A Stochastic Dynamic Programming Approach to Balancing Wind Intermittency with Hydropower

Sue Nee Tan, Christine Shoemaker

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Abstract

Hydropower is a fast responding energy source and thus a perfect complement to the intermittency of wind power. However, the effect wind energy has on conventional hydropower systems can be felt, especially if the system is subject to several other environmental and maintenance constraints. The goal of this paper is to develop a general method for optimizing hydropower operations of a realistic multireservoir hydropower system in a deregulated market setting when there is a stochastic wind input. The approach used is stochastic dynamic programming (SDP). Currently, studies on hydropower operations optimization with wind have involved linear programming or stochastic programming, which are based on linearity. SDP, by contrast, is a stochastic optimization method that does not require assumptions of linearity of the objective function. The true adaptive and stochastic nonlinear formulation of the objective function can be applied to multiple time steps, and is efficient for many time steps compared to stochastic programming. The preliminary results for the deterministic optimization demonstrates the potential of this method to guide operation of the hydro system knowing the state of the system. The research will continue with optimizing under uncertain inflows as well as wind.

Notation

$\bar{w}_t$ forecasted wind power production in day t

Δw_t wind power forecast deviation production in day t, $w_t - \bar{w}_t$

$Power_t$ commitment made to the day-ahead power market

T the end of the time horizon for the SDP optimization algorithm

w_t actual wind power production in day t

BA Balancing Authority

BPA system the 10 modeled projects in the Columbia River Basin

FCRPS Federal Columbia River Power System

ISO Independent systems operator

MCP market clearing price, or the price at which the aggregate demand curve (which represents the consumers' willingness to pay) matches the agrregated supply curve (which represents the suppliers' marginal cost)

NLP non-linear programming

RPS Renewable Portfolio Standards

SDP Stochastic Dynamic Programming

USACE U.S. Army Corps of Engineers

USBR U.S. Bureau of Reclamation

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1 Introduction

In mid-2006, several states in the United States adopted Renewable Portfolio Standards (RPS), requiring utilities operating within a state to provide a designated percentage of power that comes from renewable resources by a certain target date. For example the California RPS sets a goal of 33 percent of total energy produced in the state to be from renewable resources by 2025 [1]. The date and the percentage of total power produced differs from state to state. This led to a vast expansion of renewable energy sources.

Renewable energy sources have may benefits such as no fuel costs and no carbon emissions from power generations. However, the inherent intermittency in renewable energy sources such as wind prevent their large-scale adoption in the power grid. When the penetration level of wind energy is low (on the order of 1 to 2 percent of total energy generation), the effects of wind intermittency can be ignored. However, at higher penetration levels, the stochastic nature of wind becomes a significant issue, requiring a large amount of reserves to prevent sags in supply when there is no wind available [2]. To provide a frame of reference, the average retail price of electricity in the US in 2008 was approximately \$100/MWh, while the average cost of producing wind energy from new wind power projects built in 2009 in the US was about \$61/MWh. Currently the forecast errors as a fraction of the wind power plant capacity usually average about 5 percent in hourly time scales, and between 15 to 25 percent on daily time scales [3]. However, forecast errors of 20 to 50 percent are not uncommon [4].

Because of simple physics of the power grid and the current lack of large-scale energy storage, power supplied has to be exactly equal to the power consumed. However, this does not necessarily mean that the power consumed equals the power demanded. Rather, power supply that does not meet the quantity demanded results in a decrease in frequency in the power system which affects the quality and reliability of the power supplied to consumers. To avoid this, it is the role of the system operator or balancing authority to ensure the reliability of power systems by employing regulation (hour-to-hour) and real-time (minute-to-minute) balancing reserves [5].

Exisiting hydropower systems with large storage capabilities can provide this flexibility to the system at a low environmental and economic cost. However, the use of hydropower to provide capacity reserves may lead to the violation of other constraints on the hydropower system, such as flood-storage, environmental releases, and maintaining reservoir levels for navigation and recreation. Thus, careful coordination is required in order to prevent the violation of these constraints [6].

The goal of this paper is to develop a general methodology for the optimization of the daily operation of a realistic multireservoir system in a deregulated market setting when there is a stochastic wind forcing in the system. Our approach is from the perspective of a balancing authority that controls a hydropower system and is trying to balance wind energy using the available hydropower storage in the system. A stochastic dynamic approach will be utilized that will take advantage of the sequential decision making process that occurs during the planning process. Power commitment to the day-ahead market will be used as a hedging strategy for wind imbalances.

