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Stochastic valuation of energy storage in wholesale power markets

Nanpeng Yu*, Brandon Foggo

University of California Riverside, 900 University Ave, Riverside, CA, USA

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ABSTRACT

Energy storage systems are well poised to mitigate uncertainties of renewable generation outputs. Grid-scale energy storage projects are major investments which call for rigorous valuation and risk analysis. This paper provides a stochastic energy storage valuation framework in wholesale power markets which considers all key revenue streams simultaneously. As part of this framework, an operational optimization model is developed to determine the energy storage system's optimal dispatch sequences. A future curve model is built to capture the volatilities of electricity prices. In addition, a frequency regulation service price forecasting model is developed. Simulation results with a realistic battery storage system reveal that the majority of the market revenues comes from frequency regulation services. Simulation results also show that both round-trip efficiency and power-to-energy ratio are crucial to the cost effectiveness of energy storage systems.

1. Introduction

Distributed renewable generation, such as rooftop solar photovoltaic, has grown exponentially in the past few years. The intermittency of renewable resources creates new operating and planning challenges to the transmission and distribution system operators around the world. These new challenges include loss of system inertia, increasing needs for ancillary services, voltage excursions, and unbalanced phase loading. Energy storage systems are well poised to mitigate uncertainties of renewable generation outputs. They also play a key role in facilitating the integration of renewable generation resources into electric grids. However, there are several challenges to the widespread deployment of energy storage. As identified in the U.S. Department of Energy report (Gyuk et al., 2013), the most crucial hurdle to energy storage system adoption is the uncertainty in its cost competitiveness with other energy resources. The first step to overcome this hurdle is to develop a comprehensive optimization and valuation model which allows energy storage systems to provide multiple electricity market products simultaneously.

Most of the existing literatures either ignores key energy storage revenue streams or models various grid services separately. The economics of electric energy storage for energy arbitrage and regulation was evaluated in the New York and Pennsylvania, Jersey, Maryland (PJM) Power Pool (Sioshansi et al., 2009; Walawalkar et al., 2007). The energy shifting service and frequency regulation service are not co-optimized in the economic analysis. The authors in Oudalov et al. (2007) only considered value of energy storage systems for primary frequency control. Only energy shifting benefits are included in estimating the value of energy storage systems in Denholm and Sioshansi (2009), Mokrian and Stephen (2006). In Oudalov et al. (2006), the revenue streams of battery systems are considered separately. A real options approach is taken in evaluating the profitability of investing in a battery bank (Bakke et al., 2016). The revenue from energy shifting and ancillary services are modeled simultaneously. However, the capacity market value is ignored in Bakke et al. (2016), Denholm and Sioshansi (2009), Mokrian and Stephen (2006), Oudalov et al. (2007), Sioshansi et al. (2009). This paper corrects these problems by developing a comprehensive energy storage system valuation framework. The proposed valuation framework optimally allocates and partitions available storage capacity to a combination of grid services in order to maximize market value.

The lack of understanding of investment risks associated with energy storage is another obstacle to its widespread adoption. Due to peculiar properties of electricity, electricity prices exhibit excessive volatility and spikes which are unmatched by any other commodities and financial assets (Yu et al., 2010b). Therefore, the value of energy storage systems are highly uncertain. A stochastic valuation framework is much needed to characterize the distribution of energy storage revenue streams. A stochastic valuation framework built upon the electricity price future curve is developed in this paper to rigorously measure the risks associated with the energy storage investment.

The remainder of this paper is organized as follows. Section 2 presents the stochastic energy storage valuation framework. Section 3

* Corresponding author.
E-mail address: nyu@ece.ucr.edu (N. Yu).

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derives the technical methods used in this paper which includes electricity future price curve modeling, principal component analysis, electricity spot price sample path generation and energy storage system co-optimization. The numerical study results are shown in Section 4. The conclusions are provided in Section 6.

2. Energy storage systems valuation framework

A comprehensive stochastic energy storage valuation framework is proposed in this section and presented diagrammatically in Fig. 1. The energy storage valuation framework jointly models key energy storage system revenue streams including energy shifting, ancillary services, and electricity supply capacity. The stochastic valuation process consists of five steps and works as follows. In the first step, a multi-factor stochastic process is developed to model the electricity future price curve dynamics. The parameters of the multi-factor model are estimated based on historical future price curves. In the second step, Monte Carlo simulations are conducted to generate sample paths for monthly electricity prices based on future prices at the current time. The monthly price forecast samples are then converted into hourly locational marginal prices for energy and ancillary services in the third step. In the fourth step, these sample paths are fed into a price-based energy storage optimization to generate dispatch schedules. At last, stochastic valuation of energy storage system is generated based on the optimal dispatch schedules and capacity market value.

3. Technical methods

In this section, we present the technical methods used in the energy storage stochastic valuation framework. The technical methods include electricity future price curve modeling, principal component analysis, multi-factor model parameter estimation, electricity spot price sample path generation, ancillary service price modeling, and the energy storage operation optimization technique.

3.1. Electricity future price curve modeling

As a commodity, electricity has many peculiar characteristics such as instantaneous delivery, limited storability, inelastic short-term demand, and compliance with Kirchhoff's laws (Yu et al., 2010b). Unlike many other commodities, the supply and demand condition for electricity can change drastically in a few minutes. These unique properties of electricity make ad-hoc financial models for spot price dynamics less appropriate.

Instead of spot price models, future price curve models (Audet et al., 2004; Bjerksund et al., 2010; Clewlow and Strickland, 1999; Fleten and Lemming, 2003; Kiesel et al., 2009) are typically used to characterize the stochastic behavior of electricity prices. Electricity future price curve models make simplifying assumptions about how the full future curve changes over time rather than making simplifying assumptions about how the spot price changes. The electricity future price curve summarizes the relationship between prices of electricity at different times. It also reveals the market's view on the supply and demand of electricity in the future and status of the underlying physical power network.

