FINANCIAL LOSSES FROM GENERATION OVERSUPPLY IN HYDROPOWER-DOMINANTED SYSTEMS WITH GROWING WIND CAPACITY

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ABSTRACT

Yufei Su: Financial Losses from Generation Oversupply in Hydropower-Dominated System with Growing Wind Capacity
(Under the direction of Gregory Characklis)

The rapid expansion of intermittent forms of renewable energy makes it difficult to balance electricity supply and demand at the grid-scale. While much attention has focused on the risk of shortfall, oversupply (supply > demand) also presents challenges that can lead to financial losses by utilities and/or consumers when renewable energy is “curtailed”. Few studies have addressed this problem, so an integrated hydro-economic systems model is developed for the Columbia Basin to assess the frequency and severity of financial losses arising from oversupply due to wind power generation, particularly during wet years in which hydropower is abundant. Losses are evaluated under several future scenarios including increased wind capacity, changing natural gas prices and greater transmission capacity for moving excess electricity to export markets. Results indicate that oversupply losses increase as a function of installed wind capacity, but the cost of additional transmission capacity is substantially more than the resulting reduction in oversupply losses and is therefore difficult to justify.
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LIST OF ABBREVIATIONS

ARMA       AutoRegressive-Moving-Average
BPA        Bonneville Power Administration
CAISO      California Independent System Operator
ERCOT      Electric Reliability Council of Texas
FCRPS      Federal Columbia River Power System
HYSSR      Hydro System Seasonal Regulation model
K-NN       K-nearest neighbor
MISO       Midcontinent Independent System Operator
NPV        Net Present Value
TDG        Total Dissolved Gas
Wind power capacity worldwide is increasing at a rapid rate, with installed global wind capacity having increased roughly 2400% in the 15-year period from 2000 to 2015 (GWEC 2016). Nonetheless, an ongoing challenge with increasing wind capacity is managing wind power’s intermittency (Bélanger & Gagnon 2002; Nrel 2011). Wind speeds can change dramatically on a sub-hourly basis, and existing power systems sometimes struggle to accommodate these sudden changes (Bélanger & Gagnon 2002; NREL 2011; Jaramillo et al. 2004). One challenge associated with the intermittency of wind is generation “oversupply”. Oversupply occurs when the total electricity generation in a region exceeds the electricity demand (Lew et al. 2013; Olson et al. 2014). In general, generation oversupply happens due to the combination of “must run” thermal generation (e.g., nuclear) and hydropower (especially during extremely wet periods) resources that cannot be turned off or sufficiently ramped down—with variable renewable energy, such as wind or solar. During over supply events, excess electricity that cannot be exported to another region due to grid congestion or stored via batteries or pumped storage (Li et al. 2015) must be curtailed in order to maintain the integrity of the electricity grid. In many cases of oversupply, renewables like wind and solar power are curtailed because it is the most economically or/and viable way to balance load (electricity demand) and generation (Bird et al. 2014; Lew et al. 2013). Without significant improvements in transmission, energy storage and demand side management, over supply is likely to become a greater challenge in the future as wind and solar capacity increases (Klinge Jacobsen 2012; Denhol &
Tran 2012; Olson et al. 2014; Bird et al. 2014). Figure 1, which shows data from the U.S. illustrates how curtailment increases as wind power capacity increases. The capacity factor, which is the ratio of the actual output over its nameplate capacity, decreases as more wind power is installed and subsequently curtailed.

![Figure 1. Wind Capacity Factor Loss from Curtailment due to Wind Capacity Growth (Wiser et al. 2015)](image)

Many studies have looked at the renewable energy curtailment from an economic perspective. Some point out that the renewable curtailment is a waste of energy that leads to economic losses for both utilities and society (Denhol & Tran, 2012). Others, however, have concluded that, given the cost of transmission and energy storage options, renewable energy curtailment may be a socially optimal choice (Klinge Jacobsen & Schrroder, 2012). The range of conclusions drawn from previous studies suggests that oversupply problems in different systems can be very distinct, suggesting that system-specific models are required to study this problem. The financial losses associated with curtailment may depend on a number of factors, including complex interactions between different types of generation, as well as climatic and environmental factors, making for challenges in both characterizing the problem and solving it.
Power systems in Germany and China, as well as regional energy systems in the U.S. (e.g., PJM Interconnection and ERCOT (Electric Reliability Council of Texas) and MISO (Midcontinent Independent System Operator)) have experienced generation oversupply due to the combination of must run thermal generation and a growing penetration of renewables, in particular wind power. Another form of generation oversupply occurs in hydropower dominated systems, especially in situations where high levels of renewables are present (Bird et al. 2014). Hydropower, due to its operational flexibility, is often regarded as an ideal resource to compensate for the intermittency and unpredictability of wind power (Kern et al. 2014). However, as more wind penetrates the electricity mix, hydroelectric dams may be limited in their ability to accommodate wind power by reducing generation when wind is available.

Perhaps the most prominent example of oversupply in hydropower dominated systems is the U.S. Pacific Northwest, where hydropower meets more than 60% of regional electricity demand, with most generation coming from the Federal Columbia River Power System (FCRPS), a network of hydroelectric dams spanning several states. Most of the Pacific Northwest’s electric power system is operated by Bonneville Power Administration (BPA), a federal agency that is in charge of power plant operations, transmission, and grid balancing (BPA 2015). Within BPA’s footprint, there are 31 federal hydroelectric dams, many additional non-federal dams, and 1 nuclear plant (BPA 2015). This system has experienced rapid growth in wind power capacity and is already experiencing oversupply issues, with two major wind related oversupply events occurring in 2011 and 2012.