1.1 Power Market overview

Power market deregulation occurred to provide a more efficient trading system between power providers and consumers. An efficient market means that (1) the output is produced by the cheapest suppliers, (2) it is consumed by those most willing to pay for it, and (3) the right amount is produced. To act competitively in the power market, power suppliers should act as "price takers," or optimize its production as if it could not affect the market price, i.e. it produces to the point where its marginal cost equals the market price. This means suppliers will take the market-clearing price (MCP) and use this price to plan how much to produce, then adjust their price if they notice excess supply or demand in the market [5].

A typical system operating scheme follows a sequence of events: a day-ahead forecast of the demand is made for each hour of the following day. Power generators bid for producing energy and operating services for the next day and the Independent System Operator (ISO) or balancing authority (BA) schedules an appropriate mix of energy generating resources to meet demand, spinning reserves and transmission requirements and constraints [4].

There are two dominant modes of trading: bilateral trading and competitive electricity pools. For bilateral trading systems, two parties (a buyer and a seller) negotiate a price, quantity and auxiliary conditions for the seller to give to the buyer at a given time. Bilateral agreements tend to vary from different negotiations, so the contracts have to be approved by the ISO or BA. In competitive electricity pools, many buyer and sellers participate in a single market cleared by an independent third party (typically, the ISO). Each seller (buyer) submits an offer (bid) for energy at a desired price. The ISO then aggregates these bids and offers to form an aggregate supply and demand curve. The intersection of these curves determines the market clearing price. Suppliers that submit bids below this price and buyers that submit offers above this price are scheduled. All scheduled parties pay or are paid the MCP.

1.2 Literature Review

Much of the early research on the coordination of hydropower and wind power has so far been heavily focused in Europe and Canada [7], but the field has recently gained momentum in the United States [8, 9, 10]. A significant amount of research has focused on studies such as the one conducted by Castronuovo and Lopes

[11], where pumped storage hydro is coupled with a wind farm to reduce the uncertainty of wind power production in the system. However, large multireservoir systems with storage capacities can also have enough flexibility to handle short-term fluctuations in wind forecast without pumped storage. However, this requires proper planning [12, 13, 14].

The power generation functions for hydropower plants are nonlinear, thus much of the previous research has focused on using mixed-integer linear programming as their method of planning for hydropower production [14, 12, 15]. The intermittent nature of wind power and the difficulties experienced in forecasting wind necessitates a stochastic approach to the optimization of hydropower production. Previous research employ scenario trees with scenario reduction schemes to decrease the number of decision variables for mixed-integer linear programming [15, 12]. Our research uses a stochastic dynamic programming approach to simulate day-to-day decisions of a typical balancing authority, while maintaining the nonlinearity of the generation function by using nonlinear programming to optimize for the best decisions on hourly timescale. Wind forecast is modeled as a Markov process, while the forecast deviations are modeled as a conditional distribution to the forecast.

Coordination of the wind and hydropower production has been shown to be mutually beneficial to both hydropower and wind power producers, particularly in the reduction of penalty payments for wind deviations [14, 12, 16, 15]. However, the hydropower producers can experience a loss in profit when operated jointly with the wind, especially when wind penetration levels are high [14, 9]. Thus a coordinated bidding strategy may only be tractable to hydropower producers if there is a shared profit scheme between the hydro and wind power producers [13], or if the hydro and wind are both owned by the same utility [15, 14, 16]. In light of this, the focus of this research is on investigating the ability of the hydropower operator to profit from bidding on the day-ahead market separately from the wind power producer.

2 Optimizing the operations for the hydropower system with wind

Optimization of the multireservoir hydropower system is performed using a time-decomposition approach. On the daily timescale, stochastic dynamic programming (SDP) is used to simulate decisions made by the BA for the day-ahead market. The objective at each stage t (i.e. at each day) is to maximize the present and future benefits by changing the daily power commitment. The state variables are the storages at each of the reservoirs where release decisions are being made s_t, and the wind power forecast $\bar{w}_t$.

