Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach

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Abstract In this paper we develop a real options approach to evaluate the profitability of investing in a battery bank. The approach determines the optimal investment timing under conditions of uncertain future revenues and investment cost. It includes time arbitrage of the spot price and profits by providing ancillary services. Current studies of battery banks are limited, because they do not consider the uncertainty and the possibility of operating in both markets at the same time. We confirm previous research in the sense that when a battery bank participates in the spot market alone, the revenues are not sufficient to cover the initial investment cost. However, under the condition that the battery bank also can receive revenues from the balancing market, both the net present value (NPV) and the real options value are positive. The real options value is higher than the NPV, confirming the value of flexible investment timing when both revenues and investment cost are uncertain.

Keywords Real options · electric energy storage · Markov regime switching · economic dispatch · least squares Monte Carlo

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1 Introduction

In July 2015, one of the largest hydropower producers in Europe, Statkraft, announced the launch of a grid scale battery project in Germany[1]. Indeed, electric energy storage is receiving attention in the energy market as a potential investment opportunity. The integration of large amounts of renewable energy sources (RES) in the European market has created a need for decentralized storage systems while the cost of lithium-ion battery banks are dropping. Deutsche Bank is actually suggesting a 20-30% annual cost reduction for lithium-ion batteries and predicts a mass adoption potential of battery banks before 2020 (Shah and Booream-Phelps, 2015).

Investments in electric energy storage technologies have been a popular topic in the literature over the last decade (Korpaas et al, 2003; Reuter et al, 2012; Fertig et al, 2014; Del Granado et al, 2016). Pumped hydroelectric storage has received the most attention, because it is the dominant technology accounting for 99% of the world's storage capacity. In spite of this, there are a number of other storage technologies in the market(Chen et al, 2009). The choice of storage technology depends on a number of factors such as market design, characteristics required, costs, location, and expected revenues. For markets with large imbalances and large portion of RES, there is demand for quick response technologies such as batteries.

In this paper we apply a real options framework to value investments in lithium-ion battery banks in Germany and the United Kingdom. It is interesting to consider battery technology, because of the rapid decrease in battery cost and its favorable characteristics (i.e. quick response time and regulated power output). Batteries also possess a number of other desirable features such as pollution free operation, high round trip efficiency, scalable power and energy output, long life cycle and low maintenance costs (Dunn et al, 2011; Kim et al, 2014).

To consider the potential revenues, we must study the electricity market in more detail. In the past two decades electricity markets around the world have been restructured (European Commission, 2013). Many electricity markets are divided in two parts, the spot market and the balancing market. European spot markets are day ahead markets with high liquidity, where the suppliers are paid for the amount of electricity they provide. The balancing market consists of different types of ancillary services that are required by the transmission system operator in order to balance demand and supply. In the balancing market suppliers are receiving two forms of payments; availability payments for making their unit available for ancillary services, and utilization payments for the energy delivered as instructed by the system operator. Battery banks can participate in both markets, but can not allocate the same capacity in both markets at the same time.

[1] *Launch of battery project in Germany* Press release by Statkraft 27.07.15 `http://statkraft.com/media/news/20151/launch-of-battery-project-in-germany/`

The spot price in general exhibits strong seasonality on the annual, weekly and daily level, mean reversion, high volatility, clustering effects and extreme price changes known as spikes. Two of the most common approaches to capture the spiking behavior of the power price are jump diffusion models and Markov regime switching (MRS) models (Weron et al, 2004). The jump diffusion model introduces spikes through a Poisson jump component. It is however not able to generate consecutive spikes, because the jumps are independent (Cartea and Figueroa, 2005; Weron et al, 2004). MRS is able to generate these with a transition matrix that includes the probability of the spot price having another spike (Weron et al, 2004). It has therefore been used extensively to capture the unique behavior of the spot price (Weron et al, 2004; Arvesen et al, 2013; Janczura and Weron, 2012, 2010; Paraschiv et al, 2015). There has also been recent work on other regime switching models, such as the LSTR model proposed by (González et al, 2012).

Previous research that consider investment in batteries often find that it is not profitable (Sioshansi et al, 2009; Kazempour et al, 2009). Our results contrast with these papers by showing that a lithium-ion battery that receives revenues from both spot and balancing markets are profitable. It is essential to include revenues from both markets, as well as capturing the characteristics of the prices to discover the total value of the investment.

The investment cost has generally been considered to be fixed or deterministic (Dixit and Pindyck, 1994). However, for real world investment decisions the investment cost will change over time because of changing market conditions such as rise in commodity prices, decrease in demand and technology development. We assume that investment cost follow a geometric Brownian motion.

The main contribution of this paper is a quantification of the value of investing in a battery bank in a real options context. In addition, we use a state of the art MRS for the spot price that captures the characteristics of the prices. We are also the first to propose a MRS for the balancing price. Further, the approach for optimal hourly dispatch of the battery bank includes participation in both the spot and balancing market. Finally, the model takes into account the uncertainty of the investment cost and the revenues by applying the real options framework.