The occurrence of oversupply events and the compensation scheme is as following (Figure 2): During high flow periods (typically summer snowmelt), hydroelectric dams in the FCRPS produce massive amounts of hydropower. In response, thermal power plants are shut
down or ramped down to their operational limits (EIA 2011; BPA 2012; Bonneville Power Administration & Corps 2011), to maximize the use of hydropower. Nonetheless, with wind power capacity in the region growing quickly, the combination of summer hydropower production and wind power can create periods of regional generation over supply. During oversupply periods, dam operators may wish to reduce hydropower production (thereby maximizing the use of wind power) and store water for release at a later time. However, high flow periods drive reservoir levels higher, constraining the ability of dam operators to store additional flows. The next option available to dam operators to reduce generation is to “spill” water (discharge it from reservoirs without generating electricity). In the FCRPS, however, environmental regulations on flows downstream of some hydroelectric dams can obligate them to operate in more ecologically friendly way, which can limit the dams’ ability to accommodate high wind energy penetration. Specifically, spilling large volumes of water via spillways can cause elevated downstream levels of total dissolved gases, primarily nitrogen (Sale 2006), and violate federal water quality standards. Thus the combination of high reservoir levels and water quality concerns can effectively turn dams in the FCRPS into “must run” resources that have no choice but to generate electricity. At the same time, transmission capacity (i.e., the ability to export excess electricity out of the region) is limited. As a result, during over supply events, it is often wind producers in the region who ordered to shut down in order to maintain a grid balance between supply and demand. Wind power curtailment results in the loss of revenues from wind power generation, which is further compounded by the loss of associated renewable credits and tax credits that producers could receive only when the generators are active. Wind producers’ losses are then compensated by BPA, and this bill is ultimately passed to all the rate payers (Bonneville Power Administration 2013).
The financial losses caused by these recent oversupply events in BPA’s system (as well as discussion of strategies for mitigating future losses) have drawn significant media attention (Peter 2011). Wind power capacity in this region is expected to grow dramatically in coming decades, potentially leading to more severe financially consequences from oversupply. Installed wind capacity increased from almost 0 MW in 2000 to 4782MW by the end of 2014. An additional 3000-4000MW of wind power capacity is planned to be installed by the end of 2025.
BPA has conducted a preliminary analysis of potential oversupply losses moving forward, suggesting that annual losses could be as much as $50 million U.S. dollars (Peter 2011). However, the analysis is limited in the following ways. First, BPA assessed potential oversupply losses in only four, non-consecutive sample years from the historical hydrological record, neglecting large swaths of the distribution (Figure 3) and making no effort to project losses over longer, representative time frames. In addition, BPA’s preliminary analysis also assumed static or very limited changes in installed wind capacity, transmission availability and electricity prices over time. Given the projected rapid growth of wind power in the system (Figure 4), and the uncertainty with respect to these other factors, a more comprehensive approach is desired to understand how the challenge of managing over supply in hydropower dominated systems like BPA’s may evolve in the future, and how transmission planning and electricity price behavior may contribute to either lessening or worsening the problem.

To address these issues, this study uses a system-based hydro economic model, one built specifically for the combined reservoir-power system in the Pacific Northwest, to investigate the...
oversupply problem faced by BPA. The BPA system is evaluated dynamically to characterize the
dollar value of wind power loss from curtailment in both current and future scenarios. A
synthetic hydrologic record, based on the historical streamflow distribution, is generated to
capture a wider range of streamflow dynamics on multiple time scales. This is combined with
models of daily reservoir operations, wind generation, electricity demand and transmission
exports (mostly to California Independent System Operators), and hydropower scheduling, to
develop a probabilistic estimate of potential oversupply losses. This integrated model is then
used to assess Net Present Value (NPV) losses from oversupply over a 25-year period providing
a basis for making estimates of the value of potential mitigation strategies (e.g., construction of
additional export transmission capacity). The results of this work provide a more integrated and
improved understanding of financial losses from over supply in hydropower dominated systems,
allowing for the development of better planning and financial loss management strategies.
CHAPTER 2: METHODS

As a federal power market administration whose system is well established and monitored, BPA has large amounts of publicly available operating data and operates the majority of the electricity generation and transmission capacity in the region. All data used in this study are publicly available. Inflow data at hydropower dams in the FCRPS (Figure 5) were obtained from BPA’s modified flow dataset. This dataset provides 80 years of river flow data (from 1928-2008) that account for factors such as withdrawals and return flows from irrigation, evaporation and other water consumption in the region. Eight years (from 2007 to 2014) of wind, regional electricity demand, transmission exports and thermal generation data are available from BPA’s balancing authority website (BPA, 2015). Eighty years of daily temperature data, from 1928 and 2008, were obtained from the National Oceanic and Atmospheric Administration.
2.1 Integrated Modeling

Several independent modules are integrated in order to develop the entire modelling platform (Figure 6). Exogenous drivers of the model are simulated first (i.e., synthetic streamflow, electricity demand, wind energy production, and transmission exports). These simulated products then serve as inputs to the power system “decision making” process, which includes the daily reservoir operations and hourly power scheduling models. The output of the scheduling model is then processed to calculate oversupply related losses.
2.2 Synthetic unregulated streamflow

A primary goal of this study is to gain a more robust probabilistic understanding of the potential for financial losses caused by oversupply events in the BPA system. Meeting this goal requires use of an expanded hydrological dataset longer than the historical record (1928-2008).

Two main challenges exist in developing synthetic unregulated streamflow data for use in the daily reservoir operations model. First, the synthetized streamflow has to be able to replicate statistical characteristics of historical flows at hydroelectric dams in the FCRPS. Second, the method must be able to generate daily values that demonstrate accurate spatial cross-correlations, as well as temporal autocorrelations.
Many synthetic streamflow generation methods exist in the literature. One method that sufficiently addresses both the aforementioned challenges is presented by Nowak et al. (2010). This is a nonparametric stochastic approach for generation of synthetic daily flows for multiple sites using a K-nearest neighbor (K-NN) resampling. Use of this method can be briefly explained as follows:

1) For each site in the reservoir system, daily observed unregulated streamflow values are converted to a proportion of the total annual flow of that particular year. This generates \( P \), a three-dimensional matrix (years \( \times \) sites \( \times \) 365). In this study, years = 81 and sites = 48.

2) A corresponding two-dimensional matrix \([Z]\) (years \( \times \) sites) is generated. Each location (row, column) of \( Z \) is equal to the total annual flow in each year (row) at each site (column).

3) A (1 \( \times \) years) vector, \( z_{\text{sum}} \), is also calculated with each element equal to the total annual unregulated streamflow across all 48 sites.