Heath-Jarrow-Morton (HJM) Heath et al. (1992) framework is adopted to describe the electricity future curve dynamics. Rather than modeling the evolution of a single forward contract, HJM framework models the interest rate forward curve as a whole. The changes in the full set of future prices Fut_{tT}, are characterized by the following set of price equations. Note that Fut_{tT} denotes the price of electricity future contract traded at time t for delivery in Month T.

$$dFut_{tT} = \alpha(Fut_{tT}, t, T)dt + \sum_{i=1}^{N} \Gamma_i(Fut_{tT}, t, T)dW(t)_i^T \tag{1}$$

The instantaneous change in future curve is represented by a linear combination of the drift term $\alpha(Fut_{tT}, t, T)dt$ and random perturbations. Each perturbation is specified as the product of a deterministic function $\Gamma_i(F_{tT}, t, T)$ and a Gaussian factor $dW(t)_i^T$ (Eydeland and Wolyniec, 2003).

Three simplifications can be made due to the specific characteristics of the electricity future price curve (Goldberg et al., 1997). First, it is recognized that the futures price of electricity is a martingale under the risk-neutral measure $\tilde{P}$ (Shreve, 2004). By following the martingale representation theorem, we rewrite the full set of future prices by the following set of price equations.

$$dFut_{tT} = \sum_{i=1}^{N} \tilde{\Gamma}_i(Fut_{tT}, t, T)d\tilde{W}(t)_i^T \tag{2}$$

$$\tilde{\Gamma}(u) = \left(\tilde{\Gamma}_1(u), \ldots, \tilde{\Gamma}_N(u)\right) \tag{3}$$

The process $\tilde{W}(t)^T$ is an N-dimensional Brownian motion under $\tilde{P}$ and $\tilde{\Gamma}(u)$ is an N-dimensional adapted process.

The second simplification is motivated by the fact that the future price curve shifts in a fairly smooth manner (Eydeland and Wolyniec, 2003). This assumption can be explained by the fact that market disturbances such as major generation outages and changes in market design will persist over a period of time. This implies that a smaller set of uncertain factors $d\tilde{W}(t)_i$ can explain majority of the variations in the electricity future price curve (Goldberg et al., 1997). The last simplification is usually made in practice by assuming the uncertain term $\tilde{\Gamma}_i(Fut_{tT}, t, T)$ is only a function of future price and time to maturity $\tau = T - t$ with seasonality.

Applying the above-mentioned three simplifications, the full set of future prices can be rewritten as:

$$\frac{dFut_{tT}}{Fut_{tT}} = \sum_{i=1}^{N} \tilde{\sigma}(t)\tilde{\Gamma}_i(T-t)d\tilde{W}(t)_i \tag{4}$$

where $\tilde{\sigma}$ (t) represents the seasonality of the uncertain term.

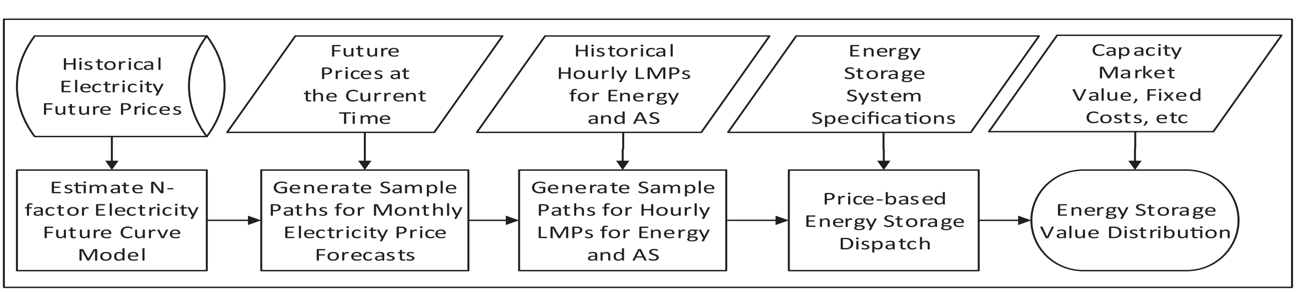

Fig. 1. Energy storage stochastic valuation framework.

The solution of the stochastic differential Eq. (4) has the following form.

$$Fut_{tT} = Fut_{0T} \times exp\left(-\frac{1}{2}\sum_{i=1}^{N}\int_0^t \tilde{\sigma}(s)^2\tilde{\Gamma}_i(T-s)^2 ds + \sum_{i=1}^{N}\int_0^t \tilde{\sigma}(s)\tilde{\Gamma}_i(T-s)d\tilde{W}(s)_i\right) \quad (5)$$

The spot price of electricity can be linked to future price by using the relationship $P_t = Fut_{tt}$.

3.2. Principal component analysis

In this subsection, principal component analysis is conducted to determine the number of uncertain factors needed to explain majority of the variations.

To characterize the variations of the future price curve, the theoretical covariance of the change in logreturns of future prices needs to be derived. First, applying Itô-Doeblin formula for the Itô process Fut_{tT} in Eq. (5), we have

$$\frac{dln(Fut_{tT})}{\tilde{\sigma}(t)} = \sum_{i=1}^{N}\tilde{\Gamma}_i(\tau)d\tilde{W}(t)_i - \frac{1}{2}\sum_{i=1}^{N}\tilde{\sigma}(t)\tilde{\Gamma}_i(\tau)^2 dt \quad (6)$$

$$dln(Fut_{tT}) = ln(Fut_{t+dt,T}) - ln(Fut_{tT}) \quad (7)$$

The covariance of the change in logreturns of the future prices has the following form

$$Cov\left(\frac{dln(F_{tT})}{\tilde{\sigma}(t)}, \frac{dln(F_{tS})}{\tilde{\sigma}(t)}\right) = \sum_{i=1}^{N}\tilde{\Gamma}_i(S-t)\tilde{\Gamma}_i(T-t)dt \quad (8)$$

It is assumed that we have M observations of E electricity monthly future contracts in the futures market. The corresponding covariance matrix is denoted by ψ and has a dimension of $E \times E$. Let ψ have eigenvalue-eigenvector pairs (λ_i, p_i) with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_E \geq 0$. The covariance matrix ψ can be expressed by its eigenvalues and eigenvectors. To explain the covariance structure with a few factors, we approximate the theoretical covariance matrix using the first K eigenvalues.

