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## **A DYNAMIC PROGRAMMING APPROACH TO BALANCING WIND INTERMITTENCY WITH HYDROPOWER**

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The goal of this research is to develop a general method for optimizing short-term hydropower operations of a realistic multireservoir hydropower system in a deregulated market setting when there is a stochastic wind input. In order to take advantage of the power market structure, a stochastic dynamic programming (SDP) approach is used to optimize day-ahead power commitments, while a nonlinear programming model optimizes the within-day releases.

### **INTRODUCTION**

Renewable energy sources have many 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 [1]. In the Bonneville Power Administration (BPA) balancing area in the Pacific Northwest, the current wind capacity is about 17% of the total generation capacity, and is projected to reach about 21% of the generation capacity in 2017 [2].

Existing hydropower systems with large storage capabilities can provide a fast balancing service for the intermittency of wind to the system at a low environmental and economic cost. An example of such a system is the Federal Columbia River Power system, which is dispatched and marketed by BPA. However, the use of hydropower to provide capacity reserves may lead to the violation of other constraints on the 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 [3].

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 [4],[5],[6],[7]. However, the hydropower producers can experience a loss in profit when operated jointly with the wind, especially when wind penetration levels are high [4],[8]. 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 [9], or if the hydro and wind are both owned by the same utility [4],[6],[7]. 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.

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 [4],[5],[7]. 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 [5],[7]. In this paper, stochastic dynamic programming (SDP) is used for this analysis.

## **METHODOLOGY**

A time-decomposition approach is proposed where SDP is used to simulate daily decisions and a nonlinear programming method (NLP) is used to solve for within-day hourly decisions. This coupled SDP-NLP approach is expected to be more computationally efficient than traditional stochastic dynamic programming, which would treat each hour as a stage and thus require many stages to go out to a one week time horizon. The true adaptive and stochastic nonlinear formulation of the objective function can be applied to multiple time steps, and is efficient for optimizing under uncertainty in multiple stages compared to stochastic programming [10],[11].

The decision variable for the SDP is the day-ahead power commitment for the system. The state variables are the storages at controlled reservoirs, and the aggregated wind power forecast for a given day. The SDP operates on a daily time step, out to a 1-week horizon.

In the day-to-day transition between states, the wind power production forecast is analogous to the “hydrologic state variable” rather than actual wind power production. The wind power production forecast is modeled as a Markov process. Stedinger et al. [12] showed that the use of the best forecast as a hydrologic state variable, instead of the preceding period's outcome, resulted in substantial improvements in simulated reservoir operations with derived stationary reservoir operating policies.

Present benefits are calculated using a deterministic NLP which maximizes the value of hydropower production by optimally distributing releases through the powerhouse and spillway. The SDP and NLP modules are linked by the SDP decision variable, which is passed into the NLP as an input for the objective function. The wind power production is also treated as an input into the NLP. In addition to the present benefits, the NLP also provides the storages at the controlled reservoirs at the next time step given a set of inflows. These inflows are assumed to be known ahead of time.

The future benefits are calculated given the state variables at the next time step. In solving the backwards recursion Bellman equation, the value function is known at the discrete states. Johnson et al. [13] and Chen et al. [14] showed that the use of smooth approximation functions such as cubic piecewise polynomials or multivariate adaptive regression splines (MARS) can reduce computational efforts compared to tensor product linear interpolation. In this analysis, the future value function at each discrete storage point is interpolated using a radial basis function (RBF). RBFs are a flexible interpolation method that do not require a uniform grid

[15]. Regis and Shoemaker [16] have shown the utility of RBFs in other optimization algorithms.

## INITIAL FINDINGS

We model the operations at a hypothetical 2-reservoir system based on the Grand Coulee and Chief Joseph dams in the Federal Columbia River Power System in the Pacific Northwest. Decisions are made at Grand Coulee, the most upstream reservoir with the most flexibility. The outflows from Grand Coulee are passed through the Chief Joseph, which maintains a fixed forebay elevation. Day-ahead forecast and actual generation data for hourly aggregate wind generation from the wind farms in the balancing area for BPA is available. This is used to develop a Markov Chain model for wind forecast for the next day conditional on the current day's forecast. In this implementation of the SDP, the demand, inflows, and prices are assumed to be well defined, and can be treated as deterministic variables.

Preliminary results on a deterministic wind case demonstrate the potential of this method to guide operation of the cascaded hydropower system. As the storage in Grand Coulee increases, the optimal day-ahead commitment increases. The value function shows a tradeoff between wanting to commit a large amount on the day-ahead market, and wanting to be in a higher storage in the next time period. The within-day optimization model distributes the flows and storages optimally over the different time periods.

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