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Simulating price-aware electricity storage without linear optimisation

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ABSTRACT

Electricity storage could prove essential for highly-renewable power systems, but the ability to model its operation and impacts is limited with current techniques. Studies based on historic market prices or other fixed price time-series are commonplace, but cannot account for the impacts of storage on prices, and thus overestimate utilisation and profits. Power systems models which minimise total system cost cannot model the economic dispatch of storage based on market prices, and thus cannot consider large aggregators of storage devices who are not perfectly competitive.

We demonstrate new algorithms which calculate the profit-maximising dispatch of storage accounting for its price effects, using simple functional programming. These are technology agnostic, and can consider short-term battery storage through to inter-seasonal chemical storage (e.g. power-to-gas). The models consider both competitive and monopolistic operators, and require 1–10 s to dispatch GWs of storage over one year.

Using a case study of the British power system, we show that failure to model price effects leads to material errors in profits and utilisation with capacities above 100 MW in a ~50 G W system. We simulate up to 10 GW of storage, showing dramatically different outcomes based on ownership. Compared to a perfectly competitive market, a monopolistic owner would restrict storage utilisation by 30% to increase profits by 85%, thus reducing its benefit to society via smoothing demand and output from intermittent renewables by 20%.

1. Introduction

"Energy storage is like bacon: It makes everything better" [1]. It offers the potential of 'baseload renewables' by managing their intermittent output, and of hyper-flexible large thermal generators so that even nuclear reactors could match variable demand. This could revolutionise grid management, facilitate deeper decarbonisation and significantly reduce the requirement for fossil fuels to provide flexibility. Electricity storage is therefore considered one of the most important issues within the energy industry [2], with "the potential to dictate the pace and the scale of the energy transition". It is one of the necessary foundations for clean energy according to the Global Apollo Programme Report [3] and Bill Gates's Breakthrough Energy deem low-cost storage to be "transformational" [4].

Realising the potential of storage requires continued technological development and cost reductions, and for sufficient revenue to exist from providing bulk energy arbitrage to justify the large-scale investments required. As with any emergent, disruptive technology, the modes in which storage will be operated, their effects on the wider electricity system and their potential profitability are all uncertain. It falls to the modelling community to offer quantitative insights into these issues and the wider implications for the electricity and energy sectors.

The main purpose of this paper is to present a new method for including bulk electrical energy storage (EES) in electricity market models without the need for an optimisation framework. The presented algorithm derives an optimal dispatch schedule that maximises profits for storage owners taking account of price-effects; that is, it includes the impact that deploying large amounts of storage has on system price, due to the dispatch of other generators. The approach can be applied within any market model formulation that produces a time-series of wholesale prices. In this paper, the algorithm is coupled with a simple merit order stack (MOS) pricing model, resulting in extremely fast calculation times, allowing rapid testing of the storage algorithm across a wide scenario-space. We illustrate our description of this new approach with a demonstration of the model on the British power system.

We present two variants of the algorithm, corresponding to two extremes of storage market behaviour: perfect competition (i.e. an atomistic market comprising many small merchant storage operators) and perfect monopoly (i.e. a market in which a single large utility owner or technology aggregator can exert market power). In the case of perfect competition the optimised dispatch maximises the utilisation of

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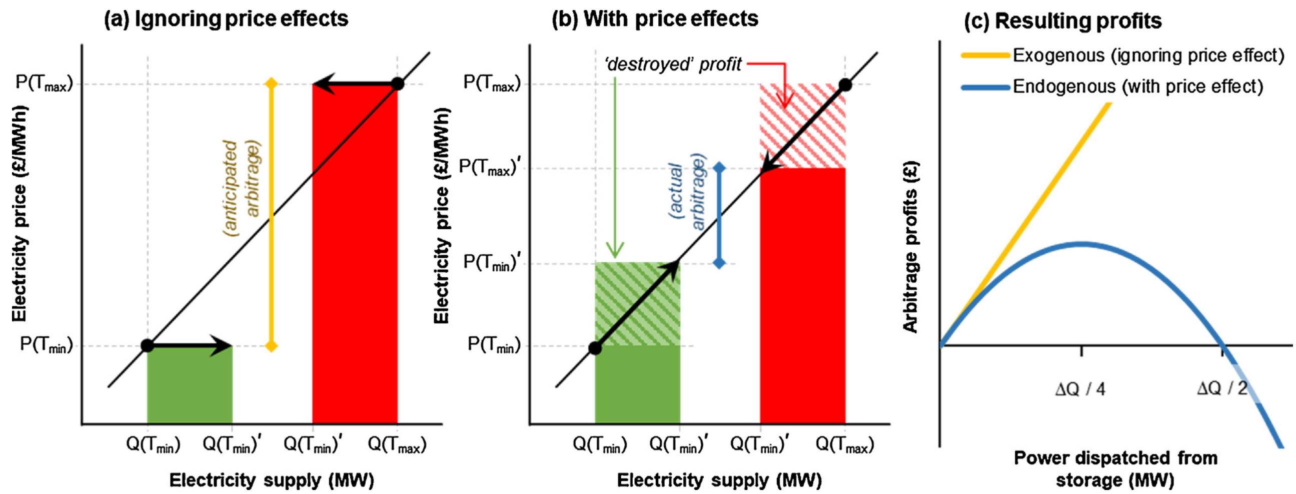