The total population variance is equal to the sum of variances of the principal components $\sum_{i=1}\lambda_i$. The proportion of the total variance explained by the first K principal components is $\sum_{i=1}^{K}\lambda_i \Big/ \sum_{i=1}^{E}\lambda_i$.

Next, we conduct the principal component analysis on the California electricity market data. Four California electricity future contracts are traded on Intercontinental Exchange (CAISO, 2015). They are on-peak and off-peak contracts at the existing zone generator trading hub, north/south of path 15(SP15). In this study, the future prices at SP15 are studied. The study period is chosen to be between April 1, 2009 and Dec 31, 2012. April 1, 2009 is chosen as the start date of the study period because it is the “go live” date of the California Independent System Operator’s Market Redesign and Technology Upgrade (MRTU). Before April, 1 2009, CAISO had been operating under a zonal market structure. The MRTU introduced the location market pricing mechanism. Therefore, there is regime change in the price volatility structure on April 1, 2009.

As shown in Table 1, the principal component analysis results show that the top 3 factors explain more than 90% of the variability of the electricity future price curves. Note that this finding from the California electricity market is very different from that of the Nordic electricity market (Koekebakker and Ollmar, 2005) where 8 factors are needed to explain 90% of variation. In this empirical study, we choose a 3-factor model so that more than 90% of variation can be explained.

Table 1
Variance Explained from PCA.

Number of factors	% Variance explained	% Cumulative variance explained
1	84.5 %	84.5 %
2	5.4 %	89.9 %
3	1.8 %	91.7 %
4	1.2 %	92.9 %
5	1.1 %	94.1 %
6	0.9 %	94.9 %
7	0.8 %	95.8 %

The volatility factors in the California electricity future market have similar shapes as that of yield curves in interest rate theory. To accurately model the 3 volatility factors, we adopt a variation of the Nelson-Siegel model for yield curve in interest rate theory (Nelson and Siegel, 1987).

$$\tilde{\Gamma}_i(T-t) = \sigma_i^0 + \left[\sigma_i^1 + \sigma_i^2(T-t)\right]e^{-k_i(T-t)} \quad (9)$$

3.3. Estimate a parametric multi-factor model for electricity future curve

The multi-factor model parameters can be estimated through minimizing the difference between the theoretical and empirical covariance of log-returns. The initial condition of the optimization problem can be estimated by using deterministic seasonal volatility factors and volatility parameters estimated from the PCA (Benth et al., 2008).

The nonlinear optimization problem is solved by using the Nelder-Mead simplex algorithm (Lagarias et al., 1998). It is implemented in the fminsearch function of MATLAB. The estimated model parameters using the the fminsearch function are shown in Table 2. The parameter estimates from Table 2 are used later in the electricity spot price sample path generation. The estimated volatility function parameters are not very sensitive to the study period. For example, if the study period is shortened to be between April 1, 2009 and Nov 30, 2012, then the model parameters only change 0.77% on average.

3.4. Electricity spot price sample path seneration

In the 3-factor model, the relationship between the spot price and future price can be written as

$$P_t = Fut_{0t}exp\left[-\frac{1}{2}\sum_{i=1}^{3}\int_0^t \tilde{\sigma}(s)^2\tilde{\Gamma}_i(t-s)^2 ds + \sum_{i=1}^{3}\int_0^t \tilde{\sigma}(s)\tilde{\Gamma}_i(t-s)d\tilde{W}(s)_i\right] \quad (10)$$

Table 2
Volatility function parameters estimated from fminsearch function.

January	February	March	April
0.2729	0.2616	0.3061	0.2804
May	June	July	August
0.3187	0.2745	0.3197	0.2582
September	October	November	December
0.2974	0.2837	0.3491	0.3210
σ_1^0	σ_1^1	σ_1^2	k_1
0.4330	1.1682	−0.2165	0.9754
σ_2^0	σ_2^1	σ_2^2	k_2
−0.2387	0.7970	−0.6892	1.4750
σ_3^0	σ_3^1	σ_3^2	k_3
−0.0656	−1.1043	7.6830	4.9629

By defining $w_i(t)$ as follows,

$$w_i(t) = \int_0^t \tilde{\sigma}(s)\sigma_i^0 d\tilde{W}(s)_i + e^{-k_i t}\int_0^t \tilde{\sigma}(s)\left[\sigma_i^1 + \sigma_i^2(t-s)\right]e^{k_i s}d\tilde{W}(s)_i \tag{11}$$

The relationship between the spot price and future price can be simplified as

$$P_t = Fut_{0t}exp\left(-\frac{1}{2}\epsilon(t)^2 t + \sum_{i=1}^{3} w_i(t)\right) \tag{12}$$

where

$$\epsilon(t)^2 \triangleq \frac{1}{t}var[ln(P_t)] = \frac{1}{t}\sum_{i=1}^{3}\int_0^t \tilde{\sigma}(s)^2\tilde{\Gamma}_i(t-s)^2 ds \tag{13}$$

In order to simulate P_t, we need to generate sample paths for $w_i(t)$ where $i = 1, 2, 3$. Since $w_i(t), i = 1, 2, 3$ have similar structures, we use $w_1(t)$ as an example in the following derivations. By using the functional form of volatility function in Eq. (9), $w_1(t)$ can be written as:

$$w_1(t) = \int_0^t \tilde{\sigma}(s)\left\{\sigma_1^0 + \left[\sigma_1^1 + \sigma_1^2(t-s)\right]e^{-k_1(t-s)}\right\}d\tilde{W}(s)_1 \tag{14}$$