The decision variable is the day-ahead power commitment, $Power_t$ (in MWh). A positive value for the day-ahead commitment indicates that the power is to be sold in the day-ahead market, while a negative value for the day-ahead commitment indicates that the power is to be bought from the day-ahead market. The power production by the hydropower system (and subsequently, the releases from each reservoir) is made based on the power commitment, the occurrence of stochastic wind power, and contracted loads out of and within the system. Here, we assume that the inflows into the system are known.

A backwards recursion algorithm is used to calculate the values of being at the different states at any given time. Starting from T the end of the horizon, at each time step $t = T, T-1, ..., 1$ the algorithm maximizes equation (). For stage $t = T$, a terminal value function is needed. It is assumed that the BA prefers that the reservoirs be at a particular state. A linear penalty function is applied for states that deviate from the target state. This penalty function is used as the terminal value function for the backwards recursion SDP.

The non-linear programming (NLP) environment optimizes the releases made, power bought, and power sold on the hour-ahead market as determined by the forecasted load, and commitment to the day-ahead market on an hourly basis. The deterministic non-linear program is solved for each forecasted wind scenario, $\bar{w}_t$ and each deviation from the forecast, Δw_t. The NLP returns to the SDP algorithm the benefit function and the corresponding releases from the reservoirs as a function of the wind power and the day-ahead power commitment $R_t(\Delta w_t, \bar{w}_t, Power_t)$.

To calculate the future benefits, the states for the next time step are determined based on the releases made (which affects the storage at the different reservoirs) and also the wind forecast for the current day (which affects the wind forecast for the next day). To evaluate values for states that fall between the discrete state space points, an interpolation method is used.

Once the optimization is carried out to the end of the time horizon, the algorithm outputs a matrix of the value function $V(s_t)$ for each state s and each stage t, as well as the optimal policy corresponding the the value function. To apply the policy that is suggested by the optimization , a one-step reoptimization is performed using the future value of water for the next timestep (as calculated by the SDP algorithm) as the terminal value function.

Oftentimes, the model used in the SDP optimization is simpler compared to the model used in the one-step reoptimization. This is because as the state space gets larger, the runtimes for the SDP increase exponentially, therefore a simple, robust model would serve to provide an estimate of the future value of water in the next day, and a more complicated simulation model can be used to perform the reoptimization step. Tejada-Guibert et al. [17] show that the advantages of reoptimizing with the value functions obtained using the SDP optimization provides a better representation of actual allowable flows in the system and also allows for more complex objective functions.

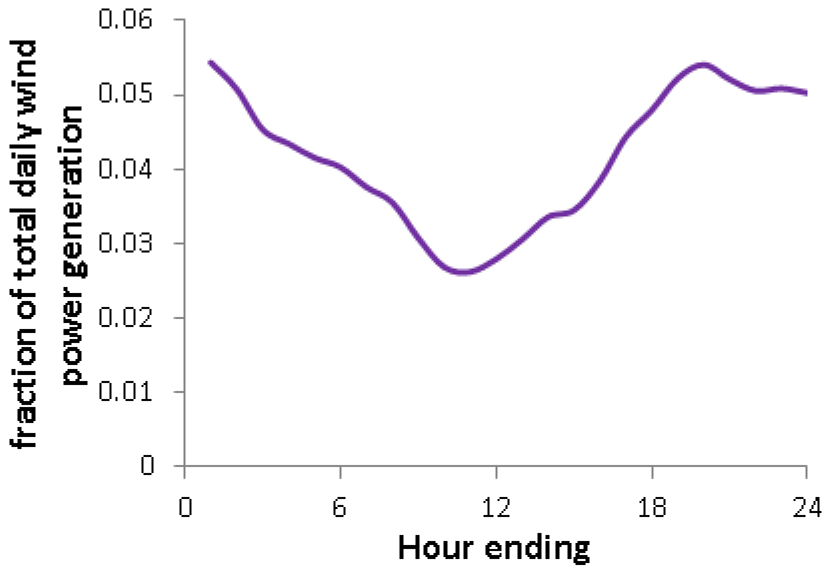

Figure 1: Average hourly wind generation profile for the month of October, obtained using data provided by the BPA from the period 2008 - 2012. The wind power production at each hour is given on the vertical axis as the fraction of the total daily wind power production.