4) An theoretically unlimited number of synthetic members of \( z_{\text{sum}} \) is then generated (this can be done using an daily AR(1) model fit to \( z_{\text{sum}} \) or a lag 1 K-nearest neighbor method, as presented by Lall and Sharma (1996)). For each synthesized value, we identify its K-nearest neighbors within historical observations of \( z_{\text{sum}} \), with:

\[
K = \sqrt{\text{years}}
\]

Neighbors are identified within \( z_{\text{sum}} \) as those observations that are closest to the newly synthesized value. Then a weight \( W \) for each neighbor is calculated using the
following equation, where \( i \) is the “neighbor index” with \( i=1 \) being the closest and \( K \) is the number of nearest neighbors.

\[
W(i) = \left( \frac{1}{i} \right) / \sum_{i=1}^{K} 1/i
\]

(2)

5) One of the \( K \)-nearest neighbors (a historical year \( y \)) is chosen randomly based on the weighted resample present in equation (2). The \( y \)th row of matrix \( Z \) is selected (\( z_y \), i.e., annual streamflow totals in year \( y \) for each site), as is the \( y \)th plane in \( P \) (\( P_y \), i.e., daily flow proportions at each site in year \( y \)). A matrix of daily unregulated streamflows at each site is then calculated by multiplying each element of \( z_y \) times the vector in \( P_y \) corresponding to the same site.

2.3 Wind Power Time Series

A number of methods exist for modeling wind power production, with different methods able to excel under different conditions and study requirements (Billinton & Chen 1996; Castino et al. 1998; Morgan et al. 2011). For this study, an integrated representation of wind power production in the BPA system across four temporal scales: annual, seasonal, daily and hourly was developed. On an annual basis, the gradual increase of wind power capacity need to be accounted for. Wind power generation in the BPA system also demonstrates strong seasonality, with production tending to peak during from mid-summer to early fall. On a daily basis, wind power generation demonstrates significant levels of autocorrelation; and on an hourly level, wind power generation demonstrates a diurnal pattern (i.e. wind speed and production is higher during night and lower during the day).
In this study, a series of ARMA (AutoRegressive-Moving-Average) models is used to represent these multi-scale processes and their connections. This method is able to take into account the appropriate statistical properties of monthly and daily wind energy generation, while maintaining similar level of autocorrelation and diurnal patterns. This approach also provides an ability to simulate hourly wind power production conditioned on any theoretical amount of installed wind capacity. The synthetic wind power generation method employed in this work is described below.

First, the original dataset need to be transformed to a normalized hourly wind power production, for a given month and year can be approximated by applying the following equation:

$$\text{Normalized}_{\text{Wind}}_{h,m,y} = \frac{\text{Observed}_{\text{Wind}}_{h,m,y} - \text{Observed}_{\mu_{m,y}}}{\text{Observed}_{\sigma_{m,y}}}$$  \hspace{1cm} (3)

Where:

\(h = \text{hour of the day, } \in \{1, 2, 3...24\}\)

\(m = \text{month of the year, } \in \{1, 2, 3...12\}\)

\(y = \text{sampling year, } \in \{2007, 2008...2014\}\)

\(\text{Observed}_{\text{Wind}}_{h,m,y} = \text{observed wind production data at hour } h, \text{ month } m \text{ and year } y,\)

\(\text{Observed}_{\mu_{m,y}} = \text{the mean of all observed hourly wind production in month } m \text{ and year } y,\)

\(\text{Observed}_{\sigma_{m,y}} = \text{the standard deviation of all observed wind production in month } m \text{ and year } y\)

The above transformation generates a matrix \(\text{Normalized}_{\text{Wind}}_{h,m,y}\), which is the hourly wind generation signal with monthly and annual (installed capacity effects) removed. However,
Normalized_Wind\textsubscript{h,m,y} contains negative numbers (i.e. low production day minus monthly average), which need to be adjusted before log-transformation.

\[
\text{Normalized_Wind}'\textsubscript{h,m,y} = \text{Normalized_Wind}_{h,m,y} - \min(Y_m) + 1 \tag{4}
\]

Where:

\[Y_m = \text{Normalized_Wind}_m = \text{all normalized data in month } m \text{ across all years.}\]

This adjustment makes \text{Normalized_Wind}'\textsubscript{h,m,y} a matrix that only contains positive numbers with the minimum value of 1, enabling log transformation this leads to,

\[
\text{Log}_\text{Normalized_Wind}'\textsubscript{h,m,y} = \text{the log-transformed, adjusted, and normalized wind matrix at hour } h \text{ month } m \text{ and year } y,
\]

Then the mean and standard deviation of all log-transformed, adjusted, and normalized wind energy data for each of the 8760 hours in all observed years were calculated, resulting in:

\[
\overline{\mu}_{h,m} = \text{Log}_\text{Normalized}_\mu'\textsubscript{h,m} = \text{the mean of Log}_\text{Normalized}_\text{Wind}'\textsubscript{h,m,y} \text{ in hour } h \text{ and month } m \text{, across all years}
\]

\[
\overline{\sigma}_{h,m} = \text{Log}_\text{Normalized}_\sigma'\textsubscript{h,m} = \text{the standard deviation of Log}_\text{Normalized}_\text{Wind}'\textsubscript{h,m,y} \text{ in hour } h \text{ and month } m \text{, across all years}
\]

Finally, the diurnal pattern in hourly wind power production is removed from Log\_Normalized\_Wind\textsubscript{h,m,y} by subtracting the expected hourly values and dividing by their standard deviation. This leads to the calculation of following,

\[
U = (\text{Log}_\text{Normalized}_{\text{Wind},h,m,y} - \text{Log}_\text{Normalized}^\prime_{h,m})/\text{Log}_\text{Normalized}^\prime_{h,m} \tag{5}
\]
U is a matrix of hourly wind energy data with annual capacity, seasonality (monthly patterns) and diurnal signals removed. Next, twelve separate ARMA models are constructed, one for each month, in order to capture the hourly statistics and time series characteristics of the remaining signals. In this study, an ARMA(3,2), which is a combination of lag 3 autoregressive model and a lag 2 moving average model, process was selected as the best fit for the models in terms of autocorrelation (Figure 8). A set of optimizations are run to fit the best parameter for the ARMA(3,2) models.