$w_1(t)$ can be represented as the sum of three Itô integrals, $I_1^1(t)$, $I_1^2(t)$, and $I_1^3(t)$.

$$\begin{aligned} w_1(t) = &\int_0^t \sigma(s)\sigma_1^0 d\tilde{W}(s)_1 \\ &+ e^{-k_1 t}\int_0^t \sigma(s)[\sigma_1^1 - \sigma_1^2 s]e^{k_1 s}d\tilde{W}(s)_1 \\ &+ te^{-k_1 t}\int_0^t \sigma(s)\sigma_1^2 e^{k_1 s}d\tilde{W}(s)_1 \\ =&I_1^1(t) + I_1^2(t) + I_1^3(t) \end{aligned} \tag{15}$$

Apply Itô -Doeblin formula in differential form to the three Itô processes $I_1^i(t)$ separately, we have

$$dI_1^1(t) = \tilde{\sigma}(s)\sigma_1^0 d\tilde{W}(s)_1 \tag{16}$$

$$dI_1^2(t) = -k_1 I_1^2(t) + \tilde{\sigma}(s)\left[\sigma_1^1 - \sigma_1^2 t\right]d\tilde{W}(s)_1 \tag{17}$$

$$dI_1^3(t) = \frac{1-tk_1}{t}I_1^3(t)dt + t\tilde{\sigma}(t)\sigma_1^2 d\tilde{W}(t)_1 \tag{18}$$

It can be shown that the solution to differential Eqs. (16) and (17) have the following form:

$$I_1^1(t) = I_1^1(0) + \int_0^t \tilde{\sigma}(s)\sigma_1^0 d\tilde{W}(s)_1 \tag{19}$$

$$I_1^2(t) = e^{-k_1 t}I_1^2(0) + \int_0^t \tilde{\sigma}(s)\left[\sigma_1^1 - \sigma_1^2 s\right]e^{-k_1(t-s)}d\tilde{W}(s)_1 \tag{20}$$

Similarly, for any $0 < u < t$, we have

$$I_1^1(t) = e^0 I_1^1(u) + \int_u^t \tilde{\sigma}(s)\sigma_1^0 d\tilde{W}(s)_1 \tag{21}$$

$$I_1^2(t) = e^{-k_1(t-u)}I_1^2(u) + \int_u^t \tilde{\sigma}(s)\left[\sigma_1^1 - \sigma_1^2 s\right]e^{-k_1(t-s)}d\tilde{W}(s)_1 \tag{22}$$

The solution to differential Eq. (18) has the following form (Glasserman, 2003).

For any $0 < u < t$

$$I_1^3(t) = I_1^3(u)\left(\frac{t}{u}e^{k_1(u-t)}\right) + \int_u^t \frac{t}{s}e^{k_1(s-t)}s\tilde{\sigma}(s)\sigma_1^2 d\tilde{W}(s)_1 \tag{23}$$

Given $I_1^1(u), I_1^2(u), I_1^3(u)$ the vector $\left[I_1^1(t), I_1^2(t), I_1^3(t)\right]$ follows a joint normal distribution with a mean vector of μ and a covariance matrix Σ.

To simulate $I_1^1(t), I_1^2(t)$, and $I_1^3(t)$ at times $0 < t_1 < \ldots < t_n$, we may therefore set

$$I_1^1(t_{i+1}) = I_1^1(t_i) + Z_{i+1}^1 \tag{24}$$

$$I_1^2(t_{i+1}) = I_1^2(t_i)e^{-k_1(t_{i+1}-t_i)} + Z_{i+1}^2 \tag{25}$$

$$I_1^3(t_{i+1}) = I_1^3(t_i)\left(\frac{t_{i+1}}{t_i}e^{k_1(t_i-t_{i+1})}\right) + Z_{i+1}^3 \tag{26}$$

where $\left(Z_1^1, Z_1^2, Z_1^3, \ldots, Z_n^1, Z_n^2, Z_n^3\right)$ are independent draws from $N(0, \Sigma(t_i, t_{i+1}))$. The elements of the covariance matrix can be derived as follows.

$$\begin{aligned} \Sigma(t_i, t_{i+1})_{11} &= \int_{t_i}^{t_{i+1}} \tilde{\sigma}(s)^2(\sigma_1^0)^2 ds \\ \Sigma(t_i, t_{i+1})_{22} &= \int_{t_i}^{t_{i+1}} \tilde{\sigma}(s)^2\left[\sigma_1^1 - \sigma_1^2 s\right]^2 e^{-2k_1(t_{i+1}-s)}ds \\ \Sigma(t_i, t_{i+1})_{33} &= \int_{t_i}^{t_{i+1}} \left(\frac{t_{i+1}}{s}e^{k_1(s-t_{i+1})}\right)^2 s^2\tilde{\sigma}(s)^2(\sigma_1^2)^2 ds \\ \Sigma(t_i, t_{i+1})_{12} &= \int_{t_i}^{t_{i+1}} \tilde{\sigma}(s)^2\sigma_1^0\left[\sigma_1^1 - \sigma_1^2 s\right]e^{-k_1(t_{i+1}-s)}ds \\ \Sigma(t_i, t_{i+1})_{13} &= \int_{t_i}^{t_{i+1}} t_{i+1}\tilde{\sigma}(s)^2\sigma_1^0\sigma_1^2 e^{-k_1(t_{i+1}-s)}ds \\ \Sigma(t_i, t_{i+1})_{23} &= \int_{t_i}^{t_{i+1}} t_{i+1}\tilde{\sigma}(s)^2\sigma_1^2\left[\sigma_1^1 - \sigma_1^2 s\right]e^{-2k_1(t_{i+1}-s)}ds \end{aligned} \tag{27}$$

Note that in the first iteration $I_1^1(t_1) = Z_1^1, I_1^2(t_1) = Z_1^2, I_1^1(t_3) = Z_1^3$.