The paper is structured as follows: In Section 2 we describe the data used and the characteristics of the spot and balance price in Germany and the United Kingdom. In Section 3 we explain the model for the valuation of the battery bank. This consists of the real options valuation, the optimal dispatch of the battery bank and the MRS for the spot and balancing prices. Results are presented in Section 4 and the conclusion in Section 5.

2 The datasets

The datasets in this study include market data from Germany (2010–2014) and the United Kingdom (2010–2014). This allows for an evaluation of investment under different market conditions. The UK market is isolated because of its location on an island, which creates a need for balancing. The price level for both spot and balancing is also high. The German market on the other hand is much more interconnected and the spot price has decreased more than 32% since 2010. However, it exhibits variable market behavior with extreme spikes and it has a rapidly growing portion of RES installed. In combination with the decision to close down all nuclear plants by the end of 2020, this escalates the need for balancing, which increases the prices in the balancing market.

2.1 Time series of market prices for the United Kingdom (2010–2014)

The data set includes the hourly market clearing price from the Amsterdam Power Exchange (APX Power UK) and the hourly balancing price from the system operator National Grid. The historical data for both the spot and balancing prices are mean reverting. There are however hours with extreme values, which we define as negative and positive spikes. Inspecting the time series, it is also clear that the prices have diurnal, weekly and seasonal patterns. The volatility is greater in some periods than others, indicating a clustering effect. Another important observation is that the spot price is nonnegative. This is because of the market design that forbids participants to enter trades with a negative spot price. The time series of prices in week 5 of 2014 is presented in Figure 1.

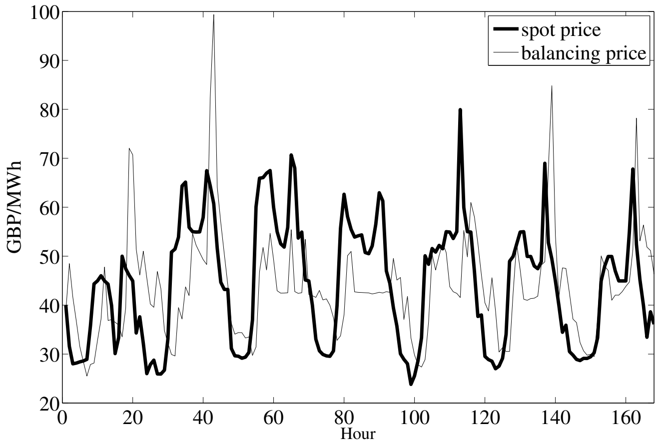

Fig. 1 Spot and balancing price UK week 5, 2014.

2.2 Time series of market prices for Germany (2010–2014)

This data set includes the hourly market clearing price from the European Energy Exchange AG (EEX) and hourly balancing price from the system operator TenneT. By evaluating historical data from the German market, it is clear that the spot and balancing prices have the same characteristics as in the UK market. The only exception is the spot price, which has no price floor. Refer to Zhou et al (2016) for an analysis of battery operation policies emphasizing the implications of the presence of negative electricity prices. Figure 2 shows the time series of prices in week 5 of 2014.

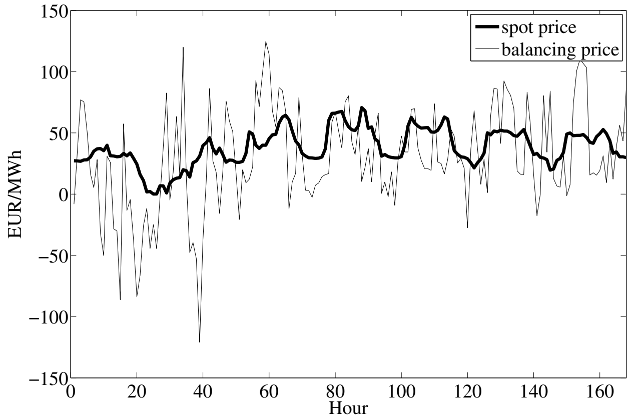

Fig. 2 Spot and balancing price Germany week 5, 2014.

3 Model description

The valuation of the battery bank consists of four steps: price forecasts of the spot price and balance price, an optimization model for operation of the battery bank, investment cost dynamics and a real options valuation (see Figure

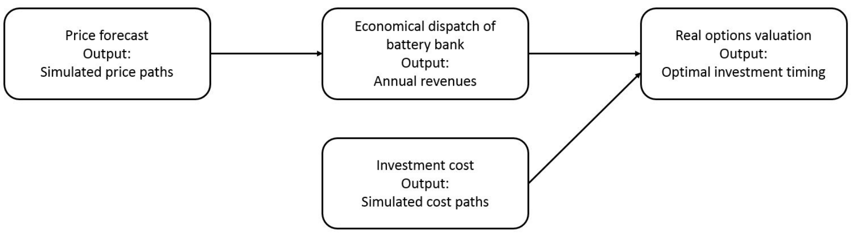

Fig. 3 The structure of the approach.

