River basin located in New England

2.3. The System Objectives

2.3.1. Ecological Objective

Richter et al. (2003) emphasize the application of frequency of violating ecosystem flow requirements for evaluating flow alterations in water resources systems. In this study, this approach is used to quantify the ecological objective. In this regard, the ranges of flows in which various species prosper are estimated after consultation of biologists and ecologists in the Connecticut River basin (Steinschneider et al., 2014). At stakeholder meetings, The Nature Conservancy (TNC) used expertise of local aquatic ecologists, biologists and other environmental experts to specify the levels of alterations that was believed to have negligible impacts on different species at different locations (econodes). For this research, formulations are developed that consider this measure as reliability of meeting flows in ecologically desirable bounds. For econode en, the reliability is measured using constraints (2.1) and (2.2); and the Ecological Objective for the basin is calculated using (2.3) as follows:

$$F_{en,t} < N_{en,t}\left(1 + H_{en,t}\right) + \left(1 - EZ_{en,t}\right) \times B_{eco}, \forall\ t = 1, \dots, T \tag{2.1}$$

$$F_{en,t} > N_{en,t}\left(1 + L_{en,t}\right) - \left(1 - EZ_{en,t}\right) \times B_{eco}, \forall\ t = 1, \dots, T \tag{2.2}$$

$$EcoObj\ = 100. \sum_{en\,=\,1}^{EN} \sum_{t=1}^{T} \frac{EZ_{en,t}}{T \times EN} \tag{2.3}$$

where $F_{en,t}$ denotes the modeled flow at the econode en during time t; $N_{en,t}$ denotes the estimation of natural flow at the econode en for time t; $H_{en,t}$, $L_{en,t}$ are fractions of natural flows for the same time step and econode that respectively refer to the upper and lower boundaries of flows (these two parameters together form a desirable flow bound beyond which the floodplain species are negatively affected); B_{eco} is a large value used to provide an extended flow bound when they deviate the desirable bound; $EZ_{en,t}$ is a zero-one variable for econode en and time t; and T, EN are respectively number of time steps and econodes. Equation (2.3) characterizes the Ecological Objective that represents the reliability of meeting environmental flows within the desirable bounds across all the econodes in the basin. If the variable $EZ_{en,t}$ takes value 1, Constraints (2.1) and (2.2) together would ensure that the flow passing the econode during the time t, is within the desirable bounds specified by $H_{en,t}$, $L_{en,t}$. If the variable $EZ_{en,t}$ assumes a value of 0, the flows can violate the desirable bounds as there would be an extended bound, by B_{eco} units from the two sides, in which the flows will fall. Equation (2.3) measures the reliability with which flows fall within the desirable bounds across all the nodes and time-steps. This measure might be used as the overall basin health indicator in studies that focus on reoperation of the reservoirs to seek operation alternatives that balance this objective along with other operational objectives.

To assess the ecological performance across the basin, critical econodes at different tributaries and on mainstem have been identified (Figure 2.2). The most restrictive bound associated with the least flexible species at each econode is chosen as the desirable bound. Providing flows at these econodes within the desirable zones is important for different life processes of the species of the basin. The bounds depend on magnitude of flows and time of the year. Some of the bounds are narrow suggesting the aquatic species are very sensitive to alterations while some of the bounds are wider allowing more flexibility in reservoir operations (Steinschneider et al., 2014).

2.3.2. Flood Control Objective

Reservoirs can mitigate flood damages by storing floodwaters and releasing the water at a rate that minimizes negative impacts on downstream. A measure regarding flood control is the frequency of violating flow values that create flooding. To account for this measure, flood checkpoints at important locations were chosen in the basin (Figure 2.2). Flood warning levels have also been developed considering the watershed conditions.

The reliability of not violating flood warning levels, as another objective in this research, is quantified using the following constraint and equation. For a given checkpoint, fc, flood control is modeled as:

$$FF_{fc,t} < FWL_{fc} + \left(1 - FZ_{fc,t}\right) \times B_{flood}, \forall\, t = 1, \dots, T \quad (2.4)$$

$$FloodObj\ = 100. \sum_{fc\,=\,1}^{FC} \sum_{t=1}^{T} \frac{FZ_{fc,t}}{T \times F} \quad (2.5)$$

where $FF_{fc,t}$ denotes the modeled flow at the checkpoint fc during time-step t; FWL_{fc} is flood warning level at the checkpoint fc; FC is the number of flood checkpoints; $FZ_{fc,t}$ is a zero-one variable for flood checkpoint fc during time step t; and B_{flood} is a large value. Based on Constraint (2.4), if $FZ_{fc,t}$ assumes a value of one, the flow at the flood checkpoint is enforced to not to be greater than flood warning level, and if it assumes a value of zero, the flow can violate the flood warning level. Equation (2.5) quantifies the reliability of flood control across all the checkpoints, representing the Flood Control objective in this study. Applying this measure, the flow passed through the cross section of river at the flood checkpoint during the time step would be considered a flood if it is greater than the flood warning level. Although this measure does not evaluate the socio-economic damages, it provides insight on how reliably the floods are controlled.

2.3.3. Hydropower Revenue Objective

Some reservoirs in the basin generate electricity through their power plants (Figure 2.2). The electricity constitutes 11% of total energy consumed in New England. To account for

Hydropower Revenue objective, the revenue generated at these facilities is considered as another objective to be maximized. The power generated is, in theory, a nonlinear function of water head over turbine and flow rate through turbine. Because many facilities are low head, it was assumed the head changes are negligible. Assuming a constant head and knowing the turbine efficiencies results in the power produced in each time-step to be a function of discharge rate through turbine. The revenue made each time step is the product of power made and the energy price during the time-step. Thus, the total revenue of the facilities over the analysis period is maximized applying (2.6) and (2.7) as follows:

$$HydroObj = \sum_{hr=1}^{HR} \sum_{t=1}^{T} \frac{P_{hr,t} \times EP_t}{T \times HR} \tag{2.6}$$

$$P_{hr,t} = PR_{hr,t} \times PC_{hr,t}, \forall\, t = 1, \dots, T \tag{2.7}$$

where HR is the number hydropower facilities; $P_{hr,t}$ denotes the power generated at facility hr during time step t; EP_t is energy price at time-step t; $PR_{hr,t}$ is the water volume released at facility hr during time-step t; $PC_{hr,t}$ is the coefficient converting water volume released through turbines to the power generated at the facility hr during time-step t; and $HydroObj$ denotes the hydropower revenue objective. Equation (2.7) calculates the power generated at the given facility during the time-step t and Equation (2.6) calculates the average daily revenue made across at all facilities. Thus, the total revenue generated from all the power plants and for the planning horizon is maximized. It should be noted that there are constraints on the maximum releases passed through turbines that limit the power and revenue made at the facilities. Any release beyond the turbine capacity is spilled and does not contribute to the revenue made.

2.3.4. Storage Level Objective

Depending upon the primary purpose of reservoirs, there usually exist desired reservoir storage levels. For instance, water supply and recreational reservoirs are desired to be maintained full or at certain levels while flood control reservoirs are often drained (empty) in anticipation of a flood. Accordingly, storage level objectives are applied in this study based on the past operations in the Connecticut River basin. The USACE reservoirs usually fill just a small fraction of their storage enabling them to capture the maximum flood volume in case a flood occurs. Conversely, operators of water supply, hydropower, and recreational reservoirs try to maintain the reservoirs at their full capacity. Considering these operational preferences, three categories for storage level objectives are developed. The categories include USACE reservoirs, non-USACE reservoirs, and municipal reservoirs. The average daily storage for all the reservoirs of a category are optimized. These objectives minimize the USACE reservoirs average storage and maximize the average storage of the other reservoirs. This objective will cause the USACE reservoirs to be the main contributor in controlling floods which is in line with the current operation of the system. For a given category, this objective is formulated as:

$$SLObj = 1/T.\left(\sum_{r=1}^{R}\sum_{t=1}^{T} S_{r,t}\right) \tag{2.8}$$

where R denotes the number of reservoirs in the category; $S_{r,t}$ denotes storage value at the beginning of time step t for reservoir r. $SLObj$ represents the Storage Level objective for the category considered.

2.3.5. Water Supply

The municipal water demands of the cities Boston, Hartford, and Springfield are supplied by reservoirs Mare Meadow/Bickford, Quabbin, Cobble Mountain, Barkhamsted, and Nepaug. These demands are always met in this modeling exercise since they are prioritized over other objectives. Thus, there is no need to include water supply as another objective. The demand time series were included with a negative sign in the mass balances of the modeled reservoirs.

2.4. Data

Flow values, energy prices, reservoirs minimum and maximum levels, minimum and maximum release values, power production capacities, ecologically desirable bounds, and flood warning levels were collected for the system. The flow data at different locations across the basin for the period of 1961-2011 are estimated using the Connecticut River Unimpacted Streamflow Estimation (CRUISE) tool developed by the United States Geological Survey (USGS) (Archfield et al., 2012b). The tool uses regression, based on watershed characteristics, to estimate the flows.

Historic energy price data were obtained from the Independent System Operator New England (ISO-NE) website. Hourly regional historic locational marginal pricing (LMP) data are available for the period of 3/2003 – 11/2017. To develop daily prices, the average hourly values for each hour of the year were aggregated to average daily values for each day of the year. The same prices data are used for different years of the modeling horizon since the energy prices are not available for the entire horizon.

Reservoirs characteristics including minimum and maximum storage values, and minimum and maximum release requirements were gathered either through documents of reservoirs or via contacting owners/operators. The ecological bounds in which various species are not affected are developed after extensive consultation with biologists and ecologists (Steinschneider et al., 2014). These bounds are developed for various econodes in the entire basin. Given different species have different flow needs, the most limiting bounds are chosen as the desired bound. Flood warning levels across flood checkpoints were also developed and used as the upper bound in the constraints controlling flow values at the flood checkpoints.

2.5. Algorithm Development and Execution Experiment

54 largest reservoirs in the basin with the characteristics described in Table 2.1 were chosen along with 28 econodes and 13 flood checkpoints to be modeled (Figure 2.2). There are 23 power plants installed on 22 reservoirs. In terms of Storage Level Objective, reservoirs are divided into three categories of 34 Non-USACE, 14 USACE and 6 Municipal reservoirs. To model the system with these elements, an algorithm is developed for the system that incorporates a mixed-binary mathematical programming model. The program uses binary variables to quantify ecological and flood control objectives. The algorithm incorporates the data, solves the model for the first year and exports the end-of-year (calendar year) storage values to be used for the next year and

this process continues until all the years are modeled. If the program is optimized for just one year, the solver would release as much water stored in the reservoirs as possible at the end of the year to optimize Hydropower Revenue. To address this problem, constraints were added that enforce the average storage for the last few days of any year be greater than or equal to the average storage for the rest of days in the year for every reservoir.