3.5. Ancillary service price modeling

Ancillary services are important electricity market products which help maintain electric grid stability and reliability. In the CAISO market, there are four types of ancillary services products which are listed in the order of decreasing quality: regulation up, regulation down, spinning reserve, and non-spinning reserve (CAISO, 2016). Regulation up and down services have the highest quality because the energy resources providing them must be synchronized to the electric grid and able to receive and follow automatic generation control (AGC) signals. In order to provide spinning reserve, an energy resource is required to be synchronized to the electric grid but not require to have AGC capabilities. The lowest quality ancillary service, non-spinning reserve, only requires the energy resource to deliver the ancillary service award within 10 min and the energy resource do not need to be synchronized (CAISO, 2015). The CAISO tariff (CAISO, 2016) contains an ancillary services substitution rule that allows a higher quality ancillary service to substitute for a lower quality ancillary service when it is economic to do so. Therefore, the price of a higher quality ancillary service is always higher than or equal to that of a lower quality ancillary service. In this subsection, the prices of regulation service, the highest quality ancillary service, are modeled in detail. Most of the lithium ion battery storage system can accurately follow the AGC signals. Therefore, we only considered frequency regulation services in the case study. The prices of other ancillary services can be modeled in a similar way.

In day-ahead market operations, the electricity market operator co-optimizes the dispatch of energy and ancillary services. For an energy resource, the energy and ancillary service awards are dependent on each other through the resource capacity constraint (Yu et al., 2010a). The upward capacity constraint limits the summation of the energy service award and the upward ancillary service award by the resource's maximum charge/discharge power. Therefore, the ancillary service clearing price can be modeled as the summation of the ancillary service bidding price and a nonnegative opportunity cost. The opportunity cost is positive if the energy resource is selected for both energy and ancillary services and the LMP for energy is greater than the energy supply offer price. Therefore, the ancillary service price is highly correlated with energy supply offer price. The high correlation allows us to simplify the modeling of regulation up/down prices by selecting the ratio of monthly average regulation up price and monthly average energy price as the dependent variable. The relationship between monthly average regulation up prices and LMPs for energy in 2012 is depicted in Fig. 2. The relationship between monthly average regulation down prices and LMPs for energy is similar.

The price of frequency regulation services depends on the relationship between its supply and demand on a seasonal basis. Various explanatory variables are explored to model the regulation up and down prices which include monthly average CAISO system load, monthly average CAISO system level renewable generation variability, monthly average CAISO hydroelectric generation, and seasonality dummy variables. The monthly average CAISO system level renewable generation variability is estimated as the average of hourly absolute changes in CAISO system level renewable generation quantity. There are three seasonality dummy variables Q_{1t}, Q_{2t}, and Q_{3t} which represent dummy variables for winter, spring, and summer respectively.

In order to further simplify the model, forward selection (Derksen and Keselman, 1992) is applied to provide the best subset or combination of predictors for frequency regulation prices. Two years of historical CAISO data from 2010 to 2011 were used in the model selection process. With stepwise selection, the final regression model has the following form:

$$Reg_t^u/P_t = \beta_0 + \beta_{11}Q_{1t}Y_t + \beta_{12}Q_{2t}Y_t + \beta_{22}Q_{2t}R_t + \beta_{23}Q_{3t}R_t \quad (28)$$

where Reg_t^u denotes monthly average on-peak regulation up price in month t. P_t represents monthly average on-peak energy price in month t. Y_t denotes hydroelectric generation in month t during

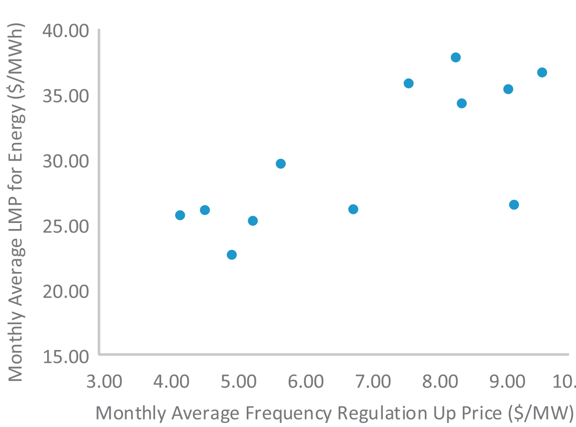

Fig. 2. Relationship between CAISO monthly average ancillary service price and LMP for energy.

on-peak hours. R_t represents average hourly changes in renewable generation output in month t during on-peak hours.

The model parameters are estimated by using the maximum likelihood estimation method. The model parameters, standard errors, and p-values are reported in Table 3. The model fitting results can be intuitively explained as follows. With fast and accurate ramping capabilities, hydroelectric generation resources have important effects on the supply side of frequency regulation services in CAISO. In the Spring and Winter, if the hydroelectric generation level is high, then the headroom left to provide upward frequency regulation service will be limited. This will tighten the supply of regulation up service and put upward pressure on regulation up prices. Therefore, the coefficients of β_{11} and β_{12} are both positive. With more than 20% renewable penetration, intermittent renewable generation resources have high impact on the demand side of frequency regulation service in CAISO. In the Spring and Summer, a higher renewable variability level will call for more demand for frequency regulation which will push regulation up price higher. Thus, the coefficients of β_{22} and β_{23} are both positive as well.