3). To be able to value a battery bank, we need to accurately forecast the power price and balance price. The forecast must capture the characteristics of the two prices and the correlation between them. The simulated future spot and balance prices serve as input to the optimization model. The economic dispatch is found by maximizing the revenues of the battery bank. Annual revenues from the optimal operation of the battery bank serve as input to the real options valuation together with the investment cost forecasts. The real options model in turn gives us the optimal decision rule for the investment.

3.1 Price dynamics

The future spot and balancing price are both forecasted using Markov regime switching with three independent regimes. In the following subsections we will go through the procedures we have used to develop the different submodels, the calibration of the parameters and the final results.

3.1.1 Spot price

The spot price dynamics must be able to capture the seasonal patterns and the stochastic behavior of the spot price. We therefore choose to let the spot price, P_t^S, be a sum of two independent parts: a deterministic seasonal component (f_t) and a residual stochastic component (X_t^S); $P_t^S = f_t + X_t^S$.

We let the deterministic component be composed of a daily (d_t) and weekly (w_t) periodic part (i.e. short term seasonal component, STSC) and a long term seasonal component (LTSC), s_t. The STSC is caused by variations in consumption throughout the day and business cycles, while the long term component is explained by the changing climate throughout the year. The deterministic component can therefore be expressed as:

$$f_t = d_t + w_t + s_t. \tag{1}$$

There are different ways of handling the seasonality of the spot price. Some authors use dummy variables for each month, day of the week or hour of the day (Fleten et al, 2011; Arvesen et al, 2013). Other use sinusoidal functions or sums of sinusoidal functions (Janczura and Weron, 2010; Janczura et al, 2013). Wavelet smoothing is another possibility that is less sensitive to outliers and less periodic (Janczura et al, 2013; Nowotarski et al, 2013). Wavelets offer a very good in-sample fit to the data, but the ability of wavelets to forecast is poor (Ramsey, 2002). As we are considering an investment that uses the forecasted prices, wavelet smoothing is not suited. We therefore choose to apply the method presented in the paper of Janczura and Weron (2010), where the LTSC is represented as a sum of sinusoidal functions.

The historical data is deseasonalized in three steps; first by subtracting s_t from P_t^S, then subtracting the daily component, and finally by removing the weekly seasonality. The daily periodic part (d_t) is found by calculating the “average day” from the detrended data ($P_t^S - s_t$). The weekly periodic part

(w_t) is found the same way as for the day, by calculating the "average week", from the detrended data ($P_t^S - s_t - d_t$). The approach used to calculate the STSC is the same as having seasonality expressed by dummy variables (Janczura and Weron, 2012). The deterministic component is found by adding all the seasonal components as in Equation (1).

We use Markov regime switching to represent the stochastic component of the spot price. It represents the observed stochastic behavior of a specific time series by more than one separate regime with different underlying stochastic processes (Janczura and Weron, 2012). The switching mechanism between the different regimes is assumed to follow a Markov chain, i.e. the underlying process does only depend upon the current state.

To capture the characteristics of the spot price, the stochastic component (X_t) is represented with three independent states:

$$X_t^S = \begin{cases} X_{t,1} & \text{if } R_t^S = 1, \\ X_{t,2} & \text{if } R_t^S = 2, \\ X_{t,3} & \text{if } R_t^S = 3. \end{cases} \tag{2}$$

R_t^S describes the actual state of the market, i.e. normal behavior, spike or drop. The three regimes are independent and the switching mechanism between the regimes is assumed to be a latent Markov chain. It can be described by a transition matrix $\mathbf{P}$, that contains the probabilities of switching from one regime i at time t to regime j at time $t+1$.

$$\mathbf{P} = P(R_{t+1}^S = j \| R_t^S = i) = \rho_{ij} = \begin{pmatrix} \rho_{11} & \rho_{12} & \rho_{13} \\ \rho_{21} & \rho_{22} & \rho_{23} \\ \rho_{31} & \rho_{32} & \rho_{33} \end{pmatrix}. \tag{3}$$

The base regime $(X_{t,1}^S)$ describes the statistical "normal" price behavior and is given by the Chan-Karolyi-Longstaff-Sanders differential equation[2]:

$$dX_{t,1} = (\alpha_1 - \beta_1 X_{t,1})dt + \sigma_1 |X_{t,1}|^{\gamma_1} dZ_{t,1}, \tag{4}$$

where α_1, β_1, γ_1 and σ_1 are constants and $dZ_{t,1}$ is the increment of a standard Wiener process. Here β_1 describes the speed of mean reversion, $\frac{\alpha_1}{\beta_1}$ the equilibrium level toward which the process drifts, σ_1 the volatility of the process and γ_1 determines the volatility's dependence on the price level.

