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Improving optimal control of grid-connected lithium-ion batteries through more accurate battery and degradation modelling

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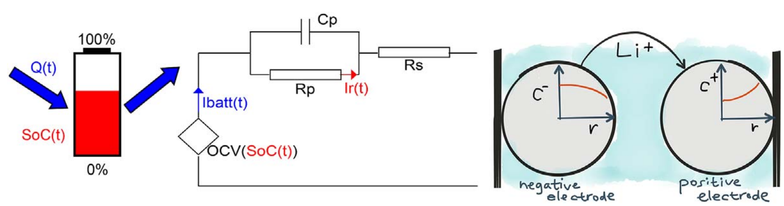
HIGHLIGHTS

- Optimal control techniques for long term optimisation of the single particle model.
- Assessment of the accuracy of three approaches to battery degradation modelling.
- Economic optimisation for electricity trading with three different battery models.
- Increased profit by 175% through 13% higher revenue and 73% lower degradation.

GRAPHICAL ABSTRACT



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ABSTRACT

The increased deployment of intermittent renewable energy generators opens up opportunities for grid-connected energy storage. Batteries offer significant flexibility but are relatively expensive at present. Battery lifetime is a key factor in the business case, and it depends on usage, but most techno-economic analyses do not account for this. For the first time, this paper quantifies the annual benefits of grid-connected batteries including realistic physical dynamics and nonlinear electrochemical degradation. Three lithium-ion battery models of increasing realism are formulated, and the predicted degradation of each is compared with a large-scale experimental degradation data set (Mat4Bat). A respective improvement in RMS capacity prediction error from 11% to 5% is found by increasing the model accuracy. The three models are then used within an optimal control algorithm to perform price arbitrage over one year, including degradation. Results show that the revenue can be increased substantially while degradation can be reduced by using more realistic models. The estimated best case profit using a sophisticated model is a 175% improvement compared with the simplest model. This illustrates that using a simplistic battery model in a techno-economic assessment of grid-connected batteries might substantially underestimate the business case and lead to erroneous conclusions.

1. Introduction

Challenges for the electricity system arise due to increasing deployment of intermittent renewable energy sources [1]. For example, balancing production and demand becomes more difficult, grid inertia decreases, and distribution grids become more congested. As part of a broad portfolio of possible solutions, battery energy storage provides a flexible option to address many of these problems. However, the

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lifetime of a battery in terms of capacity and power capability strongly impacts the profitability of battery storage [2]. The lifetime of a lithium-ion (li-ion) battery depends on how it is used because there are multiple degradation mechanisms, each influenced by different usage patterns [3].

Many previous economic assessments of storage have included a battery degradation model, usually an empirical correlation based on fitting of measured degradation tests e.g. Refs. [2,4–6]. Although empirical models can provide valuable insight, they should be used with caution [7,8]. They are based on a limited number of test conditions and do not necessarily apply to other load profiles, risking extrapolation without theoretical basis. Furthermore, battery characteristics change as batteries age, which is often not taken into account. Finally, empirical models only apply to the exact type of cell for which they have been developed.

A few researchers have used electrochemical models to address these issues, and initial results are promising: a more intelligent battery utilisation informed by a physical model could decrease battery degradation. Lawder et al. [10] compared battery models for a simple micro-grid application (ignoring degradation) and noted how accumulated errors in equivalent circuit battery models led to substantial discrepancies between the simulated and real state of charge (SoC). Multiple researchers, e.g. Refs. [11,12], used electrochemical battery models to optimise charging profiles, increasing battery life. Others have used electrochemical battery degradation models without optimisation to analyse specific case studies [9,13,14].

These cases studies showed the potential for using electrochemical battery models to improve the lifetime and therefore the economic impact of grid-connected batteries. However, to our best knowledge, due to the complexity of these nonlinear battery models, they have not been used for optimisation over a long time horizon (e.g. a year), yet this is required to truly quantify their performance. Therefore, this paper aims to identify the economic performance gains achievable by using a nonlinear, electrochemical battery model, including realistic dynamics and degradation, in an economic optimisation for a realistic grid application over a full year of data.