3.6. Energy storage optimization in electricity market

Energy storage systems can provide multiple services simultaneously to the wholesale power markets. These services include energy shifting, ancillary services, and electricity supply capacity. In this section, an energy storage scheduling algorithm will be developed to optimally allocate and partition available storage capacity to a combination of grid services in order to maximize its market value. The objective function of energy storage optimization problem is to maximize the market value of energy storage systems in wholesale power markets as shown in Eq. (29). The net revenue of an energy storage system in the wholesale power markets includes the revenues received from energy shifting service, frequency regulation services, and variable operating and maintenance costs.

$$\text{Maximize} \sum_{h=1}^{H} \Big\{ \left(d_h + p_h^u r_h^u - p_h^d r_h^d\right) LMP_h^{DA} + r_h^u Reg_h^u + r_h^d Reg_h^d - \left(|d_h| + p_h^u r_h^u + p_h^d r_h^d\right) \times VOM \Big\} \quad (29)$$

The decision variables are: day-ahead energy award at hour h, d_h, frequency regulation-up award in day-ahead market at hour h, r_h^u, frequency regulation-down award in day-ahead market at hour h, r_h^d, and state-of-charge at hour h, S_h.

The external variables are: locational marginal price for energy in day-ahead market at hour h, LMP_h^{DA}, energy storage variable operations and maintenance costs VOM, regulation-up price at hour h, Reg_h^u, regulation-down price at hour h, Reg_h^d, utilization factor of regulation-up service at hour h, p_h^u, and utilization factor of regulation-down service at hour h, p_h^d.

The optimization problem is subject to state-of-charge intertemporal constraints (30), state-of-charge upper and lower limit constraints (31), charging and discharging limit constraint in real-time operations (32,33), charging and discharging limit constraint in day-ahead market operations (34, 35), frequency regulation award

Table 3
Parameter estimates and p-value in ancillary service price model.

Parameter	Estimated value	Standard error	p-value
β_0	8.94E-02	4.66E-02	5.81E-02
β_{11}	6.33E-05	1.67E-05	2.86E-04
β_{12}	4.83E-05	1.92E-05	1.39E-02
β_{22}	1.13E-03	7.83E-04	1.54E-01
β_{23}	1.39E-03	5.45E-04	1.26E-02

constraints (36), charging and discharging energy constraint in day-ahead market operations (37, 38).

The external variables in the constraints include: energy decay rate, γ, AC round-trip efficiency, ρ, maximum discharge power, P_d^{max}, maximum charge power, P_c^{max}, and energy rating for energy storage system, E_{max}. Note that AC round-trip efficiency is defined as the ratio of energy put into the battery system to energy retrieved from the battery system which also accounts for the efficiency of the AC-DC inverter.

Subect to

$$S_{h+1} = S_h(1-\gamma) - \left(d_h + p_h^u r_h^u - p_h^d r_h^d\right) - (1-\sqrt{\rho}) \times \left(|d_h| + p_h^u r_h^u + p_h^d r_h^d\right) \quad (30)$$

$$0 \le S_h \le E_{max} \quad (31)$$

$$-d_h + p_h^d r_h^d - p_h^u r_h^u \le P_c^{max} \quad (32)$$

$$d_h + p_h^u r_h^u - p_h^d r_h^d \le P_d^{max} \quad (33)$$

$$-d_h + r_h^d \le P_c^{max} \quad (34)$$

$$d_h + r_h^u \le P_d^{max} \quad (35)$$

$$r_h^u, \quad r_h^d \ge 0 \quad (36)$$

$$-d_h + r_h^d \le E_{max} - S_h \quad (37)$$

$$d_h + r_h^u \le S_h \quad (38)$$

The optimization problem can be converted to a linear programming problem by introducing dummy variables d_h^+ and d_h^-, constrained to be nonnegative, and let $d = d_h^+ - d_h^-$. Every occurrence of $|d_h|$ is replaced with $d_h^+ + d_h^-$.

Note that the above formulation does not consider optimal day-ahead/hour-ahead bidding strategies for battery storage system with price uncertainty in day-ahead/hour-ahead electricity markets. In this paper, the battery storage system operator is assumed to have perfect foresight within each price scenario generated in Section 3.4. Therefore, the valuation provided in this study serves as an upper bound of the battery storage system's realistic value. The exact profit for each battery system depends on the specific bidding strategy, the variability of the electricity prices in day-ahead/real-time markets, and the accuracy of the price forecasting methods. The topic of optimal bidding strategy for battery storage system has been explored by other researchers using the stochastic optimization (He et al., 2015) and approximate dynamic program algorithms (Jiang and Powell, 2014). These optimal bidding strategies can be integrated into the proposed valuation framework.

4. Setup of valuation study

4.1. Energy storage system specification

A lithium-ion battery storage system is selected in the case study. The technical specification of the lithium-ion battery system is selected based on the Tehachapi energy storage project which is the largest battery energy storage project in north America as of 2015. Note that the Tehachapi energy storage project is within the SP15 generator trading hub. The AC round trip efficiency of the lithium-ion battery is assumed to be 88%. The power and energy ratings of the battery storage system are 8 MW and 32 MWh. The usable energy range of the battery system as a percentage of rated energy rating is 95%. The system auxiliary load as a percentage of rated power output is 0.875%. The self-discharge of the battery is assumed to be 1.65% per month. The rate of energy capacity performance degradation is assumed to be 2.5% per year. The probability of dispatch for regulation up and down services is estimated from historical AGC signals. The auxiliary loads are electric loads that are necessary to operate and protect the battery storage system which includes controls, cooling systems, fans, pumps, and heaters.

The economic parameters of the battery storage system under evaluation is as follows. The power-based and energy-based capital cost are \$551/kw and \$614/kwh. The balance of plant costs including land, labor, permitting is assumed to be 20% of the sum of power-based and energy-based capital costs. The fixed and variable O&M costs are assumed to be \$8.18/kW-year and \$0.00548/kWh.

4.2. Electricity market price data input

The lithium-ion battery storage system is assumed to be installed in the CAISO system. The energy and ancillary services provided by the battery system are assumed to be paid by the Day-Ahead LMP for energy and ancillary services at SP15. The monthly average SP15 on-peak electricity prices are generated based on the price sample path generation described in Section 3.4. Specifically, one thousand sample paths of spot price are generated based on the price quotes of SP15 On-Peak future contracts as of December, 31, 2012 with delivery dates from January 2013 to December 2014. The 3-factor model coefficients used in the simulation are based on results in Table 2. The simulated hourly LMPs profile is assumed to be the same as that of actual DA LMPs of 2012.