The upper regime $(X_{t,2}^S)$, that represents the sudden price jump (positive spikes), is given by independent and identically distributed (i.i.d.) random variables from the shifted log-normal distribution(Janczura and Weron, 2012)[3]:

$$log(X_{t,2} - X(Q_2)) \sim N(\alpha_2, \sigma_2), \;\; X_{t,2} > X(Q_2), \tag{5}$$

[2] The Chan-Karolyi-Longstaff-Sanders differential equation nests several processes commonly used to represent commodity prices, including the GBM, Vasicek, Merton and Brennan-Schwartz model. It can assume the form of any of these processes by altering the parametrization, without changing the solution of the equation. This allows us to incorporate elements such as mean reversion and inverse leverage effects in our model. We refer to Chan et al (1992) for further details.

[3] We refer to Janczura and Weron (2009, 2010) for a more in depth analysis of the shifted lognormal distribution and how this better fits electricity prices than other alternatives.

where $X(Q_2)$ and $X(Q_3)$ (below) are Q-quantiles of the dataset. Here we choose $Q_2 = 0.75$ and $Q_3 = 0.25$.

The lower regime ($X_{t,3}$), that represents the sudden price drops (negative spikes), is given by i.i.d. random variables from the shifted inverse log-normal distribution:

$$log(-X_{t,3} + X(Q_3)) \sim N(\alpha_3, \sigma_3), \;\; X_{t,3} > X(Q_3). \tag{6}$$

3.1.2 Balancing price

The modeling of balancing prices have received less attention than the modeling of day ahead spot prices. One of the explanations is that the design of the balancing market varies according to the country. This explains why Skytte (1999) finds that the balancing price can be explained by the day ahead market price, while Jaehnert et al (2009) indicate no correlation between the spot and balancing prices. Jaehnert et al (2009) model the balancing price as the difference to the day ahead market price, while both Olsson and Söder (2008) and Klæboe et al (2015) model it directly including correlation with the spot price.

Characteristics of the UK and German balancing price include positive and negative spikes, mean reversion and volatility clustering. To capture these price characteristics, we choose to use a MRS model with three regimes: base, upper and lower regime. We also find that the balancing prices have seasonal components that changes during the day, week and year We apply the same methods as in the last subsection to determine the deterministic seasonal components of the balancing price.

Since the balancing price is dependent on market design, the correlation between the spot price and balancing price will differ. We therefore tested the correlation between the spot and balancing price in our datasets, and found differing results. For the German market, we find no significant correlation between the spot and balancing price. The price forecast of the balancing price is therefore modeled in the same way as for the spot price in Section 3.1.1. However, for the UK market, the correlation between the spot and balancing price increments was found to be significant.

The balancing price is modeled by MRS, with the corresponding deterministic seasonal component (g_t) as for the spot price, i.e. $P_t^B = g_t + X_t^B$. There are three independent regimes:

$$X_t^B = \begin{cases} X_{t,4} & \text{if } R_t^B = 1, \\ X_{t,5} & \text{if } R_t^B = 2, \\ X_{t,6} & \text{if } R_t^B = 3. \end{cases} \tag{7}$$

R_t^B describes the actual state of the market, i.e. normal behavior, spike or drop, and is assumed to follow a latent Markov chain (see Section 3.1.1). The three regimes are assumed to be independent, where the base regime

($X_{t,4}$) is a mean reverting process, the upper regime ($X_{t,5}$) has a shifted log-normal distribution and the lower regime ($X_{t,6}$) a shifted inverse log-normal distribution.

The base regime for the UK balance price is given by the following:

$$dX_{t,4} = (\alpha_4 - \beta_4 X_{t,4})dt + \sigma_4 |X_{t,4}|^{\gamma_4} dZ_{t,4}, \tag{8}$$

where the balance price increment (dZ_4) is correlated with the spot price increment (dZ_1) by a factor ρ. From the time series ρ was calculated and approximated to 0.25.

Table 1 Calibration results for MRS models with three independent regimes fitted to the deseasonalized EEX and APX spot prices.

	α_1	β_1	σ_1	γ	α_2	σ_2	α_3	σ_3	p_{11}	p_{22}	p_{33}
EEX	4.26	0.10	4.15	0.00	2.46	0.83	2.29	1.18	0.992	0.750	0.851
APX	8.20	0.18	4.71	0.01	2.17	1.19	2.54	0.6	0.990	0.551	0.000

Table 2 Calibration results for MRS models with three independent regimes fitted to the deseasonalized EEX and APX balance prices.

	α_4	β_4	σ_4	γ	α_5	σ_5	α_6	σ_6	p_{11}	p_{22}	p_{33}
EEX	12.30	0.34	24.18	0.08	3.36	1.22	4.22	0.88	0.977	0.704	0.591
APX	7.57	0.2	0.35	0.7	2.27	1.01	2.42	1.31	0.982	0.633	0.525

3.1.3 Parameter calibration

We estimate the parameters by applying the expectation-maximization (EM) algorithm described in Janczura and Weron (2012). This procedure can be applied to all MRS models where at least one regime is described by a mean reverting process. The results from the parameter calibration of the historical EEX and APX prices are shown in Tables 1 and 2. We use the bivarate conditional expectation when determining dZ_4.

Simulated spot and balance price paths for the United Kingdom for a week are illustrated in Figure 4.