The resulting 12 monthly ARMA(3,2) models are used to simulate the hourly wind energy data process with annual capacity, seasonality (monthly patterns), diurnal signal, over any desired length of time, resulting in a vector called \( U^* \). To this time series of any length, the diurnal signal is then re-applied, the log transform is reversed, the adjustment is rescinded, and the data is converted back to its original, non-Normal form.

\[
\text{Synthetic Wind} = \left( \left( \exp(U^* \times \bar{\sigma}_{h,m}) + \mu_{h,m} + \min(Y_m) - 1 \right) \times \sigma_{m,MW} \right) + \mu_{m,MW} \tag{6}
\]

Where

\( \mu_{m,MW} = \text{mean hourly wind generation in month m, given wind capacity MW} \)

\( \sigma_{m,MW} = \text{std. deviation of hourly wind generation in month m, given wind capacity MW} \)

In order to project the mean and standard deviation of hourly wind energy for each month under much greater levels of installed wind capacity than what exists today in BPA’s system, we extrapolate relationships from observed data. For example, the gradual increase of the wind
capacity in BPA’s system has led to increased standard deviation of daily wind production (Figure 7).

Figure 7. Relationship between installed wind capacity and standard deviation of daily wind power generation.

Figure 8 and Figure 9 show the comparison of the synthetic wind energy time series model result against historical observations as a means of validation and the autocorrelation and seasonality of the historical observations appears well preserved. Note that observed wind production in Figure 9 (red line) does not have error bar. Since wind capacity in BPA’s system has grown each year, year-on-year observed wind energy data do not provide a good direct comparison in terms of seasonality. Thus only wind data from 2014 is used in this comparison, providing a qualitative sense of model accuracy, albeit one that falls a little short of formal validation. It is also important to note that, the synthetic wind energy model performs best in terms of reproducing seasonal effects during the months most important in driving over supply in the BPA system, i.e., June-August.
Electricity demand is largely dictated by activities that heat and cool buildings (Nawaz et al. 2014), so daily mean temperatures are used as a primary input in simulating electricity demand, which is synthesized via conditional resampling of the historical temperature record. Temperature can also have direct effects on the timing of snowmelt, which is a main water source of stream flow, thus it is important to understand and account for the observed relationships between temperatures and streamflow patterns when generating both synthetic flow and temperature data. To account for this, when years of flow proportions are selected (see step...
#5 in the synthetic unregulated streamflow generation process), we simultaneously resample the same year to get daily mean temperatures.

As the dominant drivers of electricity demand, temperature features prominently in most commonly used approaches for simulating daily peak electricity demand ([Engle et al. 1992; Bélanger & Gagnon 2002]). In this study, the population weighted mean daily temperature is used to capture the temperature effect on daily peak demand across BPA’s large geographical area. Population and temperature data are taken from the most populated city in each of the primary states in BPA’S footprint, namely Seattle, WA, Portland, OR, and Boise, ID. The population weighted temperature is calculated as:

\[
T_w_i = \sum_{i=1}^{3} \frac{P_i}{\sum P_i} T_i
\]  

(7)

Where:

- \(T_w_i\) = Population weighted temperature
- \(i\) = index for 3 different cities
- \(P_i\) = Population in the indexed city
- \(T_i\) = Mean daily temperature in the indexed city

### 2.5 Demand Modeling

The method used here to model hourly electricity demand combines hourly demand profiles for each day of the year extracted from historical data, with a similar time series modeling process as was used in modeling wind energy data.
First, we extract hourly demand profiles from historical electricity demand data for the BPA system. We generate 365 hourly demand profiles in a (24 x 365) matrix S, with elements equal to:

\[ S_{h,d} = E \left( \frac{L_{h,d}}{L_{h,d}'} \right) \]  

(8)

Where:

- \( L_{h,d} \) is the demand at hour \( h \) in day \( d \)
- \( L_{h,d}' \) is the maximum hourly demand in day \( d \)

Hourly demand profiles are then coupled with a synthetic daily peak electricity demand time series in order to simulate hourly demand. Similar to our approach to modeling hourly wind power production, using historical peak electricity demand data, we remove key trends and filter the linear process until it becomes white noise; then we re-build the time series using synthetic records to achieve an expanded data set.
Figure 10 shows the relationship between population weighted temperature in the BPA system with daily peak internal electricity demand. Given coincident time series of historical daily peak demand and population weighted temperature in the BPA system, this relationship can then be removed. We then normalize the remaining data by subtracting its mean and dividing by the standard deviation.

After removing the temperature effects and normalizing, the remaining process contains non-temperature related seasonality and day of the week effects. Seasonality is removed from the daily data by subtracting the expected daily demand and dividing by the standard deviation for each month, and then day of the week effects are removed using similar means. The remaining process, \( W \), is modeled using an ARMA(3,2) model.

\[
W = \frac{\left( \left( \frac{L^*_d,m - \mu_d,m}{\sigma_{d,m}} \right) - \mu_{dow} \right)}{\sigma_{dow}}
\]

(9)

Where:

\( W \) = daily peak demand data in MW, with effects from temperature, month and day of week removed.

\( L^*_d,m \) = the data with temperature effects removed

\( \mu_{d,m} \) = the expected demand of the month \( m \)

\( \sigma_{d,m} \) = the standard deviation of the month \( m \)

\( \mu_{dow} \) = the expected demand for day-of-the-week (dow)

\( \sigma_{dow} \) = the standard deviation for day-of-the-week (dow)
An ARMA model is then fit to time series \( W \) for simulation. After the simulation process, the filtered signals are added back into the simulated result \( (W^*) \), using a resampled time series of population-weighted daily mean temperature.

\[
L_{sim} = \left( (W^* \sigma_{dow} + \mu_{dow})\sigma_{d_{m}} \right) + \mu_{d_{m}} + f(T^*)
\]  

(10)

Where:

\( L_{sim} \) = simulated peak demand(MW) time series

\( W^* \) = ARMA generated simulated result

\( \mu_{d} \) is the expected demand of the weekday \( d \)

\( \sigma_{d} \) is the standard deviation of the weekday \( d \)

\( f(T^*) \) = regression of temperature effects on peak demand

\( T^* \) = synthetic population weighted daily mean temperature

After generating \( L_{sim} \) (simulated daily peak demand data), it is applied to the hourly profiles for each calendar day taken from historical data. Figures 11 and 12 show validation of the electricity demand model. This model did a very reasonable job of preserving both autocorrelation and seasonality in the original dataset.
Currently, the maximum export capacity for BPA is 13000 MW. Actual transmission exports, however, are a function of demand in systems outside the BPA footprint. As such, we model them using a similar approach as the one described in the electricity demand section (i.e., a function of seasonality and day of the week). Since BPA’s oversupply problem is at least partly a byproduct of limited transmission capacity (a constrained ability to send excess electricity out
of the BPA system), we also give some consideration to transmission upgrades as one potential solution to oversupply.

