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Abstract

Grid connected electrical energy storage could enable large numbers of intermittent renewable generators to be deployed in the UK. Many studies investigate the revenue which could be achieved through arbitrage assuming perfect foresight of electricity prices. In practice, storage operators will not have perfect foresight and will have to devise operational strategies using price forecasts. This paper investigates the impact of forecast accuracy on the optimality of storage revenue. The optimal revenue available is determined using linear programming and historic electricity prices. The results are compared to those found using dynamic programming and electricity price forecasts with increasing percentage error. A small scale lithium ion battery and a large pumped hydro energy storage (PHES) device are compared. The results show that revenue reduces at an increasing rate with increasing forecast error. The PHES device is more sensitive to forecast accuracy than the lithium ion battery. For both technologies, with a maximum error of 30%, 80% of the optimal revenue can be achieved. With increased capacity and significantly increased power rating, the lithium ion battery becomes more sensitive to price forecast accuracy.

1 Introduction

Electrical energy storage provides a potential solution to the challenge of integrating large amounts of intermittent generation to the grid. It could reduce the requirement for investment in expensive peaking plant and avoid curtailment of non-dispatchable generators. Additionally, it could reduce capital expenditure in transmission and distribution infrastructure as well as system operating costs. Strbac et al [1] have estimated that by 2050 electrical energy storage could provide savings of up to £10bn per year to the British electricity system.

With the potential value of electrical energy storage recognised, understanding the economic and market drivers for widespread storage deployment is a growing area of research. Many studies consider the revenue that could be achieved through arbitrage, i.e. taking advantage of price differentials in the wholesale electricity market. Arbitrage alone is not expected to provide sufficient revenue to storage operators. However, combined with additional services, such as delivery of ancillary services, it is likely to be an essential revenue stream.

It is common practice to assume perfect foresight of electricity prices to assess the revenue that can be achieved through arbitrage [2]. Grunewald [3] investigated the gain in revenue an operator could receive with foresight over an increasing time horizon. He showed that by increasing foresight from 1 hour to 4 hours, revenue improvements of up to 22% could be achieved. Foresight beyond 12 hours was of no additional value, as storage devices typically follow a daily cycle in line with electricity prices.

In practice, operators will not have perfect foresight and so alternative approximate optimisation methods must be used with price forecasts. Various approaches have been taken to address this. Walawalkar et al [4] assumed a fixed daily storage cycle: the device was charged overnight and discharged during the same pre-defined peak hours each day. Sioshansi et al [5] determined an optimal charging strategy using prices from the preceding two week period and applied this to the current two week period. Using this approach, approximately 85% of the optimal revenue was achieved.

Lund et al [6] and Connolly et al [7] compared different practical strategies – without foresight of electricity prices – to an optimal strategy – with perfect foresight – for compressed air energy storage (CAES) and PHES respectively. With the practical strategies implemented, CAES could achieve 80-90% of its optimum revenue. For PHES, the operator required "very accurate price predictions" to avoid a significant loss in profit. The accuracy required was not, however, quantified.

In this paper, the impact of price forecast accuracy on the optimality of storage revenue is investigated. Typical characteristics of a lithium ion battery are used as a base case. An upper bound on the revenue available through arbitrage is calculated using linear programming. This optimal solution is compared to results found using dynamic programming with notional price forecasts with increasing percentage error. The results are compared to characteristics of a large scale PHES system. The storage power capacity and energy rating are varied to investigate the sensitivity of storage size to forecast accuracy.

Electricity price processes are characterised by high volatility, large spikes, reversion to a daily pattern and seasonality as described by Amjady and Keynia [8]. Price forecasting is a broad and complex field of research in its own right. Electricity markets vary between countries depending on geographical and system specific constraints, generator types and demand profiles. Forecast accuracies depend on the electricity market being examined as well as the forecasting method being used. This paper does not attempt to compare forecasting techniques, but investigates the impact of varying forecast accuracy on the optimality of storage revenue in the British electricity market.