3.2 Optimal dispatch of the battery bank

The optimization model we develop in this paper generates the dispatch and expected profit of the battery bank for an average year, given the hourly spot price, P_t^S, and balancing price, P_t^B. The economic dispatch determines the highest expected profit based on participation in both markets. At each hour

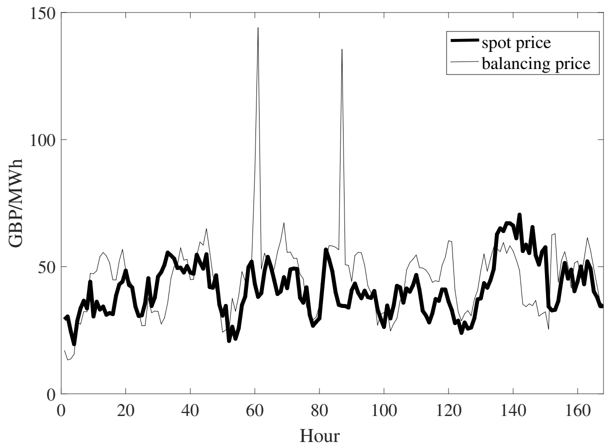

Fig. 4 Simulated spot and balance prices for one week for the United Kingdom.

Table 3 Parameters and variables in the operation of the battery bank.

Symbol	Explanation	Value	Unit
q_t	Spot discharge	-	MW
r_t	Cap. reserved in balancing mkt	-	MW
b_t	Battery charging	-	MW
l_t	State of charge	-	MWh
P_t^S	Forecasted spot prices	-	€/MWh
P_t^B	Forecasted balancing prices	-	€/MWh
C	Operation and maint. costs	0.1	€/MWh
N	Length of operation period	24	hours
U	Utilization factor	0.1	-
$\bar{Q}$	Max. production capacity	5	MW
$\bar{B}$	Max. discharging capacity	5	MW
L_0	Initial storage level	0	MWh
$\bar{L}$	Max. storage level	10	MWh
η_1	Efficiency of discharge	0.975	-
η_2	Efficiency of charging	0.975	-
θ	Penalty	0.9	-

Subscript t denotes quantities that may change hourly.

t, the battery will be in one of the following states: charging, discharging or idle. When operating in the spot market the owner of the battery bank either receives or pays the spot price, depending on the state of operation. In the balancing market, it receives the hourly balancing price and additionally the hourly spot price if the battery is called to discharge (i.e. asked to supply power into the balancing market). The probability of being called to discharge is given by U and is based on historical data (Kazempour et al, 2009; Kirby, 2007).

The battery bank is optimized over a planning horizon of 24 hours. The daily profits are summed up over the first year. This allows new information to be incorporated on a daily basis without assuming future knowledge of prices beyond a day. This means that the battery make price dependent bids, resulting in an overestimation of the profits from operation. Contreras et al (2003) found that with a good forecasting model, the error applying daily forecasted prices would be maximum 11%. In accordance with these findings, we penalize the annual revenue by multiplying by a constant (θ) to adjust for the overestimated earnings from knowing the prices in advance.

The objective of the storage owner is to optimize the operation of the battery to maximize the profit, i.e. revenues less operation and maintenance costs. The following linear programming problem maximizes the profit over a day:

$$\max \left(\sum_{t=1}^{N} P_t^S (q_t - b_t + U r_t) + \sum_{t=1}^{N} P_t^B r_t - \sum_{t=1}^{N} C(q_t + b_t + U r_t) \right), \quad (9)$$

subject to:

$$l_t = l_{t-1} - \frac{q_t}{\eta_1} + b_t \eta_2 - \frac{U r_t}{\eta_1} \quad (10)$$

$$q_t + r_t \leq \bar{Q} \quad (11)$$

$$l_t \leq \bar{L}, b_t \leq \bar{B}, q_t \leq \bar{Q}, r_t \leq \bar{Q} \quad (12)$$

All variables are nonnegative. Variables and parameters in the economic dispatch are summarized in Table 3. The operation is controlled by discharge in the spot market, q_t, what is reserved in the balancing market, r_t, and the charging in the spot market, b_t. We assume that the storage level is zero at the beginning of operation. Further, operation and maintenance cost, C, and efficiency for both charging, η_1, and discharging, η_2, are assumed constant. The efficiencies are consistent with e.g. Leadbetter and Swan (2012).

The objective function, (9), consists of three components. The first term calculates the revenue from delivering power in the spot market and the costs of charging the battery. The second term calculates the revenue from reserving capacity in the balancing market. The third term accounts for the operation and maintenance costs of operating the battery. Eq. (10) balances the energy storage level of the battery. The energy storage level is equal to the storage level at the previous time step, plus the energy charged minus the energy discharged. Eq. (11) sets a fixed maximum battery capacity. The energy sold in the spot and balancing markets in each hour cannot exceed the maximum capacity of the battery. Eq. (12) bounds the charging, discharging and storage levels.