The objectives have different units and ranges of variations. To be able to compare the objective performances, the objectives need to be normalized. To normalize the objectives, the maximum objective values are calculated first and then the objectives are divided by the maximum objective values. To calculate the maximum objective values, weights equal to zero are assigned to any objective than the objective of interest in Equation (2.9) which takes a weight equal to one. Doing so, every decision variable is optimized in a way that maximizes that specific objective disregarding any other objective. However, this makes the program infeasible for the second year. To avoid the issue, the algorithm is run for every year separately and the objective values are calculated and averaged across all the years. Thus, the average maximum possible objective values (AMPOVs) are calculated and indicated in Table (2.1). Next, the AMPOVs are used in equation (2.10) to normalize the objective values under sequent runs. The new objective function of the program developed is a weighted summation of all the objectives and is presented in Equation (2.10) as follows:

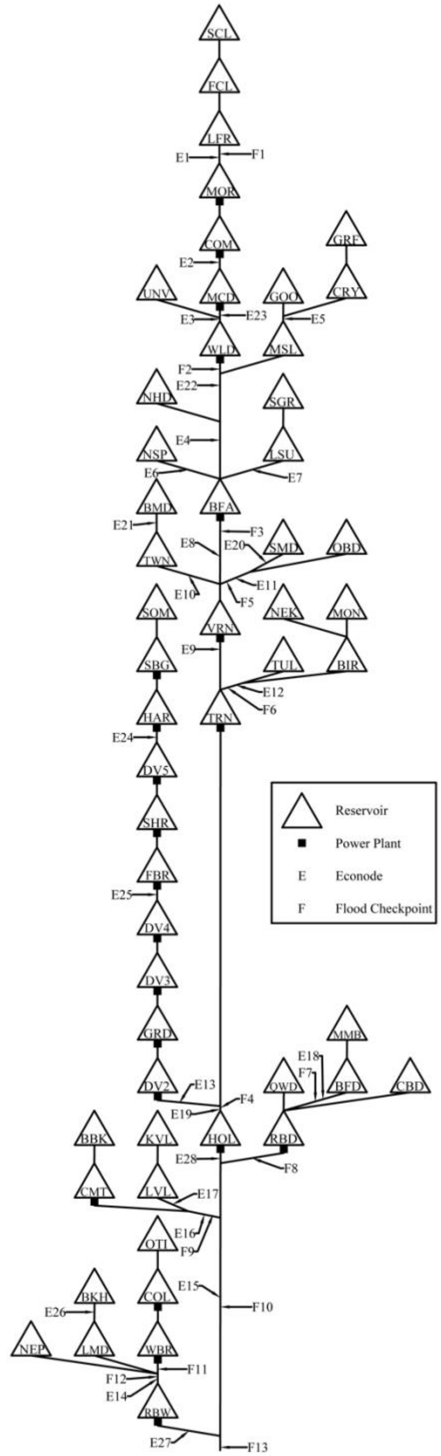

Figure 2.2. The system schematization with all the reservoirs, econodes and flood checkpoints considered

$$Z_o = \sum_{i=1}^{N} w_i \times Obj_i \tag{2.9}$$

$$Z = \sum_{i=1}^{N} w_i \times \frac{Obj_i}{AMPOV_i} \tag{2.10}$$

where Z_o denotes the initial objective function of the program used for calculating AMPOVs; Z denotes the objective function of the program and; w_i is the weight allocated to the objective i. Obj_i is the value of objective i; and N is the number of objectives modeled.

There are various constraints introduced in the program that either represent physical limitations or various operational regulations. Constraints associated with the mass balance equations of the reservoirs calculate storage values at the beginning of each time step given the release and inflow values during the time-step. There are also constraints on minimum and maximum storages values, minimum and maximum releases, and maximum flow rates passed through generators. There are around 5.4 million constraints, 760,000 binary variables, and 4.5 million continuous variables for the entire analysis horizon. The run time is about an hour for the entire modeling horizon (51 years) on the machine used (Intel Xeon Processor E5-2630 v4 25M Cache, 2.20 GHz, 16 GB RAM).

Table 2.1. List and some characteristics of the reservoirs modeled

Number	Reservoir Name	Abbreviation	Storage Level Objective Category	Usage Type	Active Storage (Mft^3)
1	Second Connecticut	SCL	Non-USACE	Storage	505.9
2	First Connecticut	FCL	Non-USACE	Storage	2178.0
3	Francis	LFR	Non-USACE	Storage	4415.9
4	Moore	MOR	Non-USACE	Hydropower	4968.1

5	Comerford	COM	Non-USACE	Hydropower	273.1
6	McIndoes	MCD	Non-USACE	Hydropower	260.8
7	Union Village	UNV	USACE	Flood Control	1655.3
8	Wilder	WLD	Non-USACE	Hydropower	581.5
9	Goose Pond	GOO	Non-USACE	Recreation	419.7
10	Grafton Pond	GRF	Non-USACE	Recreation	309.8
11	Crystal	CRY	Non-USACE	Recreation	167.5
12	Mascoma	MSL	Non-USACE	Recreation	1132.6
13	North Hartland	NHD	USACE	Flood Control	3096.2
14	Lake Sunapee	LSU	Non-USACE	Recreation	1781.6
15	Sugar	SGR	Non-USACE	Hydropower	1415.7
16	North Springfield	NSP	USACE	Flood Control	2186.7
17	Bellows Falls	BFA	Non-USACE	Hydropower	325.6
18	Ball Mountain	BMD	USACE	Flood Control	2371.8
19	Town	TWN	USACE	Flood Control	1433.1
20	Surry Mountain	SMD	USACE	Flood Control	1380.6
21	Otter Brook	OBD	USACE	Flood Control	760.1
22	Vernon	VRN	Non-USACE	Hydropower	519.5
23	Monomonac	MON	Non-USACE	Recreation	261.4
24	Nekaug	NEK	Non-USACE	Recreation	257.0
25	Birch Hill	BIR	USACE	Flood Control	2173.6
26	Tully	TUL	USACE	Flood Control	958.3
27	Turners Falls	TRN	Non-USACE	Hydropower	385.6
28	Somerset	SOM	Non-USACE	Storage	1758.3
29	Searsburg	SBG	Non-USACE	Hydropower	17.9
30	Harriman	HAR	Non-USACE	Hydropower	4007.5
31	Sherman	SHR	Non-USACE	Hydropower	156.5
32	Development 5	DV5	Non-USACE	Hydropower	5.1
33	Fife Brook	FBR	Non-USACE	Hydropower	213.4
34	Development 4	DV4	Non-USACE	Hydropower	20.3
35	Development 3	DV3	Non-USACE	Hydropower	9.6
36	Gardner Falls	GRD	Non-USACE	Hydropower	8.3
37	Development 2	DV2	Non-USACE	Hydropower	24.0
38	Holyoke	HOL	Non-USACE	Hydropower	1001.9
39	Mare Meadow/Bickford	MMB	Municipal	Municipal	467.0
40	Barre Falls	BFD	USACE	Flood Control	1045.4
41	Conant Brook	CBD	USACE	Flood Control	162.9
42	Quabbin	QWD	Municipal	Municipal	55080.2
43	Red Bridge	RBD	Non-USACE	Hydropower	139.4
44	Knightville	KVL	USACE	Flood Control	2134.4
45	Littleville	LVL	USACE	Flood Control	1001.9

46	Borden Brook	BBK	Municipal	Municipal	334.2
47	Cobble Mountain	CMT	Municipal	Municipal\ Hydropower	2846.2
48	Otis	OTI	Non-USACE	Recreation	670.8
49	Colebrook	COL	USACE	Flood Control\ Hydropower	4212.3
50	West Branch	WBR	Non-USACE	Hydropower	387.7
51	Barkhamsted	BKH	Municipal	Municipal	3186.4
52	McDonough	LMD	Non-USACE	Recreation	392.7
53	Nepaug	NEP	Municipal	Municipal	1271.2
54	Rainbow	RBW	Non-USACE	Hydropower	182.1

2.6. Weighting Scheme

After calculating the AMPOVs, the algorithm is executed under different weighting schemes (WSs) depicted in Table 2.2, to identify the objectives trade-offs. Table 2.2 indicates weights assigned to the objectives under each weighting scheme. In the first six schemes, the weights allocated to one objective is 0.60, and each of the other objectives take a weight equal to 0.08. Weights were selected this way to prioritize an objective in each run compared to the other objectives. It should be noted USACE Storage Level objective takes negative signs in the formulations since this objective is to be minimized. This approach assigns a high priority on an objective and a small weight on the remainder of the objectives in the first six schemes. WS7 is a balanced weighting scheme with equal absolute values of weights. The absolute weights values under each weighting scheme sum to 1.

Table 2.2. Weights allocated to the objectives under each weighting scheme

Weighting Scheme	Ecological	Flood Control	Hydropower	Non-USACE Storage Level	USACE Storage Level	Municipal Storage Level
1	0.60	0.08	0.08	0.08	0.08	0.08
2	0.08	0.60	0.08	0.08	0.08	0.08
3	0.08	0.08	0.60	0.08	0.08	0.08
4	0.08	0.08	0.08	0.60	0.08	0.08
5	0.08	0.08	0.08	0.08	0.60	0.08
6	0.08	0.08	0.08	0.08	0.08	0.60
7 (Balanced)	0.167	0.167	0.167	0.167	0.167	0.167

Table 2.3. Average maximum possible objective values (AMPOVs) calculated

Ecological (%)	Flood Control (%)	Hydropower ($/day)	Non-USACE Storage Level (Mft^3)	USACE Storage Level (Mft^3)	Municipal Storage Level (Mft^3)
92.4	99.652 (1.27 violation/year)	338,024 (123.3 $M/year)	40,289	18,429	63,353

2.7. Results and Discussion

The AMPOVs are calculated and indicated in Table 2.3. It is observed the value for the Ecological Objective is 92.4%. This value implies that even if any other objective is completely ignored, it is not possible to completely regulate the flows within the desirable bounds. This is mainly due to minimum/maximum release requirements that limit the operations. The value associated with the Flood Control objective is 99.652% which is equivalent to 1.27 violations of flood warning level per year on average. This indicates the floods can be controlled with a relatively high reliability if all the reservoirs contribute controlling floods across the 13 flood checkpoints considered. Other values in the table indicate the AMPOVs for hydropower revenue per day and the three different Storage Level Objectives.

