TECHNO-ECONOMICAL AND LIFE EXPECTANCY MODELING OF BATTERY ENERGY STORAGE SYSTEMS

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ABSTRACT

A techno-economical model for battery energy storage systems is presented. The model determines the costs of delivered services while considering technical constraints. An estimation of battery life expectancy is used to incorporate depreciation costs. A multi-objective optimization technique is used to determine the trade-off between the quality of the delivered service and its economic cost. The effectiveness of the model is demonstrated through a specific case study where a trade-off curve between peak shaving and incurred cost is determined for a storage setup in a residential household with photo voltaics.

LIST OF SYMBOLS

Δt	[h]	Time step
n_t, n_d	[-]	Number of steps / days
$\boldsymbol{G}$	[kW]	Generation profile ($n_t \times 1$)
$\boldsymbol{L}$	[kW]	Load profile ($n_t \times 1$)
$\boldsymbol{M}$	[€/kWh]	Market profile ($n_t \times 1$)
$\boldsymbol{E}$	[kWh]	Battery Energy profile ($n_t \times 1$)
$\boldsymbol{P_c}, \boldsymbol{P_d}$	[kW]	Charge / discharge power profile ($n_t \times 1$)
α_{DOD}	[-]	DOD window width
E_{max}	[kWh]	Nominal battery capacity
$P_{c,max}$ $P_{d,max}$	[kW]	Maximum charge / discharge power
η_{in}, η_{out}	[-]	PE efficiency to / from battery
η_c	[-]	Battery charge efficiency
δ_{sb}	[-]	Self-discharge energy loss
K^{tot}	[€/y]	Total cost
K^{fix}, K^{var}	[€/y]	Fixed / variable cost
K^{depr}	[€/y]	Depreciation cost
c^{bat}	[€/kWh]	Specific battery cost
τ^{bat}	[y]	Battery shelf-life
$LET(\alpha_{DOD})$	[kWh]	Lifetime Energy Throughput
$\boldsymbol{L_p}$	[kW]	Daily peak power ($n_d \times 1$)
L_p^{RMS}	[kW]	Daily peak RMS index
n_{cycl}	[#/y]	Number of charge cycles
n_{repl}	[#/y]	Number of battery replacements
$E_{tot,in}$	[kWh/y]	Total BESS energy input
E_{loss}	[kWh/y]	Total loss due to efficiency

INTRODUCTION

Recently, there has been an increasing interest in Battery Energy Storage Systems (BESS) for grid applications [1,2]. A BESS typically consists of a power electronic (PE) grid coupling interface, batteries and a control system to steer power flows. BESS can be used to mitigate the consequences of integrating renewable energy sources into the grid, for example, by providing peak shaving or voltage control services [3].
This paper proposes a techno-economical model for BESS applications, following the layered structure shown in Figure 1. The goal of this model is to compare different technologies and to analyse the benefits of BESS over a long period of time (years). The core elements are the BESS model, the load model and the market model. These models, which operate on a time-scale of minutes, are combined with a long-term control strategy (hours, days). The control strategy is considered as a part of the model because BESS depreciation costs are highly dependent on cycling, which in turn depends on the chosen control strategy. This control strategy involves a trade-off between the technical services provided and their associated economic costs. Multi-objective optimization techniques are used to generate a curve for this trade-off. The actual control strategy is an operating point on this curve.

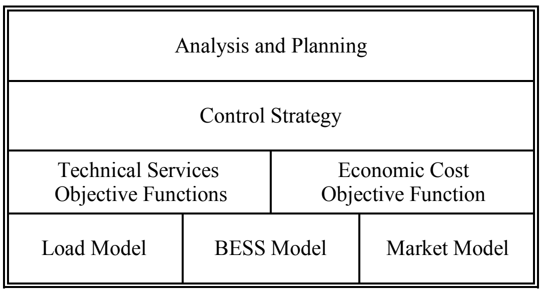

Figure 1: Layered model structure

The BESS model makes abstraction of hardware implementation details and short-term hardware control algorithms (seconds time-scale) and is applicable for different battery technologies. The BESS model in this paper is partially based on the results of [1, 4], where cost models are presented to calculate the revenues provided by grid services.
The proposed model is applied to a case study where peak shaving is performed for a typical Belgian household with a rooftop PV installation. Costs are calculated with a variable pricing scheme for residential electricity and will be compared for lead-acid and Li-ion battery technologies.