This economic dispatch is a linear program. To obtain a solution the model is formulated in the General Algebraic Modeling System (GAMS) and solved using the CPLEX solver. The whole system is solved for the whole 15 year period simultaneously. All exit states from the final hour of one day automatically carry over as input states for the first hour of the next day.

The solution to the optimal dispatch problem is the battery bank profit for one day. To get the cash flow, Z, from operating the battery bank for a year, we run the optimization problem for the number of days in the year and add up the daily profits. We choose to do this for one year, instead of for the entire lifetime of the battery bank, because the yearly profits throughout the lifetime of the battery bank are approximately the same. To get the total profit of the battery bank, F, we sum the discounted yearly profit throughout the lifetime of the battery. We assume an interest rate of 4% and a lifetime of $K = 15$ years for the battery bank. The present value of the total cash flows is:

$$F = \sum_{k=1}^{K} \frac{\theta Z}{(1+r)^k} = \theta Z \left[\frac{1-(1+r)^{-K}}{r} \right], \tag{13}$$

where θ is the price anticipation penalty and r is the risk free rate.

The optimization algorithm is repeated for the 10 000 different spot and balancing price paths, i, generated from the price models in Section 3.1. The correlation between the spot price and the balancing price is included in the generation of these price paths. This is done by including a correlation term in the balancing price. Covariance in the spot and reserve price is included, ensuring that the reserve price does not move unrealistically high or low relative to the spot price. We use the results, F_i, as an input variable in the real options valuation.

3.3 Investment cost

The cost of lithium-ion batteries for consumer electronics and electrical vehicles have decreased rapidly the last decade, with over 10% each year. However, none of the papers that consider investment in battery storage include such uncertainty in technology development for grid scale batteries (Cho and Kleit, 2015; Sioshansi et al, 2009; Kazempour et al, 2009). If investors fail to take into account the uncertainty of technology development, they risk underestimating the value of the battery as well as investing before the optimal investment time.

Since the cost for comparable technology (i.e. small and medium scale lithium-ion batteries) has steadily decreased the last decade, we assume that the cost for battery banks also will develop in a similar manner. Therefore, we let the investment cost follows a geometric Brownian motion[4] with a negative

[4] Investment costs is an economic variable that is highly affected by the business cycle. It exhibits long-term variation, and changes in the cost level be expected to persist for a long while. It is also natural to expect that changes in costs are normally distributed when considering relative changes (as opposed to absolute EUR/kWh changes). These features point toward a geometric Brownian motion for these costs.

growth rate:

$$dI = \alpha_I I dt + \sigma_I I dz_I, \tag{14}$$

where $\alpha_I < 0$ is the growth rate, $\sigma_I > 0$ is the volatility and dz_I is the increment of the Wiener process. Table 4 shows the parameters of the investment cost. Estimates are conservative compared to e.g. Hadjipaschalis et al (2009).

Table 4 Parameters of the investment cost dynamics.

Parameters	Value
Initial inv. cost (€/kWh)	1350
Capacity (MWh)	10
Growth rate	-0.1
Volatility	0.2

3.4 Real options valuation

One of the strengths of the real options approach is that it explicitly accounts for the value of postponing investment to wait for more information (Dixit and Pindyck, 1994).

We are considering the following investment opportunity: at any time, τ, the firm can pay an investment cost, I, in order to buy a battery bank, given the profit flow from operation of the battery bank F. The battery bank investment decision is characterized by a large sunk cost and a time interval during which investment is possible. We therefore choose to value the investment as a Bermudan call option. This type of exotic option allows the owner to exercise the option only once, but has flexibility to choose the optimal exercise date between a number of given discrete times during the lifetime of the option T. The lifetime of the option is set to 10 years. We have discretized the problem in such a way that the decision maker can exercise this option once every year. This makes the problem a lot less complex to solve computationally. It also more closely resembles a real life business process, where decisions like this are typically made yearly or quarterly as part of a business cycle and not in continous time. The value of the investment opportunity is calculated as:

$$ROV = \max_{0 \leq \tau \leq T} \left(\mathbb{E}_\tau \left[e^{-r\tau} (F(\tau) - I(\tau)) \right], 0 \right). \tag{15}$$

The key to optimally exercising a Bermudan option is identifying the conditional expected value of continuation. We will therefore apply least squares Monte Carlo described in the paper of Carriere (1996) and further extended by Longstaff and Schwartz (2001). This is a simulation-projection approach based on Monte Carlo sampling and where the dynamic programming-style continuation value is approximated using regressions. The continuation value is approximated using a polynomial function of second degree. This is a quite simple approximation, but several numerical tests confirm that even simple powers of the state variable gives accurate results (Longstaff and Schwartz, 2001).