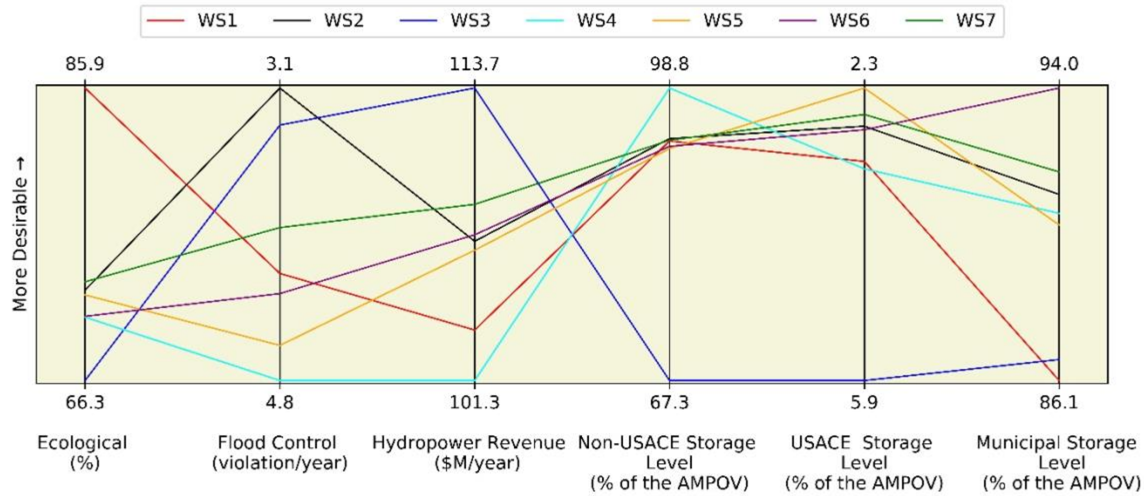

Figure 2.3. Trade-offs of the objectives modeled

The trade-offs are presented in Figure 2.3. The Ecological Objective varies from 66.3% to 85.9% while the maximum value occurs under WS1 and is expectedly less than its AMPOV, 92.4%. The second highest value for this objective is associated with the balanced weighting scheme (WS7). It is evident the WS7 results have always ranked second-best, except for the Flood Control objective in which it has ranked the third-best. Compared to the best results in the graph, it is seen adapting a balanced operation would most significantly degrade the Ecological Objective while it would affect the USACE Storage Level objective the least. This suggests a balanced WS has the potential to benefit all the objectives with some compromises. The lowest value for the Ecological Objective is 66.3% occurring under WS3. In this case, the Hydropower Revenue objective gets the highest value, 113.7 $M/year. This suggests the ecological objective is highly conflicting with the Hydropower Revenue. The Ecological Objective also highly conflicts with the Municipal Storage Level objectives and the reason might be because Municipal Storage objective encourages storing water that conflicts with providing flows close to the natural flows (the Ecological Objective is targeted to provide flows close to the natural flows).

The Flood Control Objective varies from 4.8 to 3.1 while the best value for this objective occurs under WS2 and the least desirable objective value, 4.8, occurs under WS4 in which the Non-USACE gets the best result across the seven WSs. This is an expected result since Non-USACE reservoirs have a significant storage capacity that would not be available to capture floodwaters if the reservoirs are kept full or close to full. Under WS2, Flood Control objective gets its best value, but this does not come at the expense of significant degradation for other objectives. Under this WS, results for the all objectives than the Flood Control objective are close to the results associated with the balanced WS.

The best result for Hydropower Revenue is $113.7M per year under WS3 while the worst is $101.3M under WS4. It is observed the best value for Hydropower Revenue objective is associated with the lowest (or very low) outcome for Ecological and Storage Level Objectives. This result suggests this objective is highly conflicting with any objective other than with Flood Control. Based on the graph, a compromise of near $4M a year in Hydropower Revenue could significantly improve all the objectives that would be otherwise highly degraded when trying to maximize the Hydropower Revenue objective.

The Non-USACE Storage Level objective varies from 67.3% to 98.8% of its AMPOV. The best value for the objective is 98.8% under WS4, and the lowest value is 67.3% under WS3. The best value is associated with the worst values for the Flood Control and the Hydropower Revenue objectives, indicating again there is a conflict between maintaining high storages at these reservoirs and the ability to control floods and making high revenues. USACE Storage Level objective varies from 5.9% to 2.3% of its AMPOV. The least desirable result, 5.9%, occurs under WS3 in which Hydropower Revenue is highly prioritized indicating a significant conflict between these objectives.

Figure 2.4 presents the reliabilities of meeting environmental flows at the 28 econodes across the basin for the seven WSs that can vary from 0% to 100%. Expectedly, it is evident that in almost every econode, the reliability associated with WS1 is higher than associated results of other WSs. The degree to which the associated results of WS1 are superior seems to depend on the location of the econode. In some case this alternative is significantly superior while in some other cases just slightly superior. The values associated with WS1 seem to have the highest differences with the results associated with WS3 and WS6 suggesting that Ecological Objective conflicts most with Hydropower Revenue and Municipal Storage Level objective. The conflict with Hydropower Revenue is because the revenue gained through hydropeaking conflicts with providing flows close to the natural flow values. The conflict with Municipal Storage Level might be because releasing values close to natural inflows does not allow for storing water. The results of WS1 and WS7 differ the least suggesting a balanced operation has the potential for achieving results close to the bests possible for this objective. Looking at the average values across the WSs and for different econodes, it seems the values are generally higher if the econode is not immediately downstream of a hydropower facility. This is the case for the econodes 5, 6, 7, among others. Some econodes immediately downstream of a hydropower facility are significantly negatively affected (for instance the econodes 2, 3, 23). The econodes that are on the mainstem and immediately downstream of a hydropower facility are the most negatively affected ones while the ones on tributaries or the ones that are not immediately downstream of a hydropower facility are the least degraded ones. Econodes 24, and 25 in Deerfield tributary, downstream of a few hydropower facilities, have shown low reliabilities. The low values are the case because the revenue those facilities generate conflict with the Ecological Objective.

Figure 2.5 presents the reliabilities of controlling flood conditions across the 13 flood checkpoints under the seven WSs. The reliabilities vary from 96.3% to 100%. The Flood Control objective is the average of the values across different checkpoints. That is why the results under WS2 are not always superior. For econode 9, there is a significant superiority of the Flood Control value under WS2 which highly contributes to the average value of the Flood Control objective. This is also the case for checkpoints 6, but less significantly. Checkpoint 1, located on the mainstem and not immediately downstream of a hydropower facility, has values close to 100%. Checkpoint 2 is on the mainstem and immediately downstream of two in-series hydropower facilities. As a result, the results for this checkpoint are relatively low. Checkpoints 7, and 8 have very high values which could be because they are located downstream of large Municipal reservoirs (MMB and QWD) providing significant capability to control flood conditions.

Figure 2.6. presents the average revenue made per day for various facilities across the basin under different WSs. The figure shows how different facilities contribute to the total revenue made. Under WS3 in which the greatest weight is assigned to hydropower revenue, the value of hydropower is maximized at almost every facility. It is evident

facilities on the mainstream including HOL, TRN, VRN, BFA, WLD, COM, and MOR make higher revenue since they pass higher flows through their turbines.

Figure 2.7. presents the average active storage percent values for the Non-USACE reservoirs under the seven WSs. Under WS4, storage reservoirs expectedly get the highest values while they get low values under WS3 compared to the results associated with other WSs. It is evident that reservoirs without a power plant including NEK, MON, SGR, LSU, MSL, CRY, GRF, and GOO have higher active storage percent values. The reason is because there is no immediate revenue gained if they empty their storages. Reservoir SOM gets a very low value under WS3 that might be because it is located immediately upstream of a few in-series hydropower reservoirs in Deerfield tributary.

Figure 2.8. presents average active storage percent values for the USACE reservoirs. The USACE reservoirs average storage values are more desirable if they are lower. The WS5, the weighting scheme that most heavily weights minimizing USACE storage levels, has resulted in the least values (close to zero). It is evident that results associated with WS3 (the WS that heavily weights hydropower revenue) have the least desirable values for this objective. Significant values are resulted under this WS for reservoirs COL, UNV, NHD, NSP, BMD, and TWN because they are immediately upstream of large hydropower reservoirs. The water is stored in the reservoirs under WS3 to be released later into hydropower facilities that themselves release significant water when the energy prices are higher.

Figure 2.9. presents the average active storage percent values across the municipal

reservoirs for the WSs. The best results are associated with the WS6. For these reservoirs, it was required to introduce constraints that limit the maximum release from these reservoirs to be the maximum of their inflow and the minimum release requirements. These constraints will not allow the stored water in these reservoirs to be released for improving any objective. The stored water can be released for meeting minimum release requirements and/or municipal withdrawals. Introduction of the constraints facilitated avoiding infeasibilities during solving the program. QWD (Quabbin) reservoir turned out to be robust to the infeasibilities due to its very large size.

2.8. Conclusions

Trade-off analysis of river basins requires methodologies that quantify objectives of the system and the interactions. In this regard, a multiobjective optimization methodology was presented that facilitates quantifying various objectives and was applied to the Connecticut River watershed as a case study. Results suggest the flow regime across the basin is highly altered since it is not possible to fully meet Ecological Objective even if any other objective is ignored. It was realized that the econodes on tributaries are less affected while the econodes on the mainstem and\or downstream of hydropower facilities are more severely affected. The system was found to be capable of controlling flood conditions with a high reliability if all the reservoirs contribute. Hydropower Revenue was found to be around $123M per year if other objectives are completely ignored. If the other objectives are assigned small weights equal to 0.08, the Hydropower Revenue would be around $113M per year. Much of the revenue is made by facilities on the mainstem and on the Deerfield tributary. The objective was found to be a highly conflicting objective with any objective than with the Flood Control. An attempt to maximize the objective will significantly deteriorate any objective except for Flood Control. Results suggested a compromise as big as $4M in Hydropower Revenue would significantly improve Ecological and Storage Level Objectives and would slightly improve Flood Control. The location of hydropower reservoirs is found to be an important factor in affecting results associated with econodes, and flood checkpoints. Most Econodes or flood checkpoints immediately downstream of hydropower facilities are found to be significantly affected by the hydropower operations. Reservoirs immediately upstream of a hydropower facility were usually emptied because of the hydropower operations.

A balanced weighting scheme that prioritize all the objectives equally showed performances close to the bests possible regarding any objective. This indicates there is a potential to benefit all the objective performances near to bests possible if the reservoirs are operated appropriately. It should be noted operation of hydropower reservoirs follows sub-daily variations of energy prices. The model developed in this study has a daily time-step that may not fully represent the hydropower operations dynamics. Thus, a more detailed study might be needed to more accurately assess hydropower operations.