The operation of individual thermal power plants is not modelled explicitly. Rather, it is assumed that thermal generation is always available to meet any electricity demand not provided by hydropower and wind. This is an assumption that, generally speaking, reflects how these generators are used in the BPA system given the BPA’s ability to predict short term wind and hydro conditions. During high flow periods, thermal generation is gradually ramped down to its lower operational limits to accommodate the availability of wind and hydropower.

2.7 Daily Reservoir Operations (Modified HYSSR model)

![Figure 13. HYSSR model schematic of dams in the FCRPS.](image)
In order to simulate the operations of dams and reservoirs in the BPA system, we use a modified version of the Hydro System Seasonal Regulation model (HYSSR), a model designed and built by the US Corps of Engineers. The HYSSR model is a monthly hydro-regulation model that simulates the operation of hydroelectric dams in the Columbia River Basin. It is a deterministic, mass-balance model that produces monthly results for reservoir storage, hydropower production, and reservoir outflow (USACE 2008). This model has been used by both BPA and the US Corps of Engineers for planning, operation and regulation purposes.

Since modeling oversupply events requires a time step shorter than monthly, HYSSR has been modified to a daily model. The modified model includes the operations of 48 dams (Figure 13), which are classified as either storage or run-of-river projects. Storage projects are those that operate based on a set of rules to regulate inflows, i.e., adjust the river’s natural flow pattern to adapt to needs for flood control, water supply, and hydropower production. Storage projects in the FCRPS typically capture peak runoff from spring and summer snowmelt and store it for late summer and autumn release when the natural stream flows are lower. Run-of-river projects have negligible storage capacity and simply pass inflows through turbines for hydro-power generation purposes.

The modified HYSSR model calculates outflow from each project based on inflows, minimum/maximum discharge requirements, current storage level (only applicable for storage projects) and operational rule curves to determine each project’s end-of-day storage content, outflow and power generation.

For storage dams, daily release decisions are governed by a set of rule curves, which are determined based on projected inflows, flood control requirements, power generation requirements, and a project’s physical limitations (e.g., maximum turbine capacity) and non-
physical limitations (e.g., minimum outflow for environmental purposes, minimum elevation for recreational use).

At each storage reservoir, 6 different rule curves are used in making release decisions (U.S. Army Corps of Engineers & BPA 2011):

- **Critical Rule Curves (CRC)** are determined annually based on the annual estimate of system-wide electricity demand and available generation resources. These curves ensure that each reservoir can meet its firm power production requirement even during the most critical periods (dry periods).

- **Assured Refill Curves (ARC)** define the reservoir elevations necessary to refill the reservoir by July 31st each year. The ARC is calculated based on the third lowest water year in the history, which for all projects upstream of Bonneville Dam is the period August 1930 to July 1931.

- **Variable Refill Curves (VRC)** define the reservoir elevations necessary to refill the reservoirs to limit the secondary energy (non-firm requirement) production. This is calculated based on forecasted flow of the modelling water year. In reality, VRCs are set by dam operators probabilistically using ensemble streamflow forecasts; however, in this study, we assume perfect foresight on the part of dam operators, which is a reasonable assumption given that snowmelt dominated system have accurate streamflow prediction using snowpack information, so the VRC is set based on synthetic streamflow.

- **Operating Rule Curve Lower Limits (ORCLL)** are defined as the lowest elevation that the modelled projects can reach. This is based on each project’s physical limitation, recreational requirement and/or environmental requirements.
- **Upper Rule Curves (URC)** are set by flood control requirements, representing the maximum elevation that projects can reach during the water year without imposing potential flooding risks.

- **Operating Rule Curve (ORC)** is a combination of all the above rule curves. It governs the elevation of the projects in any given water year. It is determined as follows:
  - From 1 August to 31 December, ORC is the higher of ARC and CRC
  - From 1 January to 16 April, first define Refill Curve as the lower of the ARC and VRC. ORC is then defined as the higher of CRC and the Refill Curve described earlier. The ORC cannot be lower than ORCLL
  - From 16 April to 31 July, same process as above except that ORCLL is no longer a constraint.
  - ORC must be equal or lower than URC at all times.

Using inputs of synthetic unregulated streamflow and ORCs, the modified HYSSR model yields daily values for reservoir storage and outflow and available hydropower production. It is important to note that not all of the dams in BPA system are represented in HYSSR, but the remaining dams only account for about 10% of the total hydroelectricity in this region (See the complete dam list in Appendix A). To model this system, one key assumption made is that this 10% of dams in other areas of the BPA system produce electricity proportionally to hydropower produced by dams in HYSSR.

**2.8 Hourly scheduling model**

The hourly generation scheduling model is developed to simulate the hourly operating and scheduling decision made by BPA. Despite the similar functionality as the HOSS (Hourly
Operating and Scheduling Simulator) used by BPA and USACE (USACE 2008), those 2 models are different. Our model takes internal demand, transmission exports, available hydropower and thermal generation as inputs, then schedules hourly generation, with model output adhering to the following equation:

\[
\text{Demand} + \text{Export} = \text{Hydro} + \text{Wind} + \text{Thermal}
\] (11)

A rolling 7-day planning horizon is used when scheduling hourly generation. This builds in flexibility on the part of dam operators in scheduling resources to minimize spill at dams, but it constrains their ability to incorporate future information in dam options beyond one week. During the hourly scheduling process, the default assumption is that all available wind power is dispatched (that is, until oversupply conditions occur). It is also assumed that during any period in which available wind and hydropower are not sufficient to meet internal demand and export requirements, thermal generation makes up the difference.