BESS TECHNO-ECONOMICAL MODEL

Technical model

$$\begin{gathered} E_n = E_{n-1} - \delta_{sb} E_{max} - \eta_c \eta_{in} P_{c,n} \Delta t - \frac{P_{d,n}}{\eta_{out}} \Delta t \\ (1-\alpha_{DOD}) E_{max}^{bat} \le \boldsymbol{E} \le E_{max}^{bat} \\ 0 \le \boldsymbol{P}_d \le P_{d,max}^{PE} \\ -P_{c,max}^{PE} \le \boldsymbol{P}_c \le 0 \end{gathered} \quad (1)$$

The technical part of the proposed BESS model consists of the dynamic state of charge equation and a set of battery parameter constraints, displayed in equation (1). Charge, discharge and power electronic efficiencies as well as self-discharge are taken into account. The usable range of the battery energy content $\boldsymbol{E}$ is limited by the Depth Of Discharge (DOD) limitation parameter α_{DOD}.

Economic model

Cost calculations are divided into fixed and variable costs.

$$K^{tot} = K^{fix} + K^{var} \quad (2)$$

The fixed costs cover capital costs, maintenance costs and depreciation costs of the power electronics and peripherals. The variable costs comprise energy costs and the depreciation cost of the battery.

$$K^{var} = K^{depr} + \boldsymbol{M}^T(\boldsymbol{P}_c + \boldsymbol{P}_d)\Delta t \quad (3)$$

Energy costs are calculated with a market price $\boldsymbol{M}$, which can be a variable time profile. The depreciation cost depends on the battery lifetime, which is either limited by the shelf-life or by the cycle-life, whichever is shorter. The shelf-life is independent of battery usage. The shelf-life depreciation cost is the battery replacement cost divided by the shelf-life duration.

$$K^{depr,sl} = \frac{c^{bat} \cdot E_{max}}{\tau_{bat}} \quad (4)$$

The battery cycle-life is associated with wear due to cycling, and therefore dependent on the battery energy throughput. It is generally known that a DOD limitation can extend the lifetime of a battery [5]. Consequently, the cycle-life will also depend on this DOD limitation. This dependency is modeled as a continuous curve as a function of α_{DOD}, constructed out of the battery cycle-life parameters. The cycle-life depreciation cost is the net energy input into the battery, multiplied by the battery replacement cost divided by the Lifetime Energy Throughput $LET(\alpha_{DOD})$.

$$K^{depr,cl} = \frac{c^{bat} \cdot E_{max}}{LET(\alpha_{DOD})} \Delta t \cdot \eta_c \cdot \eta_{in} \cdot \sum_{i=1}^{n_t} P_{c,n} \quad (5)$$

Table 1: Load and PV profile indicators

	Household	PV
Nominal power	9.2 kW (40A)	2.8 kW
Peak power	6.8 kW	2.5 kW
Base power	0.180 kW	-
Year total energy	3266 kWh	2296 kWh

CASE STUDY DATA

Load and injection profiles

The household load profile $\boldsymbol{L}$ is not synthetic, but measured during 2008 by a Flemish DSO. The yearly electricity consumption is typical for a Belgian household. The PV injection data $\boldsymbol{G}$ was measured at a PV installation on the roof of the K.U.Leuven electrotechnical department, also in 2008. Relevant profile indicators are shown in Table 1. The base power is defined as the 90% value of the load duration curve. Both profiles have a 15 minute resolution and one year duration.

Electricity pricing

Since the cost of electricity production is a function of time, customized pricing schemes could be deployed for consumers when smart meters become universal in a few years. In this case study, a variable pricing scheme is used, calculated from Belpex spot market 2008 historical data [6]. The average is rescaled to the rates of the cheapest single tariff residential electricity product as provided by the Flemish regulator's retailer comparison tool [7]. At the time of writing, this value is 0.18 €/kWh.

Table 2: BESS parameters

	Pb AGM	Li-ion
τ^{bat}	10 years	10 years
Cycle-life (80%)	400 cycles	3000 cycles
η_{in}	95%	95%
η_{out}	98%	98%
η_c	80%	90%
Self-discharge	5% per month	3% per month
Charge time	3 h	1 h
Discharge time	1 h	0.5 h
c^{bat}	250 €/kWh	1000 €/kWh
PE cost	230 €/kW	500 €/kW
E_{max}	3 kWh	1.5 kWh
α_{DOD}	80%	80%

Parameters

Lead-acid absorbed glass mat (Pb AGM) batteries are compared with Li-ion batteries. Parameters for both technologies are listed in Table 2. Lead-acid AGM has a low cost in terms of storage capacity, but efficiency, charging and discharging rates are inferior to Li-ion. The charging efficiency is considered independent of charging power and state of charge.