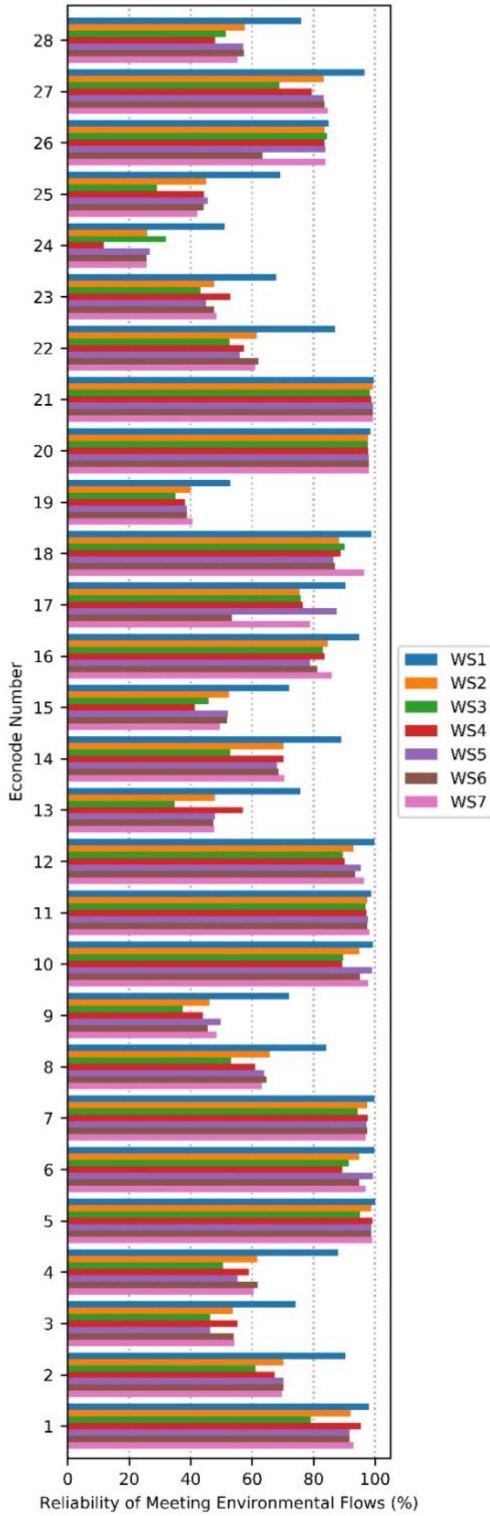

Figure 2.4. Reliability of meeting Environmental flows at Econodes for the 7 WSs

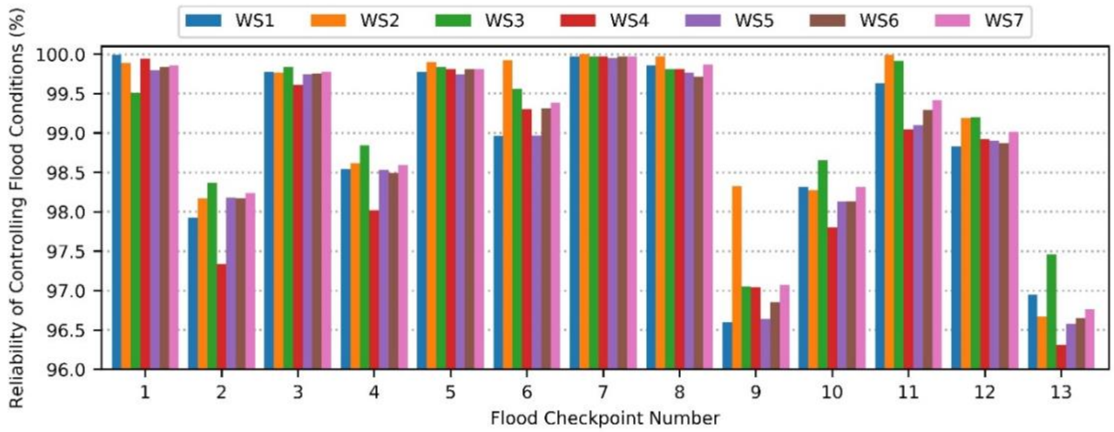

Figure 2.5. Reliability of controlling flood conditions across the 13 flood checkpoints for the 7 WSs

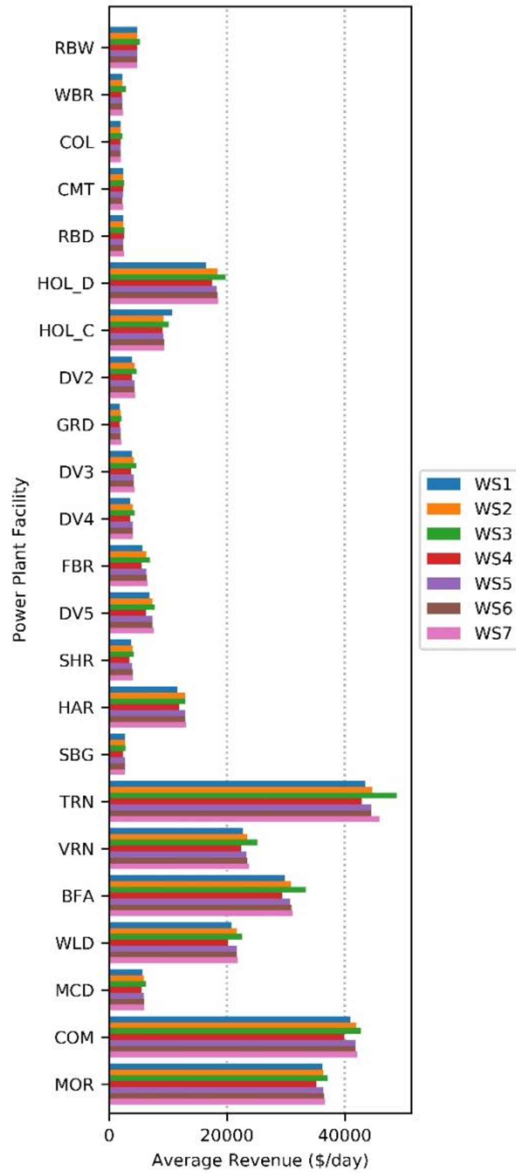

Figure 2.6. Average Revenue made per day (in $) for various power generation facilities for different WSs. (Hol_D refers to the Holyoke dam and HOL_C refers to the Holyoke Canal power plant facilities)

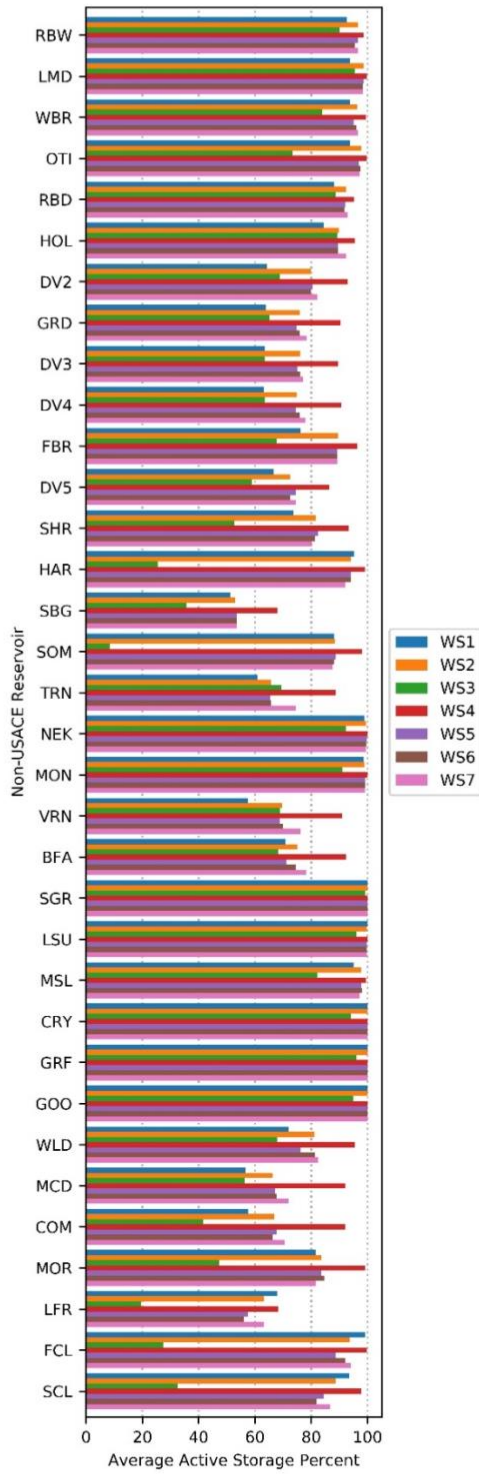

Figure 2.7. Average Active Storage Percent values for the Non-USACE reservoirs across the WSs

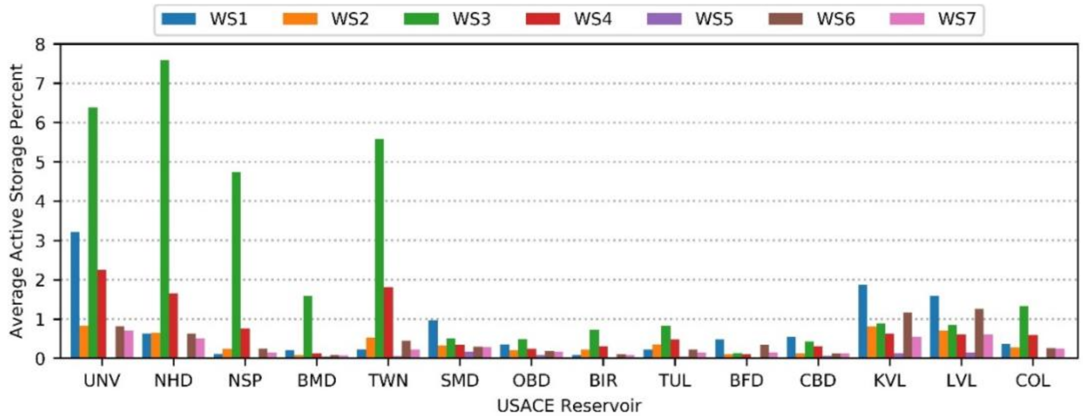

Figure 2.8. USACE reservoirs average active storage percent values across the 7 WSs

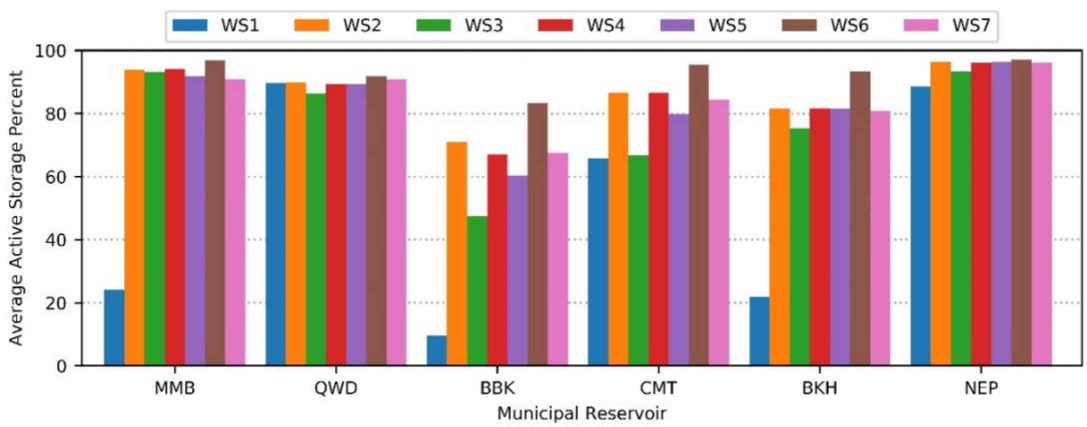

Figure 2.9. Water Supply reservoirs average active storage percent for the 7 WSs

CHAPTER 3

DEEP LEARNING AND OPTIMIZATION: COMPLEMENTARY TECHNIQUES FOR OPERATION POLICY OF MULTIPLE OBJECTIVE RESERVOIR SYSTEMS UNDER ENERGY MARKET AND HYDROLOGICAL UNCERTAINTIES

3.1. Introduction

Reservoir systems play an important role in developing human communities by providing drinking water, energy, flood control, recreational opportunities, and ecological services. Efficient management of the systems requires evaluation of different management alternatives using decision analytics. For this reason, optimization modeling and machine learning approaches can be applied to water resources systems planning and management problems. The literature on application of optimization methods to water resources systems planning is rich, including dynamic programming (Macian-Sorribes et al., 2016; Rougé & Tilmant, 2016), the Genetic Algorithms (Wang et al., 2015; Zatarain Salazar et al., 2016), and mathematical programming (Moy et al., 1986; Reis et al., 2005) while the application of machine learning approaches seems to be limited.