Fig. 1. Schematic of the impact storage dispatch has on electricity prices and demand and thus on arbitrage revenue. Panels a and b show electricity price against the power dispatched from storage charging (short bar) and discharging (tall bar). $Q(T_{min})$ and $Q(T_{max})$ denote the electricity supplied in the absence of storage at two times, T_{min} and T_{max}, while $Q(T_{min})$' and $Q(T_{max})$' denote how the supply from non-storage sources alters once storage is included. Panel c visualises how profits vary with the power supplied from storage, where $\Delta Q = Q(T_{max}) - Q(T_{min})$. A negative profit indicates that more money was spent charging the storage device than was obtained discharging it – i.e. a loss was made.

available storage and thereby achieving also maximum smoothing of national net demand and societal benefit. In the case of a market monopoly, the optimised dispatch maximises the operator's profits by restricting the utilisation of storage.

The remainder of the paper is set out as follows. Section 2 provides background on how the impact of storage on prices and how storage dispatch is modelled. Section 3 describes the algorithms we develop and the simple electricity market model we use to demonstrate them. The results in Section 4 explore the differences between the algorithms in terms of storage owners' profits, storage utilisation, dispatch patterns and influence on smoothing demand; and explore the trade-off between speed and accuracy that can be obtained with the algorithms. Section 5 discusses the implications for energy systems modellers and policy-makers, and concludes.

In the interests of promoting transparent and reproducible science, the storage algorithms and their implementation in an exemplary electricity market model are released open source, in the form of Visual Basic code and an Excel spreadsheet model. Their generic nature should allow them to be easily reinterpreted into other languages.

2. Background

Storage of electrical energy has many potential revenue sources [5–7]:

- earning profits either from arbitrage or in the ancillary markets;
- integration with existing infrastructure to reduce balancing costs;
- time-shifting delivery or managing constraints for demand centres (to reduce network service charges and peak demands); or
- deferring costly upgrades to transmission and distribution systems.

The most commonly studied revenue source is arbitrage, which unlike the other sources mentioned, exists and may be quantified solely through electricity price spreads within the market. Other revenue sources are linked to the precise set-up and compensation policies within specific markets. In this work we focus exclusively on arbitrage revenues.

A storage device discharging at peak time reduces the need for generation from the most expensive generators on the system, potentially reducing prices. Conversely, when storage is recharged, system demand is increased and prices should rise. In reality, this narrowing of the price differential means that the revenue from selling stored electricity is lower, the cost of recharging is higher, and thus the profits from arbitrage are lower than would be expected based on the prices that are observed without that storage. These so-called 'price effects' become significant as the amount of storage within a system grows [8].

It is common within the storage literature to model the profits of storage based on a fixed time-series of prices, either emerging from historic markets or based on future simulations [9–13]. Such studies commonly refer to situations in which price effects are neglected as the storage being a 'price-taker'. This is incorrect and may lead to confusion. To economists, the price-taker/price-maker terminology refers to the behaviour of individual firms within a market and their ability (or otherwise) to influence prices due to the levels of competition with the market. Specifically, a price-taker is a storage operator which is too small to move prices by itself, but still takes account of the effect that the overall fleet of storage devices has on prices. It would be more accurate to refer to storage dispatch models in which price effects are neglected as having exogenous pricing (i.e. prices are determined externally), and those that include price effects as having endogenous pricing (i.e. storage is part of the price formation process).

As we discuss both price-effects and competition in this paper, we refer to exogenous pricing (commonly referred to as price-taker) as a 'fixed-price' approach; endogenous pricing with price-taker firms as a 'competitive' approach; and endogenous pricing with price-maker firms as a 'monopolistic' approach.

2.1. The price effects of dispatching storage

The issue of price effects only becomes important once the amount of storage capacity within a market is sufficient to cause significant changes in price. Fig. 1 demonstrates this for a simple case with linear electricity supply curve (diagonal line in panel 1a and 1b). Thick arrows show the impact of storage: in panel a, charge and discharge have no effect on prices while in panel b the sloping supply curve is taken into account. The difference between the area of the solid red and solid green bars signifies the profit made from arbitrage, the hatched areas in panel b show the profit that is lost by storage influencing prices. This creates the difference between the realised profits shown by the two lines in panel c.

The profits shown in Fig. 1a and in the exogenous line of 1c cannot be obtained in the real world, but these are what a naive fixed-price algorithm would anticipate as greater amounts of storage are dispatched. The economic reality is shown in Fig. 1b and the blue line of

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