3 Wind and load modeling

3.1 Modeling wind uncertainty

We consider a model for the aggregate of wind power production over all wind farms in our model. Let w_t be the actual wind power production for day t, a function of the forecasted wind $\bar{w}_t$and the wind forecast deviation Δw_t for day t shown in equation (1).

$$w_t = \bar{w}_t + \Delta w_t \tag{1}$$

To obtain the distribution of wind within the day, analysis was performed on historical data for hourly aggregated wind power production in a day for each month of the year to obtain an average wind generation profile. An example of a wind generation profile is shown in figure 1. The set of hourly wind generation fractions is $\{shape_h\}$ for a given month. Each month has a different shape profile.

The wind power production for each hour in day t is given in equation (2).

$$w_{t,h} = (\bar{w}_t + \Delta w_t) * shape_h \tag{2}$$

To maintain the persistence of wind from day to day, the daily wind forecast $\bar{w}_t$ is modeled as a Markov process. Assume that the wind forecast can be assigned to one of n intervals, or states at time t. Given that $\bar{w}_t$ is in one of n states (e.g. state i), it transitions to another state j in the next time period with some probability $P_{ij} = Pr[\bar{w}_{t+1} = j|\bar{w}_t = i]$. The Markov transition matrix $P = \{P_{ij}\}$ is calculated using historical data using the following steps:

1. Divide the available historical data for a particular month into n intervals spaced equally between the maximum and minimum observed data points

2. Increment element (i, j) in C, the n by n square matrix which counts the number of times the wind at time t falls in interval j given that the wind at time $t-1$ falls in interval i, as defined in step 1.

3. Divide each element in C by the total number of observations to get the transition probability from i to j.

The deviations from forecast are also modeled conditional on $\bar{w}_t$. Historical daily deviations from forecast for each month are first calculated using equation (3).

$$\Delta w_t = \frac{w_t - \bar{w}_t}{\bar{w}_t} \tag{3}$$

Then, the Δw_t are sorted according to the state that the corresponding wind forecast $\bar{w}_t$is in. After sorting, conditional distributions $f(\Delta w_t|\bar{w}_t)$ are fit to the Δw_t in each interval.

3.2 Modeling system load

On daily time scales, the system load is well-behaved and can be predicted with a much higher accuracy than with wind. Thus, for our purposes the load is assumed to be deterministic from day-to-day. Like wind, an hourly load profile is assumed for each month, determined from historical data. An example of a daily load profile for the month of October based on our data set is shown in figure 2. When figure 2 and figure 1 are compared, note that in general the wind power production is uncorrelated with load.

Assuming we have a forecast of the total load for the next day $Load_t$, the hourly load is then shown in equation (4).

$$Load_{t,h} = Load_t * profile_h \tag{4}$$

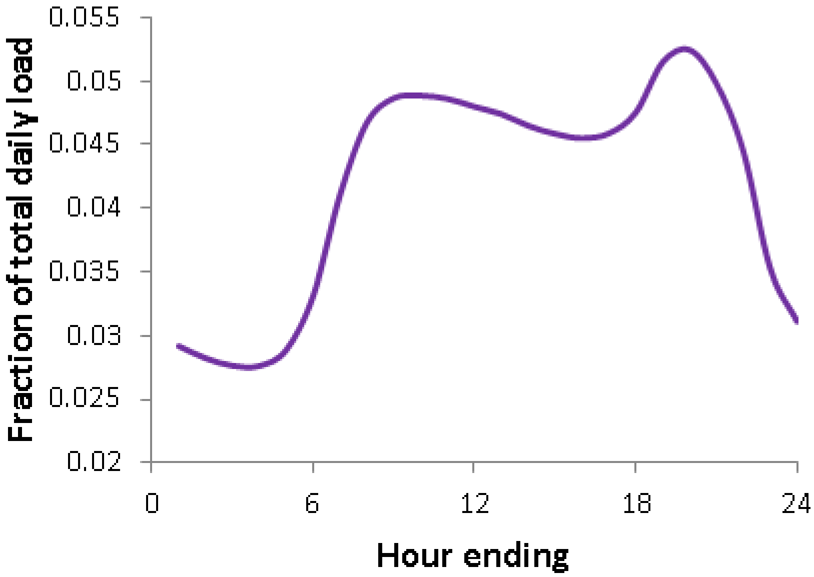

Figure 2: Average hourly load profile for the month of October, obtained using data provided by the BPA from the period 2008 - 2012. The numbers on the vertical axis are the fractions of total daily load that occur in a particular hour of the day.