Optimization approaches consider the large range of planning alternatives to come up with the best alternative (known as prescriptive analytics) (Song et al., 2013) while machine learning approaches address the bigness of past and present data for coming up with predictions of future (known as predictive analytics) (Bertsimas & Kallus, 2014). There are three primary subfields in machine learning: supervised learning (LeCun et al., 2015), unsupervised learning (Barlow, 1989) and reinforcement learning (Sutton &

Barto, 2018) that are applicable to different problems. Supervised learning is applicable to a variety of classification and regression tasks to forecast a variable or label based on the past data. Unsupervised learning is applicable to clustering of similar data. Reinforcement learning approach is applied for optimization of sequential decision-making problems using Markov decision process (Sutton & Barto, 2018). This approach has recently been applied to some reservoir systems to design operation policies and to develop the system objectives trade-offs (e.g. by Castelletti et al., 2013; Madani & Hooshyar, 2014).

Optimization and machine learning techniques are highly related. Optimization techniques are used in machine learning algorithms to minimize prediction errors (L Bottou et al., 2018; Jain & Kar, 2017). Conversely, machine learning approaches can be used for some optimization problems, e.g., by learning the optimal policies in a reinforcement learning approach. Moreover, machine learning techniques might be able to interpret and learn what optimization methods do (Li & Malik, 2016) by mining the optimization results. Optimization and learning complement each other for making better decisions. These techniques, when used jointly, have the potential to be applied to a wide variety of water resources systems problems. Machine learning provides more accurate forecasts improving the performance of optimization methods when the systems are prone to uncertainty. In the context of hydrology and water resources systems, machine learning can focus on improving predictions of hydrological and energy market variables. On the other hand, optimization can focus on prescriptions of best policies given the system objective(s), constraints and the uncertainties. Machine learning models can enable more accurate forecast of water demand, precipitation, temperature, streamflow, and energy prices by analyzing real-time or historic data. The predictions could then be fed as inputs to optimization models and algorithms to identify the system objectives trade-offs and recommendations of the optimal policy to meet conflicting objectives of water resource systems.

Another approach applicable to operation of water resources systems, followed in this research, is to optimize the systems and train machine learning algorithms on the optimal state-decisions pairs to investigate if the optimal (or near-optimal) operation policies can be derived. In fact, the machine learning algorithm parameters are adjusted in a way that minimize the prediction accuracy of the optimal policy developed based on the optimization input-output pairs. This is a form of supervised learning since for the system states, the optimal release schedule is known while training the machine learning algorithms. An applicable machine learning technique is deep learning (DL) (LeCun et al., 2015; Schmidhuber, 2015), an extension of the artificial neural networks. DL discovers complicated non-linear structures in data using the backpropagation algorithm (Neftci et al., 2017) by optimizing the internal parameters that are used to compute the representation in each layer. In the past, finding patterns in data required careful engineering to extract features that transformed raw data into appropriate representations (LeCun et al., 2015). DL has removed the need for feature extraction since it automates the task of finding the patterns. A deep neural network (DNN) with enough number of hidden layers and neurons provides the capacity to capture the patterns and specially performs well in large data sets. As a result, it is expected that DL can find an approximate relationship (operation policy) between the optimization input-output sets.

Operation policy design of reservoir systems is challenging mainly because of presence of conflict between the objectives that are usually incommensurable (Castelletti et al., 2013), and presence of multiple sources of uncertainties in water resources systems future conditions. Hydrological uncertainties (extreme precipitation, drought), and energy market dynamics both contribute to the uncertainties. To overcome these challenges, it is required to develop methodologies that 1) quantify the system objectives 2) identify the objectives trade-offs, and 3) prescribe an operation policy given a deeply uncertain future. Many optimization techniques have been used for this purpose while each method has its own difficulties and advantages usually in respect to applicability to a wide variety of problems, computational resources required, and optimality guarantee, (Labadie, 2004; Mason et al., 2018b; Yeh, 1985). Direct Policy Search (DPS) approach, also known as parameterization-simulation-optimization approach has been studied for water resources systems policy design. In this approach, the operation policy is characterized as a function of the system states while different functions can be used given the characteristics of the system under study (Giuliani et al., 2014). The function parameters are then optimized using optimization methods. One difficulty with this approach is the choice of appropriate policy function class since a bad choice could noticeably affect the optimality. As Giuliani et al. (2016) write "…*when the complexity of the system increases, more flexible structures depending on a high number of parameters are required to avoid restricting the search for the optimal policy to a subspace of the decision space that does not include the optimal solution.*", highly flexible approximators should be used to parameterize policy functions. Neural networks are nonlinear flexible approximators that can be used as the policy functions. They can relate system states to operation schedules using the parameters of the neural network. In this case, parameters' values would be decision variables that are determined in a way that optimize the system objectives. Number of parameters in the neural network depends on number of layers and neurons used. Using more layers and neurons provide more flexibility but it adds to the computational attempts required to optimize the parameters. Multiple objective evolutionary algorithms (Hadka & Reed, 2015; Reed et al., 2013) have been linked to DPS to optimize the policy functions chosen (Giuliani et al., 2018, 2016; Quinn et al., 2018). These algorithms solve for all the objectives at the same time and develop a subset of Pareto frontier after a specified number of iterations. Application of these algorithms has some difficulties: 1) they do not guarantee achieving optimal solution which is a characteristic of every nature-inspired optimization algorithm; 2) for a complex system with several objectives, the number of simulations needed increases considerably and as a result the algorithms would require significant computational efforts (Castelletti et al., 2013); 3) algorithms parameters (the parameters used in the optimization algorithm) whose values affect the performance of the algorithms need to be carefully adjusted (Quinn et al., 2018); and 4) algorithm parallelization scheme implicated affects the robustness of the policies to the system's uncertainties (Giuliani et al., 2018). Although multi-layered neural networks could be used as a nonlinear and flexible policy functions but optimization of the policy parameters with the evolutionary algorithms is computationally intractable. The difficulties of application of evolutionary algorithms from one side, and the effect of choosing any policy function on the optimality, from another side, limit application of multiple objective evolutionary algorithms DPS.

Aimed at overcoming the challenges, this study presents a novel methodology utilizing DL and optimization for developing operation policy of multiple objective reservoir systems under hydrological and energy market uncertainties. For the first time, this research investigates the application of DL for developing operation policies using the optimization results. The methodology is applied to the Wilder reservoir located on the mainstem Connecticut River considering hydropower revenue and ecological objectives. For the ecological objectives, formulations are developed that measure the frequency of meeting flows within the desirable bounds. A multiple objective optimization methodology is used that quantifies the system objectives and develops the system objectives trade-offs. Next, DL algorithms are trained on the state-decision pairs to develop an operation policy. Finally, the system is simulated using the designed policy under new set of historical hydrological and energy market variables and its performance regarding the objectives considered is compared to the best performances that could be achieved using optimization and perfect foresight of future variations. The performance of the methodology is compared with the performance of a baseline method.

3.2. System Description

The system studied incorporates the Wilder reservoir located on the mainstem of the Connecticut River (Figure 3.1), the largest river in New England. The river-basin covers parts of Maine, Vermont, Massachusetts, and Connecticut. The 400 river-mile long river originates from Canada and ultimately discharges into the Atlantic Ocean. There are 2700 dams constructed on the mainstem and tributaries, many of which are operated for hydropower. Most of these hydropower facilities were developed during New England's industrial revolution (Clay et al., 2006; Martin & Apse, 2011).

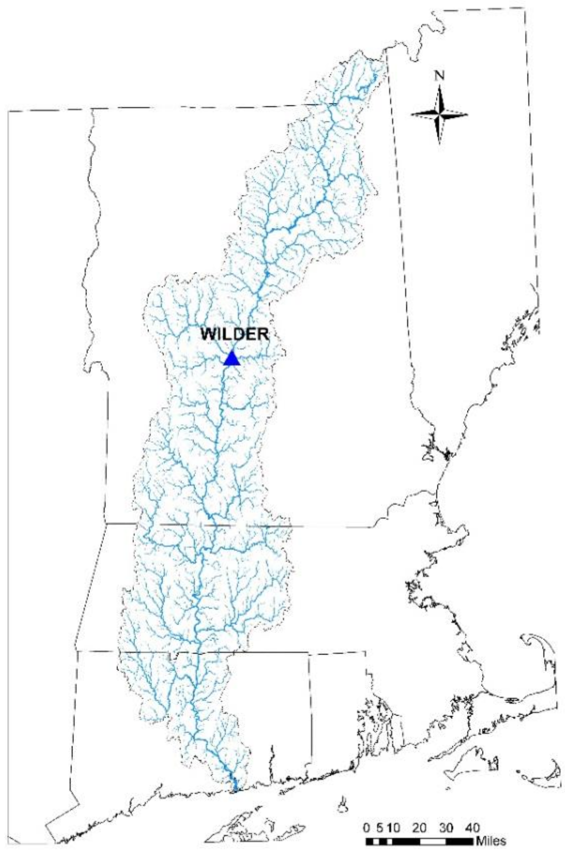

Figure 3.1. Wilder reservoir schematic located on the Connecticut River basin

The hydropower operations have caused flow regime alterations across the basin since they store water to be released when energy prices are higher during a day. The alterations have implications for the riverine ecosystem health (Benejam et al., 2014; Jager & Smith, 2008; Kennedy et al., 2016; Pang et al., 2015; Sabo et al., 2017; Winemiller et al., 2016). The Wilder reservoir whose characteristics are depicted in Table 3.1., is mainly operated for hydropower. An estimated refill time is calculated and depicted in Table 3.1. The refill time for Wilder is 25 hours, indicating the reservoir is on average filled in 25 hours. This means Wilder is not able to change average flow values on a scale greater than approximately a day. But the capacity is large enough to affect sub-daily flow regime since the operations usually follow sub-daily energy market dynamics during a day to maximize the hydropower generation revenues.