2 Method

Market index data defines the price, P_t (£/MWh), of electricity for each half hour settlement period, t, in the UK. It reflects the value of wholesale electricity in the short-term market.

The storage device is defined by the following characteristics:

S_{max} Storage capacity (MWh) - the total amount of electricity that can be stored by the device.

Q^C Charging rate (MW) – The maximum rate at which the storage device consumes electricity when recharging.

Q^D Discharging rate (MW) – The maximum rate at which the storage device can deliver electricity.

η_c Conversion efficiency (%) – the ratio of energy delivered to energy consumed excluding any losses due to self-discharge.

η_s Storage efficiency (%) - the percentage of electricity retained in storage over each time period.

The following assumptions are applied:

- The storage device has 100% availability.
- Storage is a price taker and its operation does not affect the market price of electricity.
- The network is a single bus system and storage is not subjected to network constraints.
- The device characteristics are constant.
- The conversion efficiency is modelled during charging only i.e. the discharge cycle is 100% efficient.
- The ramp rate is negligible compared to the time period.
- The cost of charging and discharging (in addition to the cost of electricity) is negligible.
- The interest rate is negligible over the time period considered.

From the charging and discharging rates, the maximum quantity of electricity (MWh) which can be charged, $q^C{}_{max}$, or discharged, $q^D{}_{max}$, in a single half hour time period is defined.

The decision variables for the storage operator are how much electricity to buy, $q^C{}_t$, and sell, $q^D{}_t$, during each time period. The state of charge of the storage device, S_t, is defined by Equation (1) and subject to the constraints given in Equations (2), (3) and (4).

$$S_t = \eta_s S_{t-1} + \eta_c q^C{}_t - q^D{}_t \quad (1)$$

$$0 \leq S_t \leq S_{max} \quad (2)$$

$$0 \leq q^C{}_t \leq q^C{}_{max} \quad (3)$$

$$0 \leq q^D{}_t \leq q^D{}_{max} \quad (4)$$

The objective is to maximise the annual revenue, R, which is the sum of the price multiplied by the net quantity sold during each settlement period. This is defined in Equation (5).

$$R = \Sigma P_t(q_t^D - q_t^C) \quad (5)$$

2.1 Linear Programming

Linear programming is used to calculate the upper bound on revenue that can be achieved with perfect foresight of electricity prices as demonstrated by Byrne and Silva-Monroy [9]. R^* is defined as $-R$ to formulate the problem as a standard minimisation problem with the objective defined by Equation (6), subject to the constraints in Equations (7) and (8).

Minimise $$R^* = -f^T x \quad (6)$$

Subject to $$Ax \leq b \quad (7)$$
$$lb \leq x \leq ub \quad (8)$$

where x is a vector of decision variables and f a vector of prices for each half hour period throughout the year. A is a matrix computed from the conversion and storage efficiencies and b a vector based on the maximum storage capacity. lb and ub are lower bounds and upper bounds; zero and the maximum charging/discharging rate respectively. A standard linear programming function implemented in MatLab, "linprog(*f,A,b,[],[],lb,ub*)", is used to solve the objective function and define the optimum operation strategy to maximise annual revenue.

2.2 Dynamic Programming

Dynamic programming is a technique used to solve a broad range of optimization problems, and is particularly applicable to multi stage stochastic optimization problems. It was formalised by Berteksas [10] and has since been used for a variety of applications including finance [11] [12].

Dynamic programming divides problems into a number of sub-problems and solves each sub-problem such that the overall solution is optimal to the original problem. In this work dynamic programming is used to solve the stochastic version of the problem defined in Section 2.1. Instead of perfect foresight of future electricity prices, a forecast is assumed with fixed maximum error. The objective of the dynamic programme is to generate a policy $\{q*_t^D - q*_t^C\}$, which is a set of time-dependent optimal decisions, with the objective function defined by Equation (9) and with the same constraints defined in Equations (7) and (8).