As shown in Eq. (28), the simulation of frequency regulation prices depends on predictions of monthly average renewable generation variability, hydroelectric generation, and SP15 On-Peak LMP for energy. The monthly average renewable generation variability is estimated based on the renewable energy interconnection plan in CAISO and correlation between renewable generation capacity and generation uncertainty. The monthly average hydroelectric generation is estimated based on the historical generation plans and inflow forecasts. The simulated hourly regulation up/down prices profile is also assumed to be the same as that of actual ancillary service prices of 2012. The value of electric supply capacity is estimated by blending short-run capacity price forecasts with long-run value of capacity. The short-run capacity values are estimated based on recent bids from request for offers. The long-run capacity values are estimated using the cost of new entry method. The revenue from electric supply capacity is calculated as the summation of the products of capacity price and net qualifying capacity (NQC) of the battery storage system. The NQC is determined by the maximum 4-h continuous discharge capability of the battery storage system.

The valuation horizon of the battery storage system is from January 2013 to December 2014. The reason why we chose a short two year valuation horizon is that with a high discount factor and huge policy uncertainty, battery storage system developers are more likely to put emphasis on the more tangible short-term information available. The methodology proposed in this paper will be complementary to the long-term system-oriented analyses.

5. Valuation results

5.1. Probabilistic valuation results

The probability density function of the battery system net revenue in the 2-year evaluation period is shown in Fig. 3. As shown in the figure, the battery system net revenue follows a log-normal distribution. The expected 2-year net revenue of the battery storage system is \$2.92 Million. The conditional value at risk (CVaR) of the battery system net revenue at 95% confidence level is \$1.80 Million.

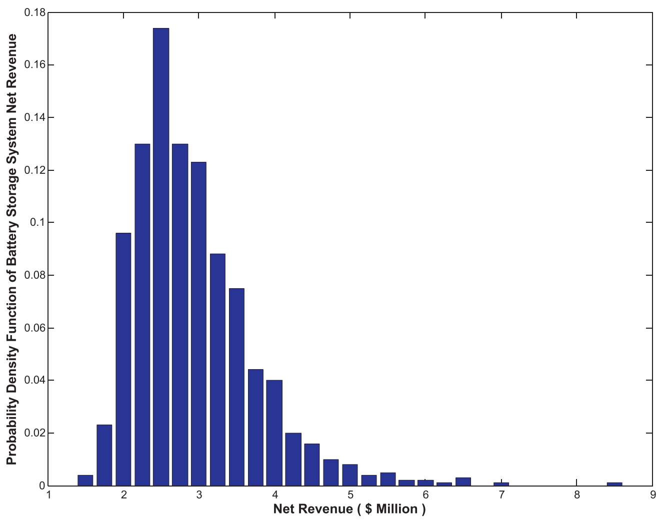

Fig. 3. Probability density function of battery storage system net revenue.

In other words, we are 95% certain that the battery system net revenue will not be lower than $1.80 Million.

The breakdown of battery storage system revenue streams and operating costs in the valuation period is shown in Table 4. It can be seen from the table that if the battery storage system is capable of following automatic generation control (AGC) signals, then 79% of the battery system revenue comes from the provision of frequency regulation services. The battery storage system operating costs are relatively small compared to its revenues. Note that the valuation results are not very sensitive to the selection of the fixed profile for hourly LMPs and hourly regulation up/down prices. By changing the base profile year from 2012 to 2011, the total net revenue is reduced by around 5%. The small change can be interpreted as follows. Majority of the battery storage system revenue comes from providing ancillary services. The ancillary service revenue is proportional to the ancillary service price when the dispatch schedule is fixed.

5.2. Effects of round-trip efficiency on energy storage valuation

Stochastic valuations are conducted based on the energy storage system specification and electricity market data described in Sections 4.1 and 4.2. The impact of round-trip efficiency on energy storage system revenue streams in the wholesale power market is illustrated in Fig. 4. As battery round-trip efficiency increases, the revenue from energy service, regulation up and down services are pushed higher. The simulation results also show that the percentage increase in energy service revenue is much higher than that of ancillary services. In other words, the net revenue from energy service has a much stronger dependence on round-trip efficiency than ancillary services. Every percentage point change in battery round-trip efficiency results in roughly 1% increase in total expected net revenue for the battery storage system. However, diminishing return effects can be observed where the marginal improvement in net revenue decreased from 1.03% to 0.87% as round-trip efficiency increased from 80% to 94%. The simulation results reveal that technological advancement in energy storage round-trip efficiency is crucial to the economic viability of energy storage systems in wholesale power markets.

Table 4
Breakdown of battery storage system's revenue streams.

Revenue/cost category	Revenue/cost($)
Net revenue from energy service	121,367
Regulation up service revenue	1,254,524
Regulation down service revenue	812,698
Revenue from capacity payment	430,240
Auxiliary load cost	53,619
Fixed O&M cost	130,720
Total net revenue	2,918,349

5.3. Effects of power-to-energy ratio on energy storage valuation

Power-to-Energy ratio is an important design variable in stationary energy storage deployment projects. It describes the ratio of installed energy and maximum discharge power of the energy storage system. A nominal configuration of 1-to-4 power-to-energy ratio is typically used in large scale battery storage projects such as AES Energy Storage's 4th Generation Grid Storage Advancion^{TM} (AES Energy Storage Advancion, 2016). The optimal power-to-energy ratio for a battery storage system depends on the grid interconnection location and electric grid services provided by the battery system. The power-based capital cost and energy-based capital costs are $551/kw and $614/kwh. The balance of plant costs is assumed to be 20% of the sum of power-based and energy-based capital costs.