Table 3.1. Wilder reservoir key characteristics

Reservoir (Abbreviation)	Operation type	Operator	Average inflow (m^3/s) (cfs)	Active storage million m^3 (acre-foot)	Estimated refill time (hr)	Power capacity (MW)
Wilder (WLD)	Peaking	TransCanada	181 (11,010)	16.5 (13,350)	25	35.6

Figure 3.2. illustrates the real-time energy prices along with the Wilder reservoir outflows and inflows for the first week of January 2003. It is evident in the Figure 3.2.a, there are usually two peaks within a day. The observed inflows and flows read from USGS gage 01144500) are illustrated in Figure 3.2.b. It is evident that the flow values downstream of the reservoir follow sub-daily energy price variations and usually peak twice during a day. One can conclude Wilder operators schedule releases to generate as much revenue as possible. Comparison of the reservoir approximate outflows (read from the USGS gage) and inflows indicates how the flow regime is altered. This kind of operation, called hydropeaking, conflicts with meeting the ecological objectives of the downstream of the reservoir (Anderson et al., 2014; Ding et al., 2018; Fanaian et al., 2015; Feng et al., 2018; W. Zhang et al., 2016) since many watershed communities rely on the flow regime characteristics like magnitude, timing and rate of change to survive and thrive

(Arthington et al., 2009; Davies et al., 2014; R. Li et al., 2015; Tonkin et al., 2018).

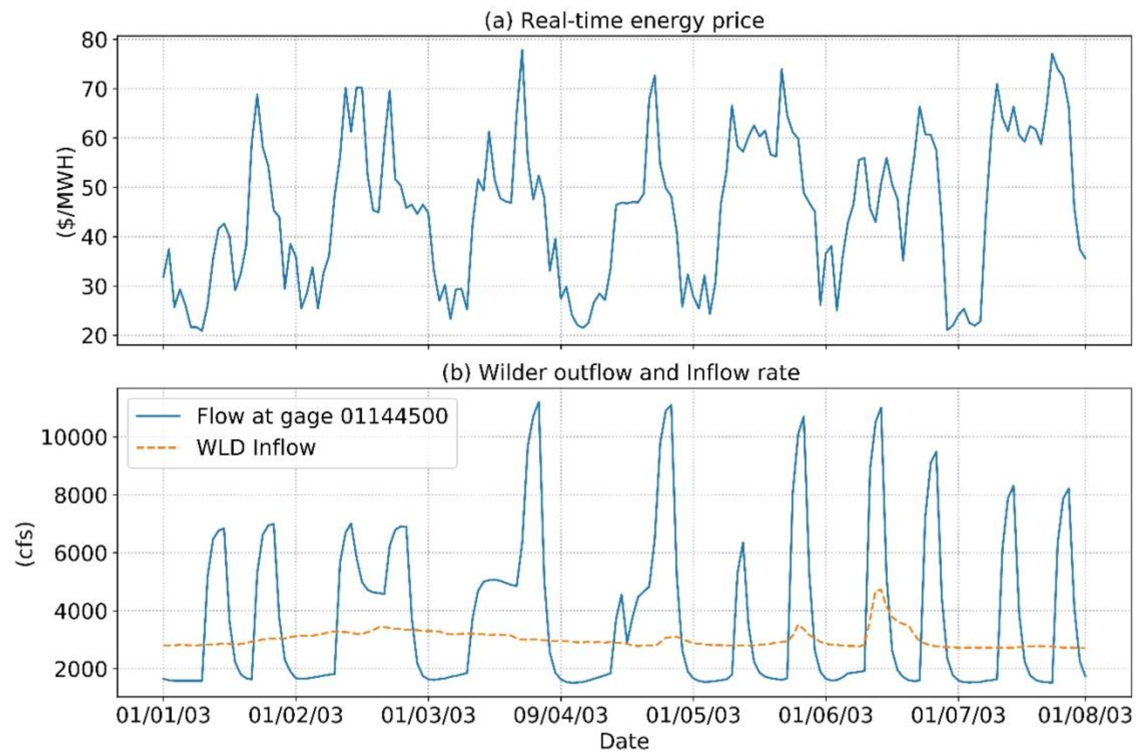

Figure 3.2. Real-time energy prices for western-central mass area, b) Wilder (WLD) approximate outflows and observed inflows for the horizon 01/01/2003 to 01/08/2003

The data collected for the system include the reservoir inflows, the flows that would have occurred if there was no regulation in the basin (called natural flows in this study), energy prices, turbine and generator characteristics, minimum and maximum storage levels, and release requirements. The natural flow data are calculated using the Connecticut River Unimpacted Streamflow Estimation (CRUISE) tool, developed by the United States Geological Survey (USGS) (Archfield et al., 2012a). Since the CRUISE outputs are daily, they are disaggregated into an hourly time-scale required for this research. Observed hourly flows at the USGS gage upstream of the reservoir (gage 01138500) are used as the

Wilder reservoir inflows. Other required data are extracted from the reservoir documents. Hourly real-time energy prices are obtained from the Independent System Operator New England (ISO-NE) website. Since the energy prices are available from year 2003, while the CRUISE data are available up to year 2011, the modeling horizon in this study is limited to 2003-2011.

3.3. Methodology

3.3.1. Overview

The methodology developed has four steps as indicated in Figure 3.3. The first step optimizes release schedules given the objectives considered and identify the objective trade-offs. The second step focuses on training DNN on the optimized state-release pairs trying to find the best policy that relates the system states to the release decisions made. The third step focuses on simulation of the reservoir operations based on the prescriptions of the operation policy derived in the second step for a test-set of system states that is not used in the training process. The last step focuses on developing the objectives trade-offs resultant of the simulated operations and comparing them with the trade-offs of the optimization method. This last step indicates how well the operation policy designed

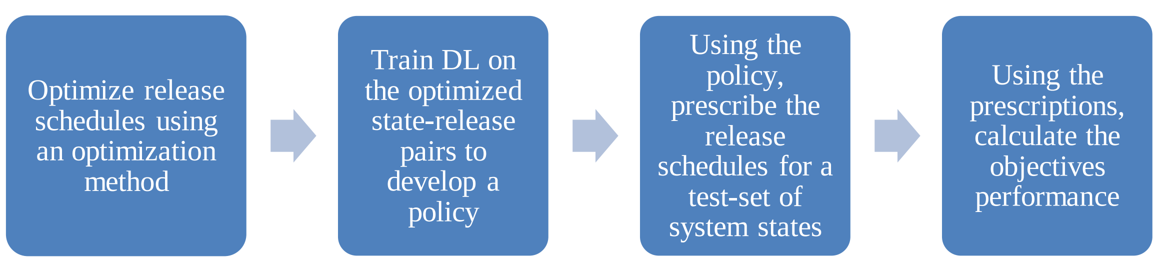

Figure 3.3. The steps in the methodology presented for operation policy design

performs in respect to any objective considered compared to the best performance that could be achieved using an optimization method.

The trade-off developed using the optimization outputs indicate a subset of Pareto frontier that serves as a comparison basis since those non-dominated solutions are optimized using the perfect foresight. In the following sections, it is explained how the optimization model and the DNN are developed and applied to the case study.

3.3.2. Operation Schedules Optimization

A mathematical (mixed-binary) programming model is developed to optimize operation schedules. Using mathematical programming solvers has a considerable advantage compared to other optimization techniques; they can find the optimal solution (or make sure the solution found is within a specified bound of the optimal solution) in a relatively short time no matter how many decision variables exist. In this study, a multiple objective optimization methodology is developed to identify the trade-offs between objectives modeled by using a mixed-binary programming model executed under different objective weights. Maximum possible objective values (MPOVs) are calculated to be used for normalizing the objective values by dividing them by their MPOVs. Doing so, the objective values are maximized compared to their MPOVs under different weightings. To calculate the MPOVs, the objective function of the mathematical programming model is formulated as follows in (3.1).

$$Max\ Z_o = \sum_{i=1}^{N} w_{0,i} \times\ Obj_i \tag{3.1}$$

where Z_o is the initial objective function used for calculating the MPOVs; N is the number of objectives modeled; $w_{0,i}$ is the weight allocated to the objective i; Obj_i is the value of the objective i. To calculate the MPOVs, the w_i value specific to Obj_i is assigned to 1, while the other weight corresponding to the other objectives takes values of 0. Each time the program is executed, Z_o returns the MPOV associated with an objective. After calculating the MPOVs, the values are used in the new formulation of the program objective function as follows in equation (3.2). The model is run with new weight values to identify the objectives trade-offs.

$$Max\ Z = \sum_{i=1}^{N} w_i \times \frac{Obj_i}{MPOV_i} \tag{3.2}$$

where Z denotes the objective function of the program; w_i is the weight value associated with Obj_i. $MPOV_i$ is the maximum possible objective value calculated for objective i. It should be noted the weight values used here are different to those weights used earlier in equation (3.1). The weight values here can vary from values close to 0 to values close to 1 for one objective while at the same time the other objective weight values vary from values close to 1 to values close to 0. Assigning the weights this way facilitates development of the objectives trade-offs.

The objectives considered for Wilder reservoir include ecological and hydropower revenue objectives. Ecological objective is modeled as the frequency of meeting ecological flow requirements as recommended by Richter et al., 2003. To model this objective, the range of desired flows for the communities downstream of the reservoir are developed after consultation of biologists and ecologists in the Connecticut River basin (Steinschneider et al., 2014). The levels of flow alteration that have negligible effects on different species were determined at stakeholder meetings held by The Nature Conservancy (Steinschneider et al., 2014). The narrowest bound associated with the least flexible species at the econode (en) downstream of the reservoir is chosen as the desirable bound. In this regard, constraints (3.3) and (3.4), and equation (3.5) are quantify the ecological objective as the frequency of meeting flows in desirable bounds as follows:

$$F_{en,t} < N_{en,t}\left(1 + H_{en,t}\right) + \left(1 - EZ_{en,t}\right) \times B_{eco}, \forall\ t = 1, \dots, T \tag{3.3}$$

$$F_{en,t} > N_{en,t}\left(1 + L_{en,t}\right) - \left(1 - EZ_{en,t}\right) \times B_{eco}, \forall\ t = 1, \dots, T \tag{3.4}$$

$$EcoObj\ = 100. \sum_{t=1}^{T} \frac{EZ_{en,t}}{T} \tag{3.5}$$

where $F_{en,t}$ is the modeled flow value at the econode en during the time t; $N_{en,t}$ is the estimation of natural flow at the econode en in time t; $H_{en,t}$, $L_{en,t}$ are fractions of natural flows that respectively refer to the upper and lower boundaries (these two parameters jointly form a flow bound beyond which the species are negatively affected); B_{eco} is a large value utilized to provide an extended flow bound when desirable bounds are deviated; $EZ_{en,t}$ is a zero-one binary variable for the econode en and time t; and T is the number of time steps. If the variable $EZ_{en,t}$ takes value 1, Constraints (3.3) and (3.4) would ensure that the flow passed through the econode during the time-step t falls in the desirable bounds identified by $H_{en,t}, L_{en,t}$. If the variable $EZ_{en,t}$ takes a value of 0, the flows can deviate the desirable bounds since there would be an extended bound by B_{eco}

units from the two sides. Equation (3.5) quantifies the Ecological Objective in percent that returns the reliability of flows falling in the desirable flow bound.