Minimise $$\mathbf{E}(R^*) = \mathbf{E}(\Sigma_t P_t(q*_t^D - q*_t^C)) \tag{9}$$

E represents the expected value with respect to the probability distribution of the electricity prices. Electricity prices are modelled as a Markov chain, i.e. the probability distribution for the prices at time t+1 depend only on the price observed at time t.

The price forecasts are artificially generated by adding a random variable with uniform distribution over an interval [-s, s] to the actual prices, where s is the maximum error of the forecast. The average error of the forecast is zero, while the absolute average error is s/2.

Further details on the dynamic programming algorithm are detailed in [13].

2.3 Data

Market price data for Great Britain is available online from the Elexon Portal [14]. For this study, the annual revenue is calculated using data from 2013. Figure 1 shows the half hourly electricity prices for the first two weeks in January 2013. This demonstrates the typical daily cycle of cheap electricity prices overnight followed by an increase in the morning and a daily peak in the evening. This cyclic pattern presents opportunities for arbitrage on a daily basis.

Characteristics for a lithium ion battery are used for this analysis. These are based on the battery system demonstrated as part of the UK Power Networks Smarter Network Storage Project [15]. This is a small scale storage device connected to the distribution network. For comparison, results are compared to a large scale PHES based on characteristics of Dinorwig [16].

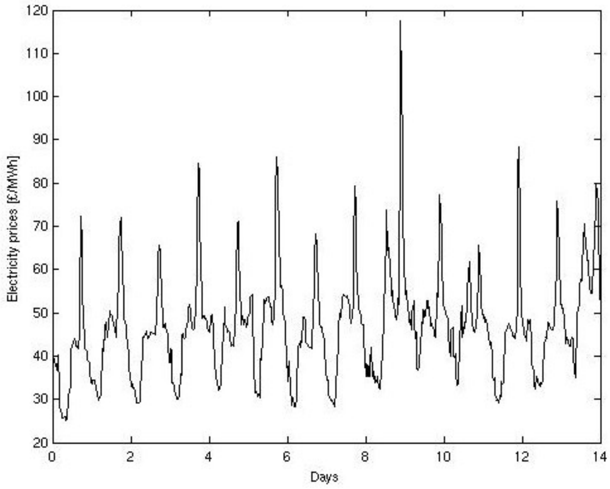

Figure 1: Electricity prices for the first two weeks in 2013

Characteristic	Lithium Ion Battery	PHES
S_{max} (MWh)	10	10100
Q^C (MW)	6	1728
Q^D (MW)	6	1728
η_c (%)	65	0.75
η_s (%)	99.5	100

Table 1: Lithium ion battery and PHES characteristics

The storage efficiency of PHES is approximated to 100%. There will, in fact, be some losses due to evaporation; however, these will be minimal compared to the size of the reservoir.

The dynamic programme is run using randomly generated forecasts with maximum errors of 1%, 2%, 5%, 10%, 20%, 30%, 40% and 50%. Ten simulations are run for each level of forecast error. The maximum percentage difference between simulations for the same error is 3%.

3 Results and Discussion

3.1 Increasing Forecast Error

For the lithium ion battery, with perfect foresight using linear programming, the optimum revenue which could be achieved based on 2013 electricity prices is £47,248. With dynamic programming, as the maximum error is increased from zero to 50%, the revenue reduces to 63.6% of the optimum. The results, shown in Figure 2, show that the revenue reduces at an increasing rate with increasing forecast error.

Hu and Taylor [17] implied that forecast errors of 10% or less could be readily realised in the short-term British electricity market. If a storage operator could achieve this level of forecast accuracy, ~98% of the optimum revenue available could be attained. Even if forecast accuracy reduces with a larger number of variable generators in the future, a significant proportion of the optimal revenue would still be available.