4 Results and Discussion

4.1 Case study

Our case study is modeled after 10 projects in the Federal Columbia River Power system (FCRPS).The FCRPS are projects owned and operated by the US Army Corps of Engineers (USACE) and the Bureau of Reclamation (USBR) in the Columbia River Basin, shown in figure 3. The Columbia River Basin spans 7 states in two countries (Washington, Oregon, Montana, Idaho, and a small part of California and Nevada in the United States; British Columbia in Canada).

The Bonneville Power Authority (BPA) acts as the BA for a large part of the Pacific Northwest. In addition to providing power to a large part of the Pacific Northwest, the FCRPS are also operated for navigation, recreation, irrigation, and water supply. The operation of the dams within the FCRPS are also constrained by the international Columbia River Treaty that outline allocations of water to each country as well as to provide flows for fish species protected under the Endangered Species Act. The USACE and USBR sets the contraints corresponding to all the non-power uses at their projects, and BPA schedules and dispatches power within these constraints. BPA markets the power generated at the FCRPS projects and also owns and operates over 16,000 miles of transmission lines that deliver electricity to over 75% of the

Pacific Northwest [18].

The wind farms that are interconnected with the BPA system are mostly located in the Columbia River Gorge, between the Bonneville and Lower Granite Dams. Other smaller projects are located near the coast in southwestern Washington, southeastern Oregon, southeast Idaho and western Montana. These wind projects have a collective nameplate capacity of 5000 MW as of 2012. The lack of geographical diversity in wind farms leads to an "all or nothing" effect with wind power generation. The BPA currently dispatches projects in the FCRPS to serve as balancing resources for when wind unexpectedly dies down.

We model 10 major projects located on the Upper Columbia, Lower Snake and Lower Columbia reaches of the Columbia River Basin. This will be referred to in later sections as the BPA system. A schematic of the system is shown in figure 4.

4.2 Deterministic Optimization

First, a deterministic optimization is performed. The deterministic optimization provides a point of comparison for the stochastic algorithm, as well as to verify that the objective function formulation is providing reasonable results.

Wind, load, inflows, prices and other system data was obtained from the BPA for the week of October 15, 2011 to October 21, 2011. Release decisions are assumed to be made from Grand Coulee dam, the most upstream project in figure 4. The state space is the storage at Grand Coulee dam. All projects on the Lower Snake River and downstream of Grand Coulee are assumed to operate as run-of-river projects. Inflows into Grand Coulee and Lower Granite dam are assumed to be known on a day-ahead basis. This is a reasonable assumption as the upstream reaches from these projects are regulated (as can be seen in figure 3).

The period in which the data was obtained corresponds to a drawdown operation of the reservoir. In order that the reservoir is not drained too quickly, the target storage is set to be the storage just below the current storage. Then, the terminal value function at the end of the 7-day optimization horizon is constructed. This function, shown in figure 5 increases rapidly in lower objective function values and levels out as it approaches the target storage. Thus, at lower storage levels, the algorithm would like to conserve water, while at higher storage levels, the algorithm would release as much water as possible.

Some samples of the SDP output for different storage levels in GCL for stage 7 are shown in table 1. For each storage level, the immediate and future benefits $B(Power_t)$ and $V(s_{t+1})$ are shown for the maximum, minimim and the mid-point of the allowable day-ahead commitment $Power_t$ along with the average hourly releases, power sold, and storage at the next stage. Generally, committing to buy power rather than to sell power in the day-ahead market corresponds to lower releases and lower immediate benefits. The power sold

Figure 3: Hydroelectiric dams in the Columbia River Basin. Source: http://www.nwd-wc.usace.army.mil/report/colmap.htm