The revenue generated at Wilder facility is considered as another objective to be maximized. In theory, power generated has a nonlinear relation with water head over turbine and the flow rate passed through turbine. Since Wilder reservoir water head variations are negligible, it is assumed the head is constant making the power generated a linear function of the volume of water released in each time-step. The revenue made at each time step is the product of power made and the real-time energy price during the time-step. The total revenue of the facility over the analysis horizon is maximized applying (3.6) and (3.7) as follows.

$$HydroObj \ = \ 8760 \times \sum_{t=1}^{T} \frac{P_t \times EP_t}{T} \tag{3.6}$$

$$P_t = PR_t \times PC_t, \forall \ t = 1, \ldots, T \tag{3.7}$$

where P_t is the power generated during time-step t; EP_t is the real-time energy price at the time-step t; PR_t is the water amount released during the time-step t; PC_t is the coefficient converting water amount released through turbines to the power generated during the time-step t; and $HydroObj$ denotes the average hydropower revenue made per year. It should be noted that the maximum release passed through the Wilder turbines is limited which itself limits the revenue made at the facility. A release value beyond the turbine capacity, would be spilled and would not contribute to the revenue made.

3.3.3. Developing Operation Policy

Before describing the design of the operation policy in this section, it should be noted the optimization solver schedules sequential releases to optimize the objective function based on various current and future system states plugged into the model. This means the optimization solver assigns release values using the perfect foresight of future hydrologic and energy market variables. That's how the task would have ideally been accomplished in a real-world water resources system as well if there existed a perfect foresight when deciding release schedules. This is usually not the case and uncertainties make the decision-making challenging and different to what an optimization method does. Thus, based on the information that reservoir operators might have access to when deciding release schedules, DNN are developed and trained to relate release schedules to current (or current and forecasted) system states including the inflow, storage and energy prices.

The optimized release series along with the system states series including energy prices, storage values, and inflows are used in the training. This is a form of supervised learning in which for every time-step there is a correct release schedule based on the energy price, storage, and the inflow values. The goal is to develop an operation policy that relate release schedule to the system states by analyzing the system states and the optimal release schedules that are output of the optimization model. This is done by optimizing the parameters of a DNN. After training the network, there would be an operation policy whose performance could be evaluated by comparing to that of the optimization method using a new set of system states. The state series are divided into three sets: training set, validation set, and the test set with division fractions respectively equal to 64%, 16%, and 20% of the entire series while the original sequence in the series is maintained. The training set is used for training the network parameters while the validation set is used during training to identify if the network is over-trained and finally the test set is used after training is completed to evaluate the operation policy developed performance. The series values need to be scaled before starting the training process. Thus, they are subtracted by their mean and are divided by their standard deviation. This preprocessing makes the training process less computationally intense.

A DNN with 5 sequential hidden layers is constructed in which there is a connection from any neuron in any hidden layer to any neuron in the next layer (fully connected network). Rectified linear unit (Relu) activation function (Dahl et al., 2013; Hara et al., 2015) is used in the neuron units. Different loss functions could be used during the training including *mean absolute error* or *mean absolute squared error*. Different optimizers could be used for training the network including ADAM (Kingma & Ba, 2014) and *stochastic gradient descent* (Bottou, 2010) among others. While there is no established rule for constructing the network architecture, usually the initial hidden layers in the network have more neurons while the sequent hidden layers have relatively less neurons. For this study, the number of neurons in the first layer equals the number of system states used and the last layer has just one neuron since there is one correct release schedule for the system states. The training process is repeated several times (each repetition is called an *epoch*) to improve the loss function. Monitoring the validation-set loss function during the training for various epochs determines whether the network is over-fitted.

3.3.3.1 Development of a baseline method

In order to compare the performance of the methodology developed, it is required to develop a simple baseline method and apply it to the problem. The results associated with this baseline methods are compared with the performance of the neural networks developed. In this study, a linear regression-based method has been used to develop a relationship between release, storage and energy prices values. The relationship has been used as an operation policy of the Wilder reservoir that determines optimized release value during each time-step based on storage, inflow, and energy prices value. The relationship is given in 3.8. α, β, γ, and δ are regression coefficients.

$$R_t = \alpha * S_t + \beta * EP_t + \gamma * I_t + \delta \ , \forall\, t = 1, \dots, T \qquad (3.8)$$

The relationship developed is used to simulate operations for the same duration used to simulate operation of other foresight scenarios. Finally, the objective performances are calculated.

3.4. Results and Analysis

In the first step, a mathematical programming model was developed in GUROBI (GUROBI Optimization Inc, 2018) solver environment. There exist 551,883 continuous and 78,840 integer (zero-one) variables and 630,723 constraints for the entire horizon. Run times vary from 1 hour to several hours based on the weighting scheme used. For the two objectives modeled the MPOVs are calculated as 86% and 13.542 million $/year for the ecological and hydropower revenue objectives, respectively. These values are associated with cases in which one objective takes a weight equal to one while the other objective takes a weight value equal to zero. It is concluded that even if the hydropower revenue objective is ignored, it is not possible to fully meet ecological flow requirements. This is mainly due to minimum/maximum release requirements of the reservoir that conflict with providing flows in ecologically desirable bounds. 9 runs are made with the objective weights depicted in Table 3.2. Weights vary from 0.1 to 0.9 for both objectives while the run 5 assigns equal weights to the objectives (called a *balanced* run in this research).

In the second step, the optimization modeling results for the executions under different weighting schemes depicted in Table 3.2, along with the associated system states are used for developing an operation policy. To determine on how foresight of future variables impacts the operation policy designed performance, the algorithm is executed for two additional cases. In these cases, it is assumed there is a perfect foresight of energy prices and reservoir inflows for the next 12 and 24 hours at every hour. This is not realistic when operating the reservoir since accurate forecast of the variables is not possible but provides insight on the value of having perfect foresight. Forecast of the energy prices and inflows would be additional system states in the DNN. In other words, the algorithm developed would take those additional system states as inputs and prescribe a release value. It is expected that the performance of the operation policy developed associated with these two cases will be superior compared to the performance of original case.

Table 3.2. The weight values used for the objectives modeled in each run

RUN	Ecological	Hydropower Revenue

1	0.1	0.9
2	0.2	0.8
3	0.3	0.7
4	0.4	0.6
5	0.5	0.5
6	0.6	0.4
7	0.7	0.3
8	0.8	0.2
9	0.9	0.1

A DNN is developed and executed in Keras (Chollet, 2015) environment under a wide variety of the network hyperparameters (parameters whose value is set before the learning process begins including the number of hidden layers, number of neurons in each layer, the optimizer used, loss function etc.) to find the parameters that result in the best performance. After trying different combinations of number of hidden layers and neurons, it was found the algorithm performs well in a reasonable time with 5 hidden layers and with respectively 2048, 2048, 1024, 512, and 512 neurons in the layers. Fewer layers resulted in an inferior performance. Adding more hidden layers or neurons did not necessarily improve the performance while it made the algorithm more computationally intense. The activation function RELU resulted in a better performance compared to other activation functions, *sigmoid* (Basterretxea et al., 2004) and *tanh* (Kalman & Kwasny, 1992). Optimizers *stochastic gradient descent* and *rmsprop* (Chollet, 2015) proved to be faster than other optimizers tried. The loss function, *mean absolute error*, was chosen because it performed better than the other loss function tried, *mean absolute squared error*.

The algorithm is executed for 35 epochs and each epoch improves the loss function compared to that of the previous epoch. Since there is a chance that the network overfits,

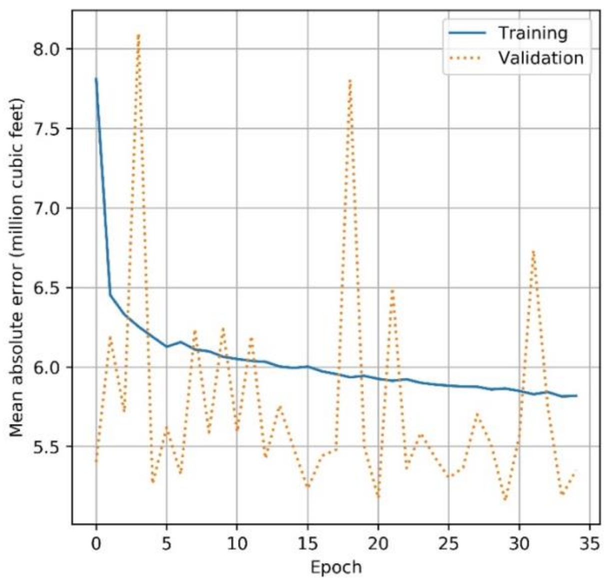

Figure 3.4. The mean absolute error variations for the training and validation set across the epochs for the balanced run of the case with no foresight

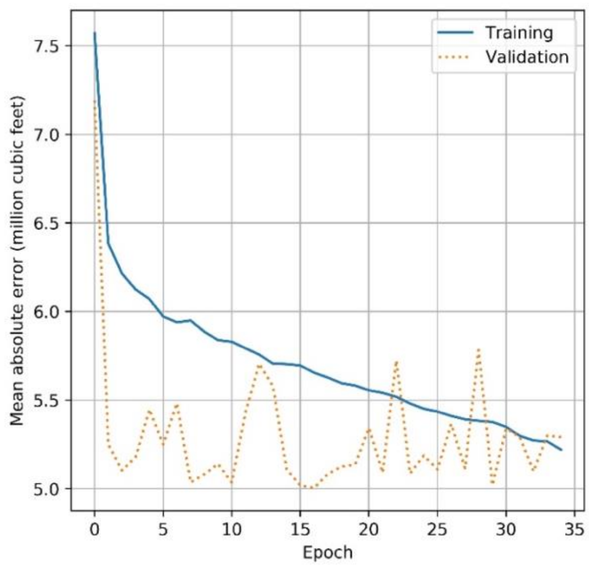

Figure 3.5. The mean absolute error variations for the training and validation set across the epochs for the balanced run of the case with 12 hour foresight

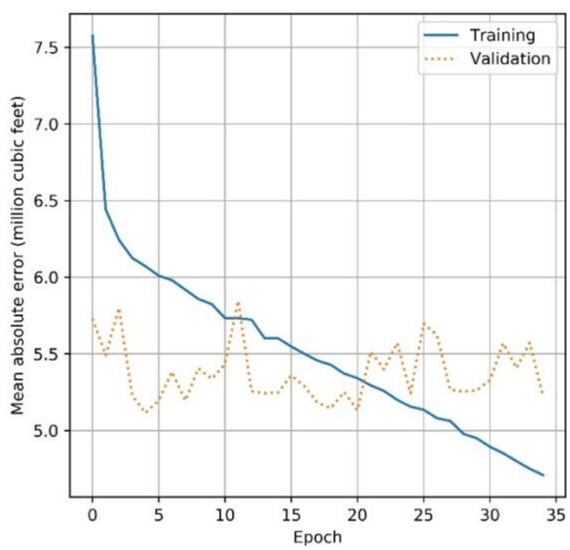

Figure 3.6. The mean absolute error variations for the training and validation set across the epochs for the balanced run of the case with 24 hour foresight

the loss function variations are investigated for the training and validation sets across the epochs. Figures 3.4, 3.5, and 3.6 show the loss function variations (mean absolute error) for the balanced run and for the training and validation sets of the three cases studied. In all the three figures, it is observed that there is a steep reduction in the error during the initial epochs. In figure 3.4 it is evident that after a few initial epochs, the training set error is declined slowly while the validation set error fluctuates across the epochs and does not indicate an increasing trend. The variations in Figure 3.5 are comparable to the variations in Figure 3.4 except for that it seems in Figure 3.5. the algorithm is starting to overfit after 34 epochs since the trend in the training set is decreasing but a slight increasing trend is observed in the validation set. An overfitting is apparent in Figure 3.6 after 21 epochs since this point forward the training set error is constantly decreasing but the validation set error is slightly increasing indicating that there is no extra gain for repeating the training process after around 20 epochs. Once the algorithm is trained, an operation policy is developed for each case that can be used to prescribe the release decisions. In the third step, the operation policy developed for each foresight scenario is used to prescribe the release schedules for a test-set that the algorithm did not have access to during the training process. Finally, in the last step, the release prescriptions for the test-set are used to calculate the ecological and hydropower revenue objective values.