During oversupply periods, the hourly scheduling model displaces hydropower first. Flow in excess of the turbine capacity is “spilled” (i.e. via non-generating spillways) until this discharge reaches the environmental limits linked to dissolved gas entrainment. If electricity supply is still greater than demand + exports, then thermal generation is gradually ramped down until it reaches a minimum operating capacity (100MW), which is set empirically based on data from BPA. A 100MW minimum thermal capacity number appears to be much lower than what BPA used in their preliminary analysis of oversupply losses (977MW for high load hours and 852MW in low load hours), but it is supported by actual operating data published by BPA (BPA, 2015), which suggests that thermal capacity is frequently reduced well below stated guidelines. As a last resort (i.e., if dams are spilling at maximum rates and thermal generation is ramped to
its minimum capacity) wind power is curtailed to ensure the supply demand balance (Bird et al. 2014).

Spill limits at dams are the maximum flow rates at which dams can spill without violating regulations on downstream Total Dissolved Gas (TDG) concentrations, which is mainly dissolved nitrogen. The TDG concentration increases downstream as a function of water spilled. Federal regulations, supported by the Endangered Species Act, set 120% TDG (meaning 120% saturation) as the legal limit (Weitkamp, 2008) as high level of TDG can be harmful to fish. However, historical data suggests that often during oversupply periods, dams spill water over the 127% level. Thus, in this study, we use 127% TDG as a spill limit for each dam. BPA provides information on how to convert spill rate to downstream TDG at each dam. This makes it possible to estimate TDG based on the spillage from dams (BPA, 2013) and determine the point at which dams can no longer spill and other generation (thermal and then wind) must be curtailed.
CHAPTER 3: RESULTS & DISCUSSION

3.1 Model validation

Results from the HYSSR model and the hourly scheduling model were compared against historical observations as a measure of model validation using the following process. First, historical daily unregulated streamflow were input to the modified HYSSR model to simulate reservoir releases and available hydropower production. Then the historical records of hourly wind power production, thermal generation, transmission exports were subtracted from hourly electricity demand for the BPA system, leaving a single hourly time series of net demand. The hourly scheduling model was used to dispatch hydropower generation to meet this net demand, which is not dissimilar to the manner in which hydropower is used in the system given the case of ramping it up/down. In instances where available hydropower production, as determined by the modified HYSSR model, was greater than net demand, remaining discharge was assumed to be spilled (released from dams without generating electricity).

In order to validate the model, all the aforementioned historical data (unregulated streamflow, wind power production, thermal generation, electricity demand, transmission exports, and spill at dams) need to be available for the same time period. Unfortunately, the available data do not always overlap in the historical record. Due to the limited data, only time period with quality data are from September 2004 to September 2007.

The hourly scheduling model is able to reproduce historical hourly hydropower generation for the BPA system quite accurately (Figure 14). In almost no case does simulated hydropower
production fall short of observed hydropower production. Another test of model accuracy comes from comparing simulated and observed spilling; if the model is over predicting available hydropower production, errors in simulated spilling would be evident.

Figure 14. Hydropower generation validation

Figure 15. Spill validation

Figure 15 shows simulated vs. observed spilling at all hydroelectric dams over the period 2004-2007. The model overestimates spilling in year 2005 while the estimate is fairly accurate in year 2006 (a particularly wet year). This result suggests the model may overestimate the occurrence of oversupply events, especially in moderate or dry years. However, cumulative financial losses of oversupply, which is the focus of this study, are driven overwhelmingly by wet years. Thus, overestimating the frequency of small or moderate oversupply events will not greatly impact
financial losses, relative to system drivers like installed wind capacity, electricity prices and transmission export capacity. Model’s performance in wet years suggests that it is accurate in estimating oversupply losses in extremely wet scenarios. Compared to a wet year, dry and moderate years may give dam operators more flexibility for exercising their own discretion in order to minimize oversupply events (e.g., dam operators have more room to draw down the storage level for accommodating occasional high flows). During a wet year, however, the threat of damaging floods makes it impossible to temporarily store more water or further draw down the reservoir, so dam operators must adhere more closely to operational rule curves, making their decisions easier to replicate in the model.

3.2 Annual Oversupply Losses

Results suggest that under current wind capacity levels, wind producers in the BPA system experience an average curtailment of 3% of wind power production per year, with losses occasionally reaching 20+, typically in very wet years (Figure 16). Under scenario involving doubled wind capacity, the average curtailment increases to 5% and the maximum possible curtailment rises to 24% of total wind power production. Assuming the historical wind capacity
factor of 0.27 (obtained from historical data), the average 5% production loss under a scenario involving double wind capacity would be equivalent of losing 500 MW wind power per year, which can generate enough power for about 110,000 average US homes.

It is also important to note that as the installed wind power capacity is doubled (going from blue to red), the distribution of losses exhibits a flatter, slightly wider distribution. This suggests under double wind capacity it may be harder for wind producers to predict curtailment losses on a year to year basis as the next year’s curtailment can be anywhere from the widened distribution.

Indeed, in Figure 17, we show the distribution of financial losses (i.e., the value of curtailed wind power production) under current and doubled wind power capacity. Financial losses are calculated as a combination reduced of energy sales and reduced credits, namely the U.S. Production Tax Credit and Renewable Energy Credit (both are flat rate credit). The modeling results indicate that under current wind capacity, the expected annual loss is about $15 million, whereas the maximum potential loss can be roughly $95 million. If wind capacity is doubled, the distribution of losses shifts to the right and demonstrates much greater variance (a wider “tail”). Annual expected losses grow to $49 million and the maximum loss estimated to be $212 million.

![Figure 17. Distribution of annual oversupply losses](image-url)
Currently, in the BPA system, wind producers who experience curtailment losses are compensated by BPA and then passed to all rate payers (Bonneville Power Administration 2016). BPA’s annual revenue from electricity sales is about $3 – 3.5 billion based on various factors, such as streamflow conditions, market conditions and temperatures (demand). Under the doubled wind capacity scenario, compensating wind power producers for oversupply losses translates to an evenly distributed rate increase (on a $/kWh basis) across all BPA consumers of as much as 4%, with an expected increase of 1%, while this value does not seem large in relative sense, the absolute value in terms of average loss, adds over time. More importantly, the threat of large financial disruptions, in excess of $200 million, will grow over time as installed wind capacity increases. This suggests that as a rate payer, the electricity bill will increase as more wind capacity is installed. For investors, this suggests that the value of the earlier wind projects can decrease as a result of more curtailment caused by more new wind capacity installed in the area.