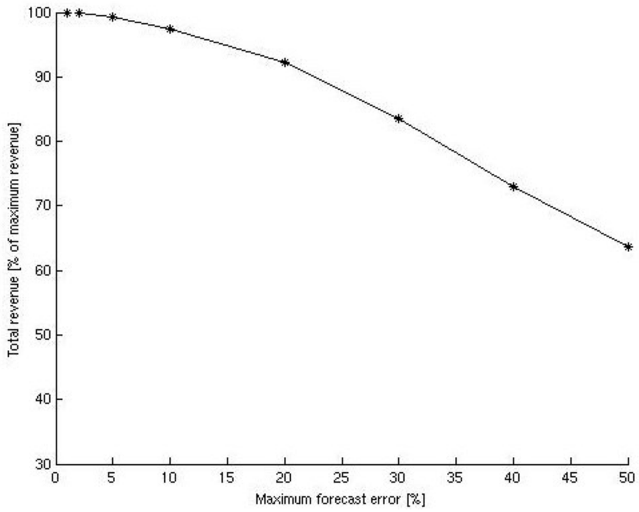

Figure 2: Loss of revenue with increasing forecast error for lithium ion battery

3.2 Large Scale Storage

For the large PHES the optimum revenue which could be achieved based on 2013 electricity prices is £50m. The optimality is more sensitive to forecast accuracy than the smaller scale battery. The results, shown in Figure 3, exhibit a similar pattern to those for the lithium ion battery, however, the revenue reduces at a faster rate as the forecast error increases. As the maximum error is increased from zero to 50%, the revenue reduces to 56% of the optimum. To maintain 98% of the optimum revenue, the forecast error must be within 5%. The optimum revenue available to the PHES operator is significantly higher than that available to the lithium ion battery operator, as a result of the differing scales of technology. This may imply that a lower percentage of the optimal revenue is more acceptable to the PHES operator; however, the costs for the PHES will also be significantly higher so this conclusion cannot be made without the cost information being considered which is out with the scope of this study.

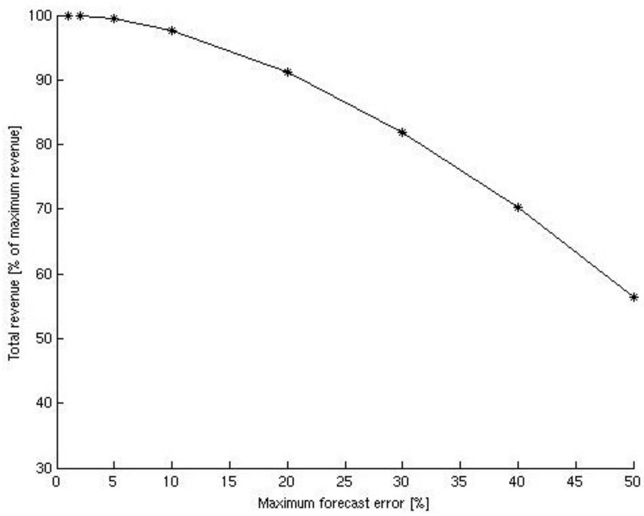

Figure 3: Loss of revenue with increasing forecast error for PHES

3.3 Variation in Storage Capacity and Power Rating

The simulations are repeated using the characteristics for the lithium ion battery, with increased storage capacity. The results are shown in Figure 4.

The optimal revenue available for storage devices with 10MWh, 15MWh and 20MWh capacities is £47,248, £57,322 and £61,503 respectively. The results show that for increased storage capacity, but fixed power rating, the device is more sensitive to price forecast accuracy.