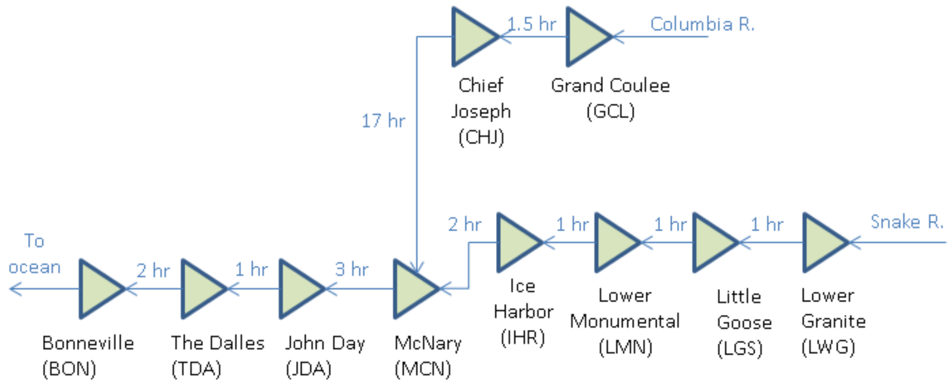

Figure 4: Schematic of the model used in our case study. The numbers in blue are the travel times from one reservoir to another. There are nonfederal projects between Chief Joseph and McNary which are not shown here. They are modeled as run-of-river projects. Source: Steve Barton, BPA.

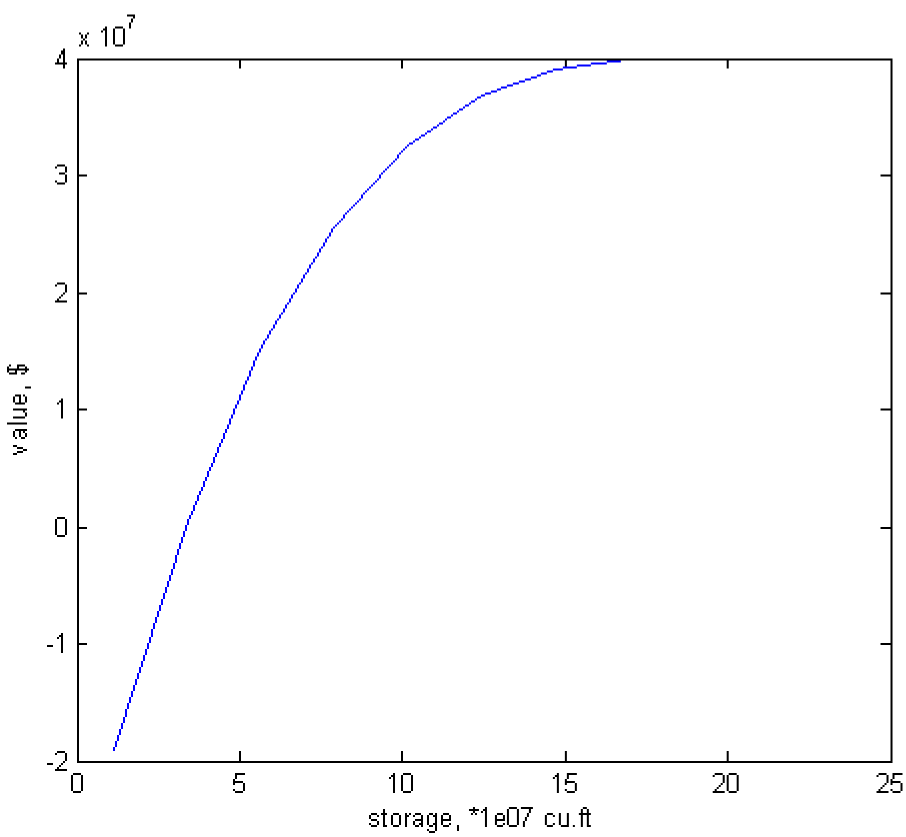

Figure 5: The terminal value function as a function of the different storage levels

Table 1: Sample of SDP output for different states (storage levels) for stage 7 (10/21/2013) at Grand Coulee (GCL) dam. For each storage level, the immediate and future benefits $B(Power_t)$ and $V(s_{t+1})$ are shown for the maximum, minimim and the mid-point of the allowable day-ahead commitment $Power_t$ along with the average hourly releases, power sold, and storage at the next stage. Storages are in units of 10^7cubic feet. Results indicate that for Grand Coulee storages below 7.91×10^7 cubic feet, the optimal policy is to commit to buy the maximum allowable day-ahead commitment, while for Grand Coulee storages of above 7.91×10^7 cubic feet, the optimal policy is to commit to selling the maximum allowable day-ahead commitment. For storages around 7.91×10^7 the optimal policy is to buy $Power_t = 880MW$ on the day-ahead market.