3.3 Comparing simulated results with BPA’s financial analysis

BPA’s own preliminary analysis suggests that the expected annual oversupply loss, given 2012 installed wind capacity, and assuming 2012 electricity prices, is $12 million with a maximum loss of $50 million. Our own results, using the same assumptions but a more detailed analysis involving a border set of conditions, suggests that the expected annual oversupply loss is $15 million with a maximum loss of $96 million. The difference in the expected annual loss is likely to be a combination of modeling bias (our model overestimates the frequency of small and moderate oversupply events) and the modelling scope (i.e. this study uses synthetic record to capture the entire distribution whereas BPA’s analysis only uses very limited data). The two different modelling approaches also show a greater statistical variance in oversupply losses, including significantly higher maximum annual losses than BPA’s preliminary analysis. This is
due in part to our use of expanded synthetic records of streamflows, wind production, and electricity demand, which provides opportunities for the occurrence of values outside the historical record (but within estimated maximum likelihood distributions of each variable). As such, it seems likely that BPA has underestimated the financial losses associated with more extreme wet weather periods, and this study’s result provides a much detailed oversupply loss distribution under all possible conditions.

3.4 Sensitivity Analysis: Electricity Prices

Beyond hydrology and installed wind power capacity, a key driver of financial losses from oversupply events in the BPA system is the price of electricity. The California Independent System Operator (CAISO) is the electricity market to which BPA exports excess wind and hydro generation (BPA 2015). Due to the heavy dependence of California generators on natural gas, wholesale electricity prices in CAISO and thus those paid for imported power from BPA, are strongly correlated with natural gas prices (Woo et al. 2016). This is important, because BPA’s initial analysis of oversupply losses assumes 2012 installed wind power capacity and 2012 electricity prices. In fact, natural gas prices were near historic lows in 2012. Although gas prices are projected to remain fairly low for the next several years (EIA 2016), BPA’s initial estimates of financial losses from oversupply may reflect a fairly unique circumstance involving low electricity prices. A comparison of expected annual financial losses from oversupply using the 2012 electricity price ($/MWh) as well as a distribution electricity prices, that incorporates the wider range of natural gas prices experienced in CAISO over the last 10 years, suggests that using the border distribution can significantly impact estimates of the mean annual oversupply loss (Figure 18). It is notable that despite similarities in the shape of the distribution, the mean annual oversupply loss increased from about $ 15 million to $ 28 million. When considering the
full range of electricity prices, the maximum oversupply loss increased to $550 million (occurring in extremely wet years with very high natural gas prices—a situation similar to that experienced in 2006), much higher than the previous estimate of $96 million. However, when only evaluating losses with the most recent 5 years (in which natural gas prices have been low and relatively stable), the mean loss was estimated at $20 million with a maximum loss of $340 million.

This suggests that oversupply losses estimated with the 2012 electricity price are likely to be substantially underpredicted, even assuming current low natural gas prices continue. That said, with the development of improved shale gas drilling techniques (i.e. horizontal drilling and hydraulic fracking), natural gas prices are expected to remain low and less volatile for the foreseeable future, having a similar effect on electricity prices. As our results show, this has an important mitigating effect on financial losses related oversupply.

Figure 18: Electricity price effect on annual oversupply loss
3.5 Long Term Net Present Value Loss

The net present value (NPV) of oversupply losses the BPA system was assessed over 1000 separate 25-year simulations, in order to understand these costs from a long term system planning perspective. In particular, these could be compared with the cost of expanding transmission capacity that could be used to export excess power. Twenty-five year NPVs were simulated under three different wind capacity growth scenarios, low/mid/high, based on BPA’s projections, having annual growth rates of 300/400/500 MW respectively. Gradual increases in electricity price were also assumed as projected by EIA, 0.9% annual electricity demand growth and a 4% discount rate. In general, the faster wind capacity is added, the greater the NPV loss from oversupply events. Result suggest that the low-wind scenario brings about losses anywhere from $273 million to $883 million over a 25-year period, with a mean of $529 million. The mid- and high-wind growth scenarios resulted in similar shaped distributions for NPV losses (Figure 19) with minimum NPV losses of $368 million and $498 million, maximum losses of $1.06 billion and $1.25 billion, respectively. The expected 25-year NPV losses for the mid and high wind growth scenarios are $681 million and $819 million respectively.

Figure 19. NPV of oversupply losses under different wind growth scenarios over 25 years.
3.6 Sensitivity Analysis: Transmission Upgrade

One potential solution for mitigating the impacts of oversupply events is building additional transmission capacity to export excess electricity, in this case to California. This is an option that has been exploited with great success in other systems experiencing oversupply issues, with Texas being the prime example (i.e. ERCOT) (Lew et al. 2013), As such, adding new transmission capacity has been considered seriously in the BPA system (BPA 2013).

The impacts, in terms of reducing present value oversupply loss, of adding transmission capacity on the 25-year present value financial losses from oversupply are shown in Figure 20. Results suggest that building a 500MW transmission line would reduce the present value loss by $50 to $60 million over 25 years, whereas building a 1500MW transmission line would reduce the present value oversupply loss by about $100 to $150 million. Although these savings are significant, the cost of building transmission lines is extremely high. On average, building a 500MW transmission line costs $1-1.5 million per mile, while 1500MW transmission lines cost $2–3 million per mile (Pletka et al. 2014). In recent years, a 215 mile 1500MW transmission line was proposed to expand existing connections between BPA and California in order to alleviate future oversupply issues, but this project was cancelled in 2015. The reason for cancellation, according to Portland General Electric (PGE), the developer of this project, had to do with the environmental impacts associated with the proposed transmission line cross a conservation area. Based on preliminary cost estimates from Western Electricity Coordinating Council, a 215 mile 1500MW transmission line would cost $400 to $600 million. This modelling activity estimates the avoided present value oversupply losses, with the transmission line in place, under 2012 electricity prices appears to be well below the cost of new transmission capacity even before considering the potential environmental impact.
It is possible, however, that this transmission project (or one like it) may be reconsidered by BPA in the future, and over time it’s economic viability may change. The discounting nature of the present value calculation means that larger oversupply losses that are likely to occur out in the future, as a result of growing wind capacity, are less impactful.