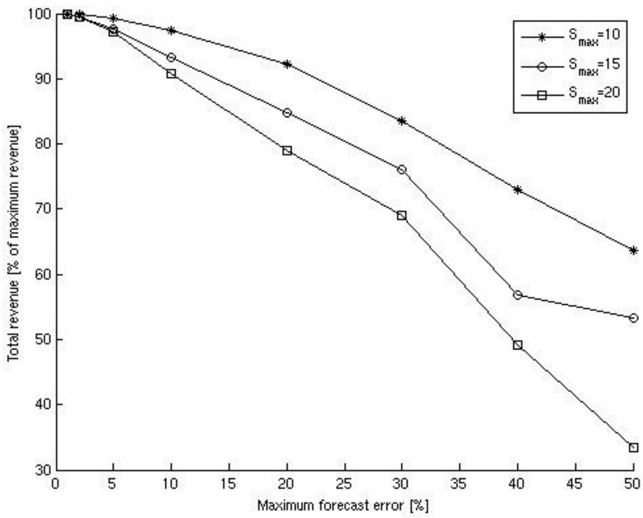

Figure 4: Loss of revenue with increasing forecast error for lithium ion battery with variation in storage capacity

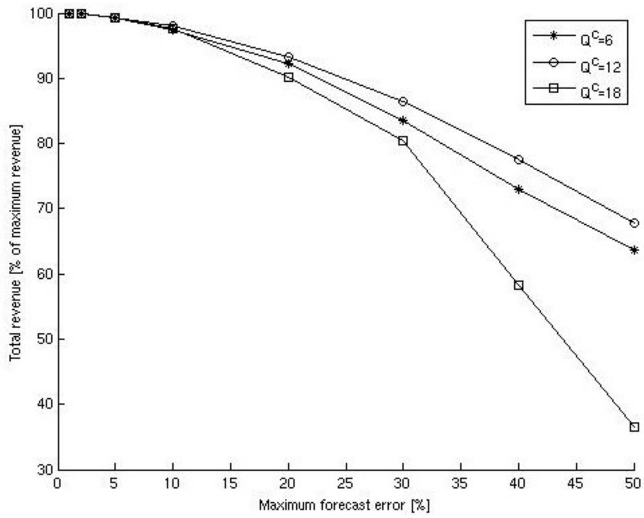

Figure 5: Loss of revenue with increasing forecast error for lithium ion battery with variation in power rating

Figure 5 shows the results using the characteristics for the lithium ion battery with fixed storage capacity but varying power rating. The optimal revenue available for storage devices with 6MW, 12MW and 18MW power ratings is £47,248, £56,772 and £60,331 respectively. The results indicate that the different power ratings have differing sensitivities to the accuracy of the forecast. Doubling the power rating leads to a small improvement, however, the revenue decreases significantly when tripling the power rating. This suggests the presence of an optimal threshold for the least sensitive power rating.

5 Conclusions

Grid connected electrical energy storage could enable a significant number of intermittent renewable generators to be connected to the electricity grid. There is a need to understand the economic case for energy storage to determine how it may be deployed in the future. One way in which storage operators can gain revenue is through price arbitrage, or time-shifting of energy. Many studies have calculated the expected revenue which could be achieved with perfect foresight of electricity prices. In practice, storage operators will not have perfect foresight and must devise operating strategies based on electricity price forecasts. Inevitably, this will lead to a reduction in projected revenue. This paper investigates the impact of price forecast accuracy on the optimality of storage revenue.

The optimal storage revenue is determined using linear programming with historical electricity prices to model a situation where perfect foresight is available. A practical strategy is then implemented, without perfect foresight, using dynamic programming and notional price forecasts with increasing percentage error. Storage characteristics of a lithium ion battery and a large scale PHES device are investigated using price data from the British wholesale electricity market from 2013.

For the technologies investigated, the optimality of storage revenue reduced at an increasing rate as the forecast error increased. The PHES device was more sensitive to forecast error that the smaller scale lithium ion battery. For both technologies, with a maximum error of 30%, 80% of the optimal revenue was achieved. These levels of forecast accuracy can be readily realised for the short term UK market. With increased storage capacity and significantly increased power rating, the lithium ion battery was more sensitive to forecast error.