CASE STUDY OBJECTIVE FUNCTIONS

Cost optimization: arbitrage

Fundamentally, the arbitrage strategy on this energy market boils down to "buy low, sell high". For such an operation to make financial sense, the price difference must also negate the depreciation cost and the cost of the energy losses due to the non-unity round-trip efficiency of a charge-discharge cycle. The arbitrage optimization is a linear programming problem that minimizes variable costs, subject to the technical battery model of equation (1).

$$K_{min}^{var} = \min_{\boldsymbol{E},\boldsymbol{P_c},\boldsymbol{P_d},K_{depr}} K^{depr} + \boldsymbol{M}^T(\boldsymbol{P_c} + \boldsymbol{P_d})\Delta t$$

Subject to equation (1) and: (6)

$$K^{depr} \geq K^{depr,sl}$$
$$K^{depr} \geq K^{depr,cl}$$

In this problem, the depreciation cost is also a variable which is constrained by equations (4) and (5).

Peak shaving

Peak shaving will be applied to the net $(L + G)$ power exchange with the electricity grid, for both positive (load) and negative (injection) peaks. The net profile after peak shaving will be $L + G - P_c - P_d$. The total consumed energy is higher when a BESS is present, due to cycling losses. The peak shaving optimization is a quadratic optimization problem that minimizes a peak shaving index L_p^{RMS}, which is proposed in this research as the root mean square of the daily peaks (L_p) in the net power profile.

$$L_{p,min}^{RMS} = \min_{\boldsymbol{E},\boldsymbol{P_c},\boldsymbol{P_d},L_p} \sqrt{\frac{\boldsymbol{L}_p^T\boldsymbol{L}_p}{n_d}}$$

Subject to equation (1) and: (7)

$$I_{td}\boldsymbol{L}_p \geq \boldsymbol{L} + \boldsymbol{G} - \boldsymbol{P_c} - \boldsymbol{P_d}$$
$$I_{td}\boldsymbol{L}_p \geq -\boldsymbol{L} - \boldsymbol{G} + \boldsymbol{P_c} + \boldsymbol{P_d}$$

The matrix I_{td} has ones in the appropriate positions to transform the daily peak $\boldsymbol{L_p}$ $(n_d \times 1)$ vector into a 15 minute based $(n_t \times 1)$ vector.

RESULTS

The results A and D in Table 3 are operating points for which only the cost objective in equation (6) is minimized. Figure 2 displays one example week profile.

Table 3: Results for operating points A-B-C (Li-ion) and D-E-F (Pb AGM).

	A	B	C	D	E	F	
K^{tot}	521	1023	617	248	827	358	€/y
L_p^{RMS}	1.83	0.55	0.68	2	0.54	0.89	kW
K^{fix}	450	450	450	213	213	213	€/y
K^{var}	71.4	573	167	34.6	614	145	€/y
K^{depr}	150	532	175	75	570	153	€/y
n_{cycl}	300	596	349	40	287	81.8	#/y
n_{repl}	0.1	0.35	0.12	0.1	0.76	0.2	#/y
$E_{tot,in}$	421	836	490	126	908	258	kWh/y
E_{loss}	68.8	242	79.9	34	247	67.7	kWh/y

The price difference needed for operating a Li-ion BESS is smaller than that of Pb AGM, this because of the higher efficiency and lower battery replacement cost to LET ratio. Consequently, A is cycled more than D: 300 vs. 40 cycles and 421 vs. 126 kWh/year throughput. Figure 2 shows that during the week, price variations in the market are large enough to cycle both, whereas in the weekend, only Li-ion is cycled.

The results B and E in Table 3 are operating points for which only the peak shaving objective in equation (7) is minimized. At about 0.55 kW, the peak shaving index (quality of the service) is similar for both technologies, but the cost of providing it is not: B costs 1023 €/year, whereas E costs 827 €/year. Although B is cycled twice as frequently, E will have to be replaced after 1.3 years, compared to 2.9 years for B.