The associated results for each foresight scenario and for each weighting scheme along with the optimized objective values associated with the optimization model are depicted in Tables 3.3 and 3.4 and are illustrated Figure 3.7.

Table 3.3. Ecological objective values for different foresight scenarios and runs (in percent)

Run	Optimized	No foresight	12-hour foresight	24-hour foresight	Regression
1	13.6	6.7	23.2	27.1	6.0
2	23.0	8.7	25.5	28.4	8.1
3	30.3	11.8	27.8	32.5	10.8
4	36.9	14.5	29.5	34.1	12.8
5	42.2	18.3	30.8	35.2	13.4
6	46.1	20.3	31.9	35.9	13.8
7	49.6	21.8	32.7	36.4	14.0
8	52.7	23.4	33.6	37.0	15.7
9	55.2	24.0	34.4	38.5	18.1

Table 3.4. Hydropower revenue objective values for different foresight scenarios and runs (in million dollars per year)

Run	Optimized	No foresight	12-hour foresight	24-hour foresight	Regression
1	10.90	8.55	9.73	10.08	9.57
2	10.38	9.26	9.59	9.87	9.37
3	10.28	9.58	9.51	9.92	9.42
4	9.96	9.09	9.66	9.53	9.05
5	9.92	9.47	9.59	9.81	9.31
6	9.89	9.28	9.62	9.85	9.35
7	9.77	9.43	9.53	9.74	9.25
8	9.62	9.28	9.44	9.53	9.05
9	9.55	9.44	9.66	9.76	9.26

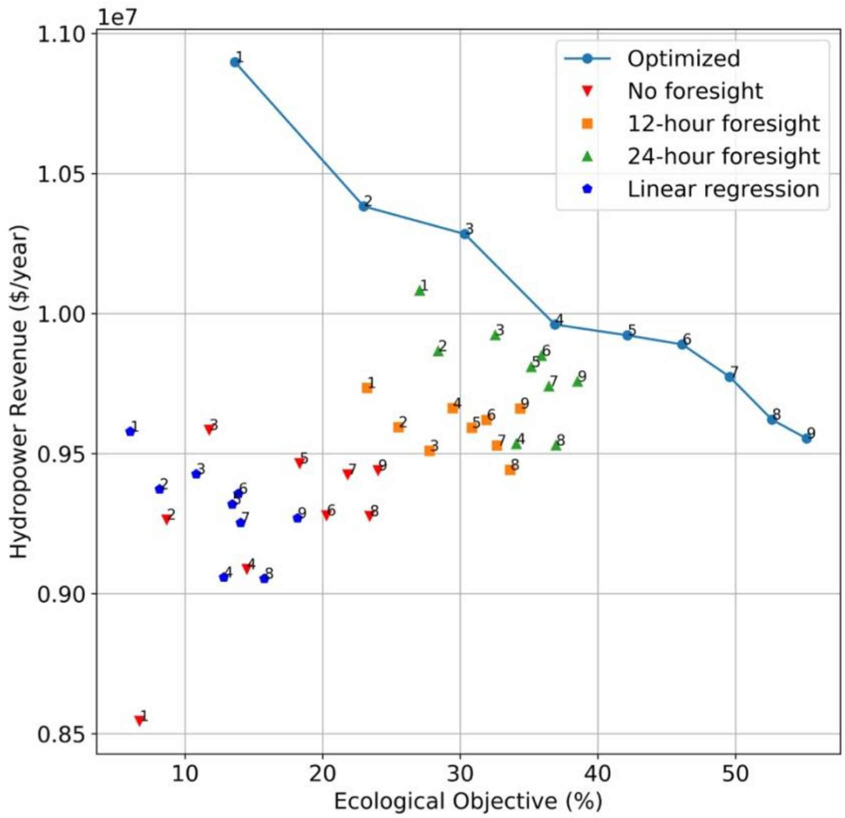

Figure 3.7. The objective values associated with different cases of foresight and for the different objective weight values along with the Pareto frontier

The results illustrated in Figure 3.7 are labeled with the run number depicted in Table 3.2. The solid line indicates the results associated with the optimization modeling, the Pareto frontier. The frontier provides a basis for comparing the performance of the operation policies designed since it indicated the best possible solutions. There are 9 points illustrated in the figure for each operation policy that determine the performance of the policies associated with No foresight, 12-hour foresight, and 24-hour foresight scenarios in respect to the Hydropower revenue and Ecological objectives. It is evident that none of the foresight scenarios has performed as well as the optimized schedules which is because the optimization modeling benefits from perfect foresight when deciding release schedules. One can observe that the 24-hour foresight scenario generally performs better than the 12-hour foresight scenario and the 12-hour foresight scenario does better than the No-foresight scenario. Moving from run 1 to run 9, the Ecological Objective increases continuously for all the foresight scenarios, but the Hydropower revenue does not change regularly.

While the results for each run can be analyzed from the Figure 3.7, the results associated with run 5 (balanced run) are analyzed in the following. For this run, Ecological and Hydropower revenue objective values for the optimization modeling are respectively 42.2% and 9.92 million dollars while the values for the No-foresight scenario are respectively 18.3% and 9.47 million dollars indicating this policy performs well regarding the Hydropower revenue but this comes at a cost for the Ecological objective equal to 23.9% absolute reduction. The results for the 12-hour foresight scenario are respectively 30.8% and 9.59 million dollars. Comparing this performance to that of the operation policy of the No-foresight case indicates a significant increase equal to 12.5% absolute increase in the Ecological objective while the gain for the Hydropower revenue is slight. The values for the 24-hour foresight scenario are 35.2% and 9.81 million dollars indicating an improvement in the Ecological objective equal to 16.9% compared to the No-foresight scenario and a slight improvement for the Hydropower revenue. It is evident that the results associated with the regression method are mostly inferior compared to the no-foresight scenario results. This indicated the benefit in using the more sophisticated method presented in this study.

3.5. Conclusions

A methodology was presented for operation policy design of a reservoir systems and was with conflicting objectives and under multiple sources of uncertainty. The methodology uses optimization and deep learning techniques to develop an operation policy. The application was investigated to the Wilder reservoir located on the mainstem Connecticut River considering Ecological and Hydropower revenue objectives under hydrological and energy market uncertainties. Operation policies were developed for different foresight scenarios; No-foresight scenario in addition to two scenarios in which it is assumed there is foresight for 12 and 24 hours. A baseline method was also applied to the problem to be used as a comparison basis.

DNNs were trained on the optimal state-decision pairs to develop an operation policy. Based on monitoring the training set and validation set loss function values, it was realized the network associated with the No-foresight scenario did not overfit after 35 epochs while the network associated with the 12-hour and 24-hour foresight scenarios started to overfit respectively after 35 and 21 epochs. Thus, it seems the more foresight, the sooner the network starts overfitting. The performance of the policies designed were investigated by simulating the operations for a test-set of data in respect to the two objectives considered. The operation policies designed associated with some foresight indicated overall improvements in the performance of the system. The policies associated with the 12-hour and 24-hour foresight resulted in 12.5% and 16.9% absolute increase in the Ecological objective while they both slightly improved the Hydropower revenue objective. All the scenarios modeled using neural network performed better than the baseline method which show the value in using the presented methodology.

The difficulties of the research followed in this chapter include 1) presence of multiple sources of uncertainty (energy prices and hydrological uncertainties) 2) designing the policies at an hourly time step which is considered fine and adds to the computational difficulties, and 3) presence of conflicting objectives that makes the analysis more complex. However, the methodology presented seems to be promising and should be investigated for other water systems around the globe to further prove its applicability. Future research might focus on application of the methodology to other systems considering case-specific objectives.

CONCLUSION

The need for new methodologies and approaches in optimal policy design and operation of water resources systems is apparent. Using optimization and deep learning techniques, this dissertation presented novel analysis and methodologies for dealing with some of the challenges in water resources systems management. The first chapter presented a mathematical programming model to assess operations of five large hydropower plants located on the Connecticut River mainstem undertaking relicensing. Models representative of alternative operation scenarios were developed to analyze the economic and flow regime outcomes associated with different operation scenarios. Future research directions in this regard include better consideration of turbine efficiency in the hydropower equations and more accurate consideration of flow routing between reservoirs. In this study, turbine efficiency was assumed to be fixed but in reality, it is a factor of flow passed through turbines. Moreover, it is assumed the flow released from a reservoir reaches the downstream reservoir in the same time step while this may not be the case as it might take a while for the flow to reach the downstream reservoir. The second chapter focused on development of a new multiple objective optimization methodology and new formulations for quantification of objectives and identification of conflicting objectives trade-offs. The methodology was applied to the Connecticut River basin considering 54 of the largest reservoirs and different ecological nodes and flood checkpoints. Future research directions associated with this chapter include more accurate consideration of flow routing between reservoirs and development of a model with a sub-daily time scale because hydropower reservoirs should be modeled on a sub-daily scale although this considerably increase computational resources required. The third chapter focused on designing operation policy of a reservoir system using deep learning and optimization under multiple sources of uncertainty and with conflicting objectives. The methodology was applied to the Wilder reservoir located on the Connecticut River mainstem considering ecological and hydropower revenue objectives. It is hoped that outcomes of this research contribute to making the communities around the world better equipped with the tools required when designing and analyzing water resources systems. The methodology applied to the Wilder reservoir indicated promising results, but this should be studied for other reservoirs with different objectives. Thus, future research directions associated with this chapter include application of the methodology to other reservoirs around the globe to investigate the performance of the methodology presented.

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