s_t	$Power_t$	$B(Power_t)$	average release (kcfs)	average P_h^{sell}(MW)	s_{t+1}	$V(s_t+1)$	$V(s_t)$
1.13	-1750	-8.60E+05	64.3	250	1.22	-1.8E+07	-1.91E+07
	0	1.56E+05	96.9	250	0.94	-2.1E+07	-2.06E+07
	1750	1.17E+06	129.7	250	0.65	-2.3E+07	-2.22E+07
7.91	-1750	-8.60E+05	62.1	250	8.01	2.60E+07	2.51E+07
	0	1.56E+05	93.6	250	7.74	2.49E+07	2.51E+07
	1750	1.17E+06	125.3	250	7.47	2.38E+07	2.50E+07
21.46	-1750	-8.60E+05	59.0	250	21.59	4.00E+07	3.91E+07
	0	1.56E+05	88.9	250	21.33	4.00E+07	4.02E+07
	1750	1.17E+06	118.9	250	21.07	4.00E+07	4.12E+07

on the hour-ahead market P_h^{sell} is kept to its maximum for all the different day-ahead commitment policies and storages, indicating that the bounds on this variable are binding constraints. Thus, the release decisions change based only the day-ahead commitment. However, low releases also result in the system being in a higher state space and thus garnering higher future benefits.

The tradeoff between immediate and future benefits is different between different states. For storages below 7.91×10^7 cubic feet, the future value of water outweights the immediate benefits gained by selling on the day-ahead market. The optimal policy is to commit to buy the maximum allowable day-ahead commitment, or $Power_t* = -1750MW$. For storages above 7.91×10^7cubic feet, the immediate benefits gained by selling on the day-ahead market outweigh the loss in future benefits from releasing the water from the reservoir. Therefore, the optimal policy is to commit to sell the maximum allowable day-ahead commitment, or $Power_t* = 1750MW$. Finally, the optimal policy for storages around 7.91×10^7 is somewhere in between that of the lower and higher storages.

An example of the generation and load curves for the state s $= 1.13 \times 10^7$cubic feet and $Power_t = 0MW$ for stage 7 is shown in figure 6. As expected, the sum of the loads (Load and power sold) are equal to the sum of the wind and hydro generations.

The evolution of the value function over each storage and for each stage is shown in figure . The x-axis is reversed to correspond to the backwards recursion algorithm, which starts at the terminal stage $T = 7$ and step backwards in time towards $t = 1$. Each line represents the value function of a particular storage at Grand Coulee. The value functions for different states evolve differently through time. Storages below 7.91×10^7 cubic feet have decreasing value functions over time, while storages above 14.68×10^7 cubic feet