2. Nomenclature

α	Degradation parameter in equivalent circuit model	
β	Degradation parameter in equivalent circuit model	
$\lambda(t)$	Wholesale electricity price at time t	€ (Wh)$^{-1}$
$\lambda_{\text{degr,Wh}}$	Cost of battery energy degradation	€ (Wh)$^{-1}$
$\lambda_{\text{degr,Ah}}$	Cost of battery charge degradation	€ (Ah)$^{-1}$
$\lambda_{\text{degr,LLI}}$	Cost of lost cyclable lithium	€ (Ah)$^{-1}$
C	Battery degradation cost	€
C_p	Parallel capacitor in equivalent circuit model	F
$c_i(r, t)$	Lithium concentration in electrode i at radius r and time t in single particle model	mol m^{-3}
$c_i^{\max}$	Maximum lithium concentration in electrode i	mol m^{-3}
E_{Wh}	Battery energy capacity	Wh
E_{Ah}	Battery charge capacity	Ah
$E_{\text{lost,Wh}}$	Lost battery energy capacity	Wh
$E_{\text{lost,Wh}}$	Lost battery charge capacity	Ah
f	Battery state space model	
g	Constraint function	
$I(t)$	Battery current at time t	A
$I_r(t)$	Current through the parallel resistor in the equivalent circuit model at time t	A
$L(T_{\text{end}})$	Lost cyclable lithium at the end of the simulation time	Ah
N	Number of cells in the battery	–
OCV	Open circuit voltage in the equivalent circuit model	V
$P(t)$	Power to/from the battery at time t	W
R	Revenue per unit of time	€ h^{-1}
R_p	Parallel resistor in the equivalent circuit model	Ω
R_s	Series resistor in the equivalent circuit model	Ω
T_{end}	Total simulation time	h
$u(t)$	Control variables at time t	
$u_n(t)$	Control variables in optimisation n at time t	
$U^{\text{opt}}(t)$	Optimal control variables at time t	
$U_n^{\text{opt}}(t)$	Optimal control variables in optimisation n at time t	
$V(t)$	Battery voltage at time t	V
V_{mean}	Mean battery voltage	V
$x(t)$	State variables at time t	
$x_n(t)$	State variables at time t in optimisation n	
$z(t)$	State of charge at time t	–

3. Methods

3.1. Problem setup

In this simulation study, a lithium-ion battery was used for price arbitrage. In other words, revenue was made by buying energy on the wholesale market when prices were low, charging the battery, and then selling energy on the market at higher prices at a later point, discharging the battery. However, usage of the battery also resulted in capacity fade. The task of a battery operator who wishes to exploit this market is to identify a load profile which maximises revenue and minimises lost capacity. For price data we used the wholesale price of the Belgian day-ahead electricity market in 2014, shown in Fig. 1, where the colour indicates the price at each hour (y-axis) of each day (x-axis). The price was assumed to be known perfectly, leading to a deterministic optimisation problem, described below.

A generic optimal control formulation was used to describe this problem mathematically (1–3). The revenue per unit of time R and the degradation cost C are both a function of the control variable $u(t)$ and the state variable $x(t)$. A state-space model f for the battery relates the state variables to the control variables and initial states. Depending on the battery state space model, a different physical meaning is given to the control and state variables. Other constraints such as the voltage limits of the battery, were incorporated into the constraint function g.

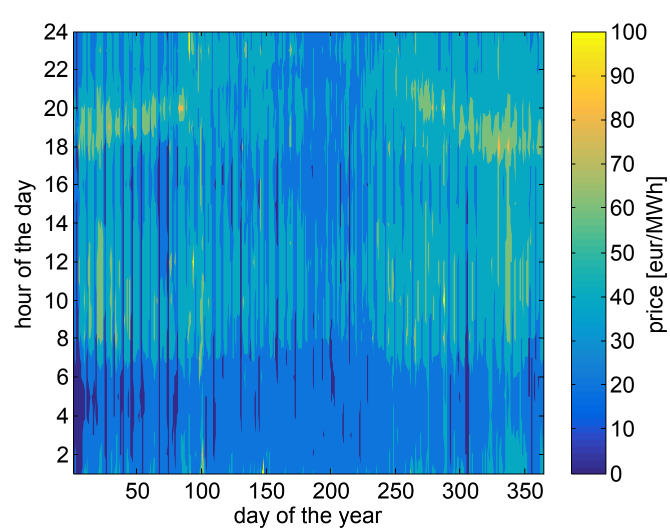

Fig. 1. Wholesale price on the day-ahead market in Belgium in 2014 [15].