In this paper, the impact of power-to-energy ratio on an energy storage system's value is evaluated in detail. Experimental design is carried out by varying the power-to-energy ratio from 1-to-1 to 1-to-8 while fixing the maximum discharge power of the battery system at 8 MW as specified in Section 4.1. The stochastic valuation results are shown in Fig. 5. As demonstrated in the figure, when the power-to-energy ratio is close to 1-to-2, then an investor of the battery system can gain the maximum net revenue from every dollar invested. This optimal power-to-energy ratio is very different from the nominal configuration of 1-to-4. An investor will receive an extra $27,687 of return for every $1 million invested in the first two years by changing the battery configuration from 1-to-4 to 1-to-2. The reason why a 1-to-2 power-to-energy ratio battery is a better investment than a 1-to-1 or 1-to-4 power-to-energy ratio battery is that by operating at 50% of state of charge, the battery could simultaneously commit to frequency regulation up and down services up to the maximum charge/discharge power. Note that this result is derived for a typical battery storage system primarily providing grid services such as frequency regulation, electric supply capacity, and energy shifting in the transmission system. If an energy storage system is integrated at a different voltage level and provides a different set of services to the power system, then the optimal power-to-energy ratio can be quite different from the optimal ratio shown above.

6. Conclusions

This paper develops a stochastic energy storage valuation framework which allows an energy storage system to provide multiple services simultaneously. The frequency regulation service and energy shifting service are co-optimized in the wholesale power market operations. Within the stochastic valuation framework, a future curve dynamics model is developed to model the variability of electricity price and quantify the risks associated with energy storage system investment. Empirical results from the California electricity future market reveal that three uncertain factors can explain more than 90% of the variability in electricity future price. Valuation studies are conducted to demonstrate the usefulness of the proposed stochastic energy storage valuation framework. It is shown in the valuation results that the stochastic valuation methodology can provide an accurate estimation of both expected return and investment risk associated with a battery storage system. In addition, the valuation results show that both round-trip efficiency and power-to-energy ratio are crucial battery system design parameters for achieving cost effectiveness. Every 1% improvement in battery round-trip efficiency results in a roughly 1% increase

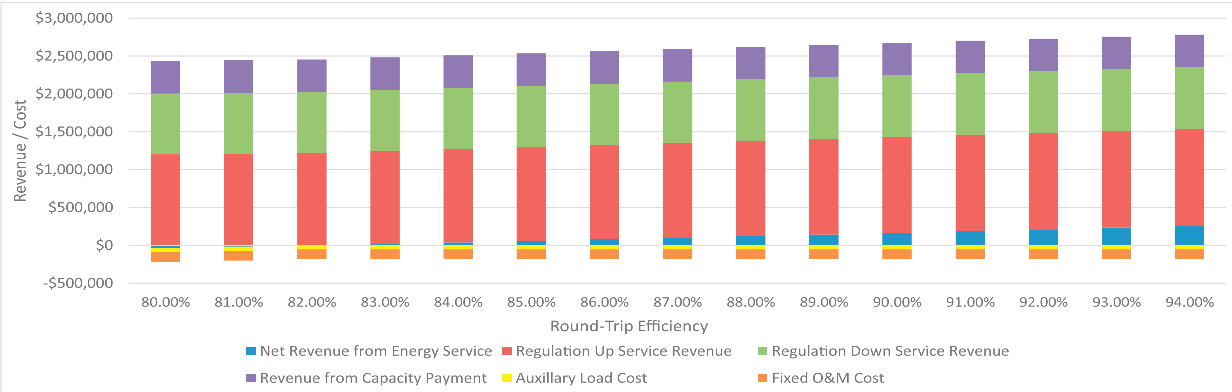

Fig. 4. Impact of round-trip efficiency on energy storage value.

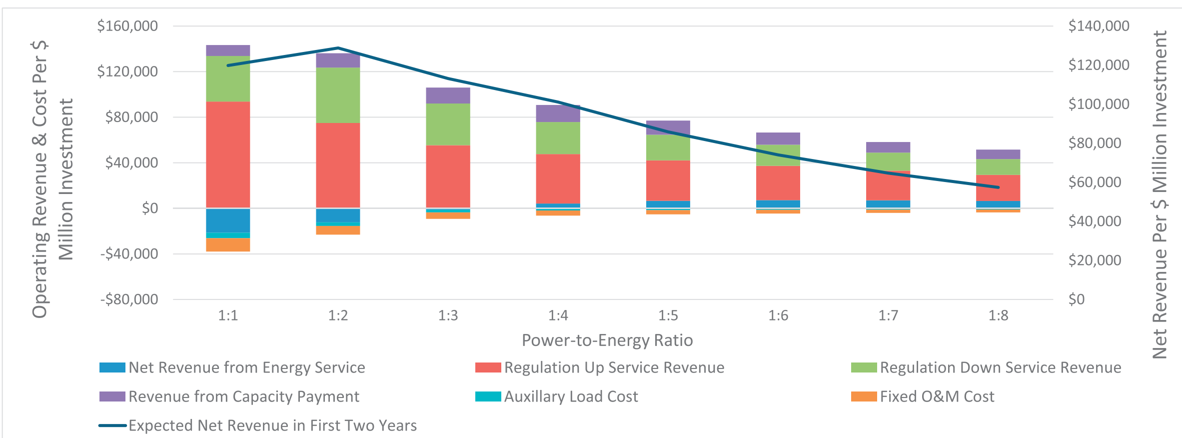

Fig. 5. Impact of power-to-energy ratio on energy storage value.

in total expected net revenue. The optimal power-to-energy ratio for wholesale power market is much higher than the nominal configuration of 1-to-4 typically used in existing energy storage projects.

Future studies will consider more detailed models for energy storage degradation and life-time economic analysis of energy storage systems. A comprehensive cost effectiveness analysis will be conducted to compare energy storage systems with traditional fossil-fueled power plants. In addition, optimal penetration level of energy storage systems will be studied under different renewable penetration scenarios.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eneco.2017.03.010.

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