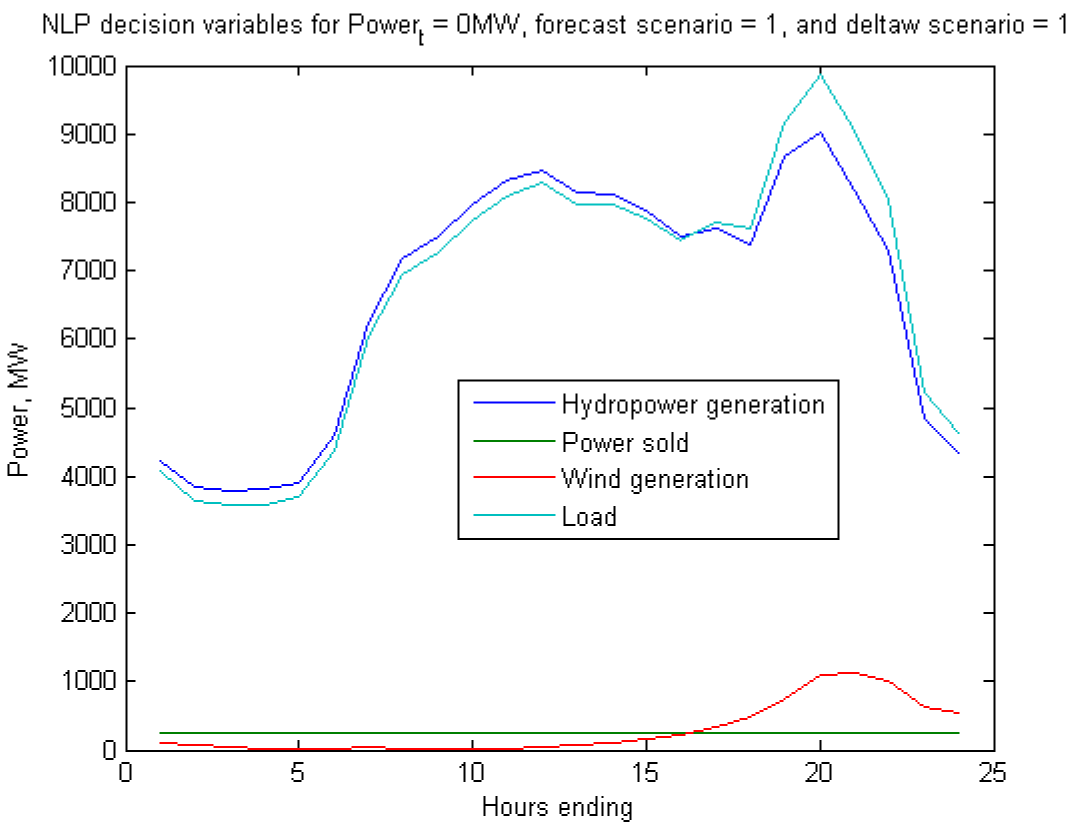

Figure 6: Example of the hourly generation and load curves output by the NLP algorithm for s $= 1.13 \times 10^7$cubic feet and $Power_t = 0MW$ for stage 7.

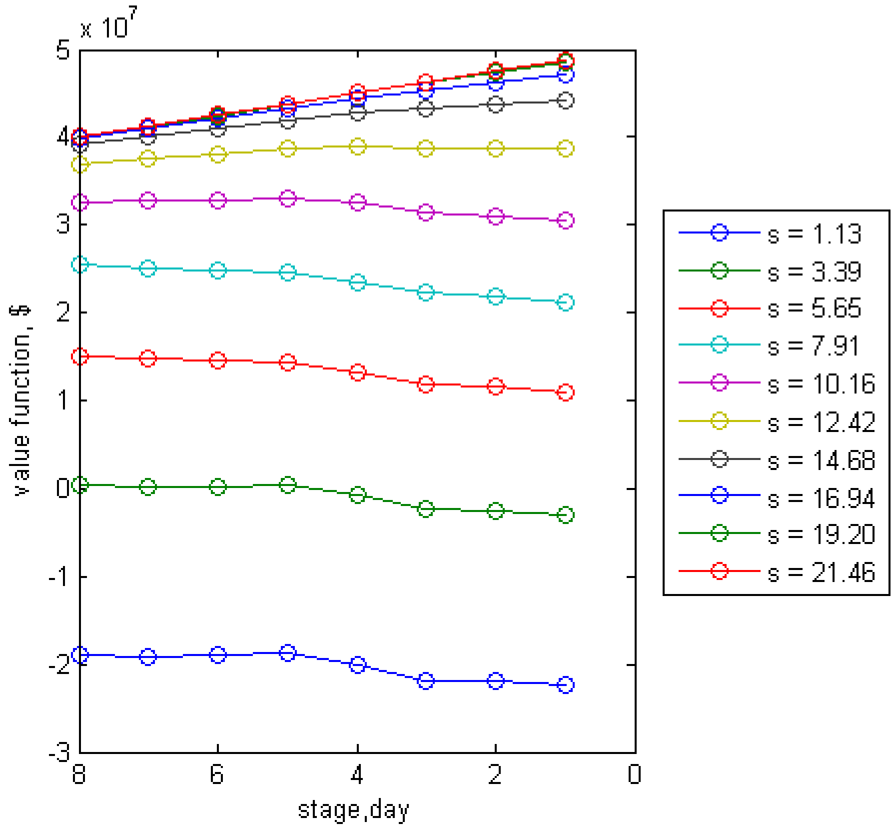

Figure 7: The value function at different states over the optimization horizon. The x-axis is reversed to correspond to the backwards recursion algorithm, which starts at the terminal stage $T = 7$ and step backwards in time towards $t = 1$. Each line represents the value function of a particular storage at Grand Coulee.

have increasing value functions over time.

Finally, the value function at t=1 is used for a one-step reoptimization for the current storage level $s_{curr} = 21.07 \times 10^7$cubic feet. The optimal policy is to commit to sell the maximum day-ahead commitment $Power_t^* = 1750MW$ resulting in a value of $41.2 million.

5 Conclusion

The preliminary results for the deterministic optimization demonstrates the potential of this method to guide operation of the hydro system knowing the state of the system. The research will continue with optimizing under uncertain inflows as well as wind.

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