Therefore, The viability of the proposed (and now cancelled) transmission line in future years was also tested (Figure 21), involving calculation of present value oversupply losses over 25 years beginning 15 years from now. Assuming continuous growth of wind and linear increases in nominal electricity price (as projected by the EIA), over the next 35 years (calculation starts in the year 2030), the 500 MW transmission upgrade project would reduce the NPV loss by about $60 million and the 1500 MW project would reduce present value oversupply losses by $160 to $210 million. This still falls well short of the cost of developing new transmission capacity suggesting that such a project is unlikely to be financially attractive in the foreseeable future.
3.7 Study Limitations and Future Work

This study has a number of limitations, many of which could be addressed in future work. One key factor not considered here are changes in snowmelt timing and streamflow dynamics that may occur as a result of climate change. The potential impacts of climate change on streamflow in the Columbia River basin have been explored and studied (USACE & BPA 2011). The distribution of total amount of annual precipitation may shift, leading to higher or lower annual total streamflow. The percentage of precipitation falling as rain vs. snow may also change, as well as the timing of snowmelt. All of this would impact the timing of high flow events that would lead to more spilling at the dams and more oversupply related losses.

It is also worth mentioning that this work did not include consideration of the dynamic nature of electricity pricing in the CAISO market. As demonstrated in Figure 18, the electricity price can have a major impact on both expected and maximum oversupply losses. Moreover, as greater amounts of wind energy (or any type of renewable energy) are utilized in this market, it
could lower the wholesale electricity price, which has a direct effect on the severity of financial losses from wind curtailment in the BPA system. Likewise, rules in CAISO for dealing with periods of oversupply may change. Currently, the market allows prices to fall below zero to encourage generators who can ramp down production to do so (i.e. producers need to pay costumers to consume their electricity). However, the current minimum price (-$20/MWH) does not impose a sufficient financial penalty on wind producers, as the combination of tax credits (REC and PTC) pays more than $20/MWh. In recent years, CAISO has considered lowering the negative floor to -$1000/MWh (BPA 2013), a change that could pose significantly greater losses for BPA and its customers when oversupply happens.
CHAPTER 4: CONCLUSIONS

As renewable energy capacity grows, particularly that associated with intermittent sources (e.g., solar, wind), curtailment of these sources will present increasing challenges. This is particularly true in the hydropower-dominated Pacific Northwest region of the U.S., where wind energy curtailment occurs, typically during very wet years when hydropower is plentiful. This study demonstrates that a systems-based hydro-economic model can be used to characterize the physical (spilling, wind curtailment) and financial consequences of oversupply events, while also providing insights on potential future scenarios that include variable electricity prices, increased wind capacity and additional transmission capacity. From a general perspective, this approach can provide a foundation for developing strategies that mitigate a renewable generator’s financial risk or be used by planners to make more informed decisions on future infrastructure investments.

With respect to the Columbia basin in particular, results from this study indicate that wind curtailment as a result of oversupply can lead to a significant squandering of energy production and financial losses. Results also suggest that the growth of wind power capacity will lead to higher and more unpredictable oversupply-related financial losses. However, we find that the electricity price assumed has a significant effect on estimates of oversupply losses, and future deviations from current (i.e. low) prices could significantly increase the maximum annual loss. However, given projections for natural gas prices to remain fairly low over the next decade, the impacts of much higher electricity prices on oversupply losses may not be a significant risk.
Results also suggest that, while additional transmission capacity could mitigate a significant portion of oversupply-related losses, these avoided losses are unlikely to justify the substantial cost of developing this infrastructure. Consequently, curtailment of wind power during oversupply conditions appears to be a more cost effective solution than new transmission capacity, at least for the foreseeable future.

Given expectations of continued growth in renewable energy capacity, we can expect that renewable curtailment will happen more often while imposing ever larger financial losses. Despite the associated energy waste and financial losses, these results suggest that curtailment can be considered a practical short- to medium-term solution to manage electrical grid stability in the face of oversupply in settings such as BPA. However, this study does not consider other economic value of building transmission infrastructure, such as reduced carbon emission and reduced fuel cost in a thermal dominated system. Such thermal dominated regions in the U.S. are actively building addition transmission line for more renewable integration partially because of these additional economic values.
# APPENDIX : TABLE OF ALL THE DAMS IN BPA SYSTEM

Table 1: List of all modelled and un-modelled hydro dams (Note: Red font is the dams that are NOT included in the model)

<table>
<thead>
<tr>
<th>List of hydro by BPA</th>
<th>Capacity</th>
<th>Modelled Hydro but Not Included in BPA’s list</th>
<th>Capacity</th>
</tr>
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<tr>
<td>Albeni Falls</td>
<td>42 MW</td>
<td>Mica</td>
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<tr>
<td>Big Cliff</td>
<td>18 MW</td>
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<td>Bonneville</td>
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<td>Kerr</td>
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<tr>
<td>Yakima Drop Plant</td>
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Summary:
- Total BPA hydro capacity: 21733.55 MW
- Modelled BPA hydro capacity: 19012 MW
- Un-modelled BPA capacity: 2721.55 MW
- Modelling percentage: 87.5%
REFERENCES


Bonneville Power Administration (BPA) & U.S. Army Corps of Engineers (USACE), 2011. BPA and Fish Passage Center study effects of changing total dissolved gas standards April 2011. Available at: https://www.bpa.gov/Projects/Initiatives/Oversupply/OversupplyDocuments/TDG_Analysis_APR_2011.pdf.


Bonneville Power Administration (BPA), 2015. Wind Generation & Total Load in The BPA Balancing Authority. Available at: http://transmission.bpa.gov/business/operations/wind/


Bonneville Power Administration (BPA), 2016, About BPA. Available at: https://www.bpa.gov/news/AboutUs/Pages/default.aspx [Accessed December 6, 2016].