The inputs for the least squares Monte Carlo valuation are two exogenous variables; battery cash flow and investment cost. Both of these exist for each of the 10 000 unique paths (i), and each year k, and we denote them F_{ik} and I_{ik}; the index for time has changed to reflect the time discretization in the algorithm. Although an investment opportunity can be considered more often than once per year, annual time steps still gives insight about the investments in battery banks. The algorithm optimizes the exercise date based on the trade off between immediately exercising and the continuation value of keeping the option alive for each individual in-the-money path. The value vector V_{ik} at each time k is given by:

$$V_{ik} = \begin{cases} F_{ik} - I_{ik} & \text{if } F_{ik} - I_{ik} > W_{ik} \\ W_{ik} & \text{else,} \end{cases} \tag{16}$$

where W_{ik} is the (discounted) continuation value of keeping the option alive. The option value is calculated by averaging the sum of all payoff paths at year zero. If the value of the option is greater than zero, the value of investing in a battery bank is positive. If the option value is zero or less, it is never optimal to invest. See Longstaff and Schwartz (2001) for a more detailed description of the approach.

4 Results

The results are based on a base case considering an interest rate of 4%, battery bank and option lifetime of 15 and 10 years, and initial investment cost of 1350 €/kWh with volatility of 20% and negative growth rate of 10%.

The results from the real options valuation of the battery bank investments are given in Table 5. To compare the investments in the two countries, we convert the option value of investing in the United Kingdom from pounds to euro applying an exchange rate of 1.3 €/ £. The option values of investing in Germany (6.5 million) and the United Kingdom (9.9 million) are both positive. Therefore, it is profitable to invest in a battery bank in both countries in our base case.

Table 5 Results of the valuation. Measures of economic worth of the battery bank.

	Germany	United Kingdom
NPV (mill. €)	6.1	9.6
Option value (mill. €)	6.5	9.9
Payback period (years)	7.6	6.3
Investment time (years)	2	1

The project with the highest option value is in the United Kingdom, with a 34% higher option value than the project in Germany. This is due to a higher price level in the United Kingdom, compared to Germany. However, the results show that it can be profitable to invest in markets with different characteristics. This is an important finding, which confirms that battery storage can be a cost efficient alternative to peak power plants.

The lifetime of a battery bank is 15 years, resulting in additional profits past the first six (the United Kingdom) and seven (Germany) years (see Table 5). If we compare this to another electric energy storage technology, pumped hydroelectric storage, the battery bank has a much shorter payback time. The reason for this is that the upfront investment cost on average is many times larger for pumped hydroelectric storage.

The average time to invest is after two years in Germany and after one year in the United Kingdom. We find this numerically by calculating the average optimal investment time of the 10 000 independent paths. For investors following a traditional NPV rule, they will invest immediately since both investments have positive NPV of 6.1 and 9.6 million. When considering the flexibility to postpone the investment decision for up to ten years, to wait for a decrease in investment cost, the value of the investment opportunities are 6.5 and 9.9 million.

The real options framework can help policy makers increase their insight on how to trigger investment in battery storage. As stated earlier, there has been a reluctance to invest in storage technologies. This investor behavior cannot be explained by the traditional NPV methodology, which assumes that an investment will be undertaken as long as the project has a positive NPV. The real options valuation however explains this behavior by showing that when there is great uncertainty, investors are favoring the option to wait for more information. This shows that the reason why investors are not investing in batteries is not because they are not profitable, but rather that investors are waiting for the cost of batteries to decrease.

From the economic dispatch we find that batteries most of the time will offer their services in the balancing market, with the only exceptions being when there are spikes in the spot price. This result indicates that battery banks earn most of their profit from ancillary services, and only makes a small profit from time arbitrage of the spot price. In fact, participation in the balancing market accounts for over 70% of its total revenues. This is consistent with the results of a growing body of research such as Steffen (2012), Byrne and Silva-Monroy (2012), Denholm et al (2013) and Xi and Sioshansi (2014). Energy storage provides more ancillary services than arbitrage, and operating in the reserve market and arbitrage market simultaneously increases revenues by a large amount relative to just operating in the arbitrage market alone. This further demonstrates the importance of convincing investors to rethink how they choose to operate the battery to maximize its profit. By only considering revenues from the spot market, investors risk underestimating its value. This contradicts Faria and Fleten (2011), which found that participating in the balancing market do not significantly impact the profit of electrical energy storage. However, in Faria and Fleten (2011), the producer participates in a hydro-dominated market, where the production is more flexible and the demand for balance power is lower than in Germany and the UK.

The main result of this paper is that a battery bank can be profitable under the conditions given in our base case. This is a contrast to recent published papers (Reuter et al, 2012; Bradbury et al, 2014; Sioshansi et al, 2009). They assume that a battery will only operate in the spot market and revenues are therefore only gained by time arbitrage of the spot price. When we use this assumption we also find it unprofitable to invest. We find that in this case both investments have a negative NPV of −12.6 (Germany) and −11.8 million (the United Kingdom). From our valuation we also find that both projects have an option value equal to zero, which means that it is never optimal to invest. These results clearly demonstrate that it is essential for the profitability of a battery bank to operate in both markets.

4.1 Sensitivity analysis

In this subsection we perform a sensitivity analysis of the option value. We choose to only consider the German market, as the effects are the same as for the UK market.