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References

[1] G. Strbac, M. Aunedi, D. Pudjianto, P. Djapic, F. Teng, A. Sturt, D. Jackravut, R. Sansom, V. Yufit, N. Brandon. "Strategic Assessment of the Role and Value of Energy Storage Systems in the UK Low Carbon Energy Future", *Energy Futures Lab, Imperial College London*, Report for the Carbon Trust, (2012).

[2] E. Barbour, I. A. Wilson, I. G. Bryden, P. G. McGregor, P. A. Mulheran, P. J. Hall. "Towards an objective method to compare energy storage technologies: development and validation of a model to determine the upper boundary of revenue available from electrical price arbitrage", *Energy and Environmental Science*, **5**, pp. 5425-5436, (2012).

[3] P. Grunewald. "The Role of Electricity Storage in Low Carbon Energy Systems: Techno-economic Drivers and Transitional Barriers", *PhD Thesis*, Imperial College London, Centre for Energy Policy and Technology Faculty of Natural Sciences, (2012).

[4] R. Walawalkar, J. Apt, R. Mancini. "Economics of electric energy storage for energy arbitrage and regulation in New York", *Energy Policy*, **35**, pp. 2558-2568, (2007).

[5] R. Sioshansi, P. Denholm, T. Jenkin, J. Weiss. "Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects", *Energy Economics*, **31**, pp. 269-277, (2009).

[6] H. Lund, G. Salgi, B. Elmegaard, A. N. Andersen. "Optimal operation strategies of compressed air energy storage (CAES) on electricity spot markets with fluctuating prices", *Applied Thermal Engineering*, **29**, pp. 799-806, (2009).

[7] D. Connolly, H. Lund, P. Finn, B. V. Mathiesen, M. Leahy. "Practical operation strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage", *Energy Policy*, **39**, pp. 4189-4196, (2011).

[8] N. Amjady, F. Keynia. "Day ahead price forecasting of electricity markets by a mixed data model and hybrid forecast method", *International Journal of Electrical Power & Energy Systems*, **30(9)**, pp. 533-546, (2008).

[9] R. H. Byrne, C. A. Silva-Monroy. "Estimating the Maximum Potential Revenue for Grid Connected Electricity Storage: Arbitrage and Regulation", *Sandia National Laboratories*, Study for the DOE Energy Storage Systems Programme, (2012).

[10] D. P. Bertsekas. "Dynamic programming and stochastic control." *Mathematics in science and engineering,* (1976).

[11] H. Ben-Ameur, M. Breton, P. L'Ecuyer, L. Karoui. "A dynamic programming approach for pricing options embedded in bonds", *Journal of Economic Dynamics and Control,* **31**, pp. 2212-2233, (2007).

[12] C. Lui, H. Song, J. Lawarree, R. Dahlgren. "New methods for electric energy contract decision making." *Electric Utility Deregulation and Restructuring and Power Technologies, International Conference Proceedings.* pp. 125-129, (2000).

[13] D. P. Bertsekas. "Dynamic programming and optimal control Vol. 1. No. 2", *Belmont, MA: Athena Scientific,* (1995).

[14] ELEXON Portal, "Market Index Price and Volume", https://www.elexonportal.co.uk/article/view/188?cachebust=t52ukg8hiq, accessed 22/04/2014.

[15] UK Power Networks. "Smarter Network Storage", http://innovation.ukpowernetworks.co.uk/innovation/en/

Projects/tier-2-projects/Smarter-Network-Storage-(SNS)/Project-Documents/Smarter-Network-Strorage-Brochure-Oct+2013.pdf, accessed 22/04/2014.

[16] Electric Mountain, "Dinorwig Power Station", http://www.electricmountain.co.uk/en-GB/Dinorwig, accessed 22/04/2014.

[17] L. Hu, G. Taylor. "A Novel Hybrid Technique for Short-Term Electricity Price Forecasting in UK Electricity Markets", *Journal of International Council on Electrical Engineering,* **4(2)**, pp. 114-120, (2014).