In Figure 3, full arbitrage (D) and full peak shaving (E) for Pb AGM are compared. It is easily verified that E shaves both load and injection peaks. During the second half of the week, peak shaving nearly perfectly evens out the load. Situation D, on the other hand, creates some new peaks. Situation F combines both objectives, but this solution is a compromise: both the costs and the peak shaving index are sub-optimal. However, at the cost of only 110 €/year more than arbitrage, the peak shaving index is already reduced from 2 to 0.89 kW. Profit is

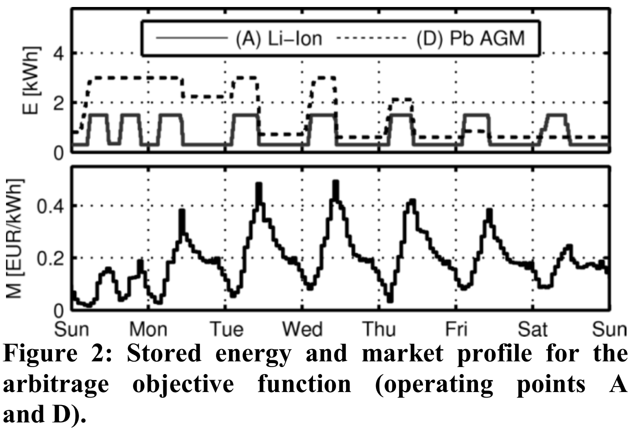

Figure 2: Stored energy and market profile for the arbitrage objective function (operating points A and D).

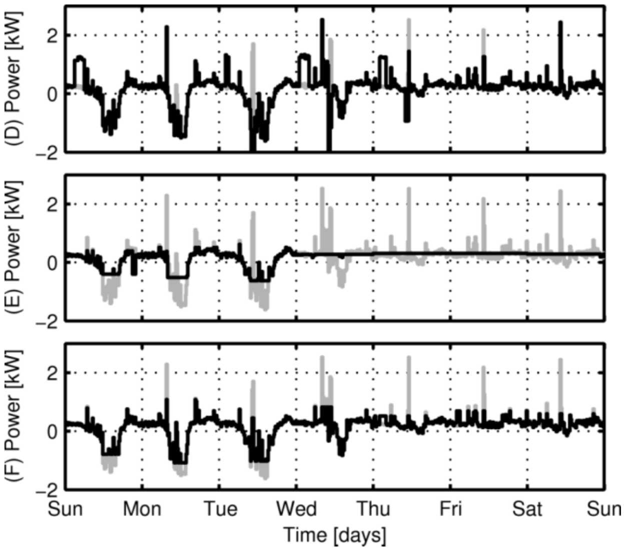

Figure 3: Stored energy and net power profiles for 3 different Pb AGM operating points D-E-F.

never attainted in any of the situations. Figure 4 visualizes the trade-offs for both technology setups. Several multi-objective algorithms exist to generate evenly spaced points on this curve. The algorithm used in this case study is the normalized normal constraint method [8]. Using the BESS for arbitrage already offers a better peak shaving index than the situation without the BESS. This is because the peak shaving objective is used to select the pareto-optimal solution in case of multiple solutions with the same optimum to the arbitrage optimization. At the same cost of owning the Li-ion BESS and not using it (peak shaving index 2 kW), trade-off point C is found, with a peak shaving index of 0.68 kW.

CONCLUSIONS

The trade-off curves generated by the proposed approach are well suited to select a control strategy to operate a BESS. The simulation model developed here, combined with grid simulation models, can be used as a basis for grid planning studies investigating the optimal combination of battery technology, storage capacity, grid connection power and control strategy to support a certain objective. Different objectives can be envisioned: e.g. integrating renewables, avoiding grid reinforcement or increasing the security of supply. The proposed simulation model shows what can be accomplished with storage, but does not tell how. It is a benchmark for control systems yet to be implemented because it needs perfect knowledge of time profiles to perform the optimization.

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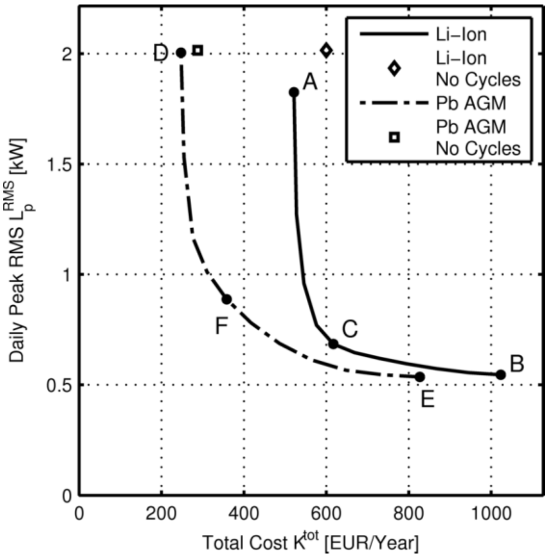

Figure 4: Calculated trade-off curves between peak shaving index and economical costs.

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