Examining the sensitivity of the option value to volatility in investment cost, Figure 5 shows how the option value changes with an increase in volatility from 0 to 30%. The figure illustrates that the option value increases with volatility, when the volatility changes from 2 to 30%. As the volatility increases, the flexibility of postponing the investment to wait for more information is more valuable, i.e. the option holder is encouraged to wait. However, a surprising result of the analysis is the nonmonotonic behavior of the option value as the volatility increases. When the volatility increases from 0–2%, the option value decreases. This is not consistent with the characteristic feature of the Black-Scholes model; that the sensitivity of the option price with respect to the underlying assets volatility is always positive, i.e. the option value increases with volatility. Permana et al (2007) argue that this does not contradict the Black-Scholes model. They reason that by increasing one of the volatilities it can lead to a lower variability of the spread, that ultimately drives down the option value. This is exactly the same result we obtain in our analysis, by increasing the volatility from 0–2% the option value decreases because of reduced difference between the investment cost and the profit flow. This suggests that for options that has more than one source of uncertainty, the option value can decrease in some intervals.

Next we will consider the sensitivity of the profit flow, keeping the parameters of the investment cost constant. An important benchmark for investors is the average annual revenue required to make the investment profitable. Figure 6 shows the option value with respect to average annual revenues. Without public support, the investment would not be profitable when the annual profit is expected to be under 0.5 million. When considering operation in both mar-

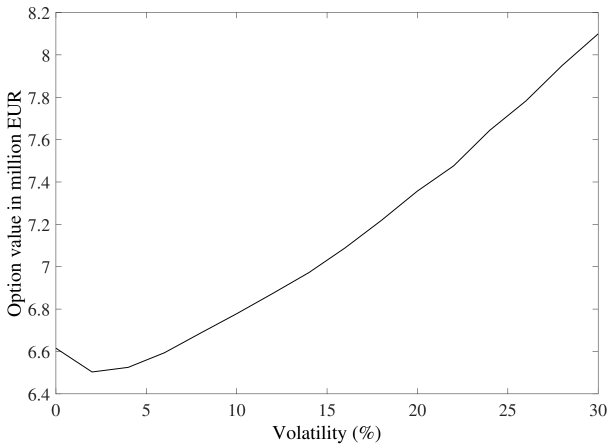

Fig. 5 Sensitivity of option value to volatility of the investment cost. The option value decrease with volatility at very low volatility.

kets, the annual revenue is 1.8 million. It is not likely that it will decrease to the 0.5 million threshold. On the other hand, when only participating in the spot market, the annual revenue is 0.2 million. Policy makers therefore have two options when wanting to trigger investment in battery banks, they can either give public support or allow batteries to participate in the balancing market.

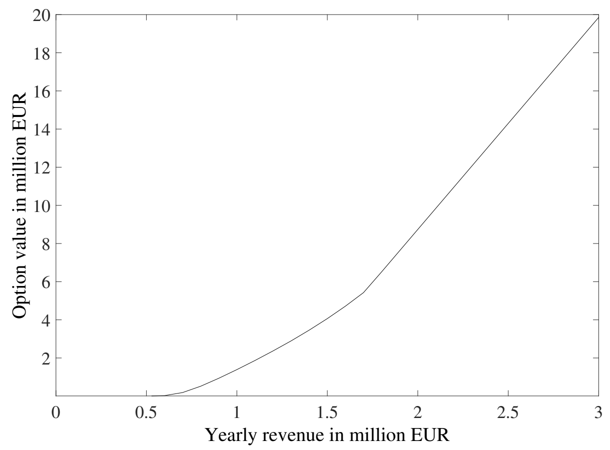

Fig. 6 Sensitivity of option value to the annual revenue. The investment is not profitable when the battery bank is only operating in the spot market (annual revenue is equal to 0.2 million).

5 Conclusion

We have analyzed the profitability of investing in a lithium-ion battery bank in Germany and the United Kingdom, considering the opportunity to operate in both spot and balancing markets. The value of the investments are found by applying a real options model, that determines the option value and optimal investment time for a battery bank under the conditions of uncertain revenue stream and investment cost. Our results show that batteries can be a cost efficient solution to help the green transition in Europe. They further show that investment is profitable in both countries, and that it is optimal to postpone any investment for at least a year.

The real options model developed in this paper can help policy makers increase their insight on investor behavior and how to trigger investments. The results from our analysis show that the reluctance to invest in storage batteries cannot be explained by batteries being unprofitable, but rather by high uncertainty. We find that high uncertainty in the development of battery costs lead investors to favor the option to wait for more information.

From the economic dispatch of the battery bank, we find that operating the battery bank by time arbitrage of the spot price is not generating high enough revenues to cover the initial investment cost. This result indicates that investors should rethink how they choose to operate the battery to maximize its profit. Participation in the balancing market accounts for more than 70% of the battery bank's total revenues. Realizing this opportunity will greatly increase the expected value of the investment. We therefore point out the importance of including revenues from the balancing market when valuing investment in quick responsive electrical energy storage.

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