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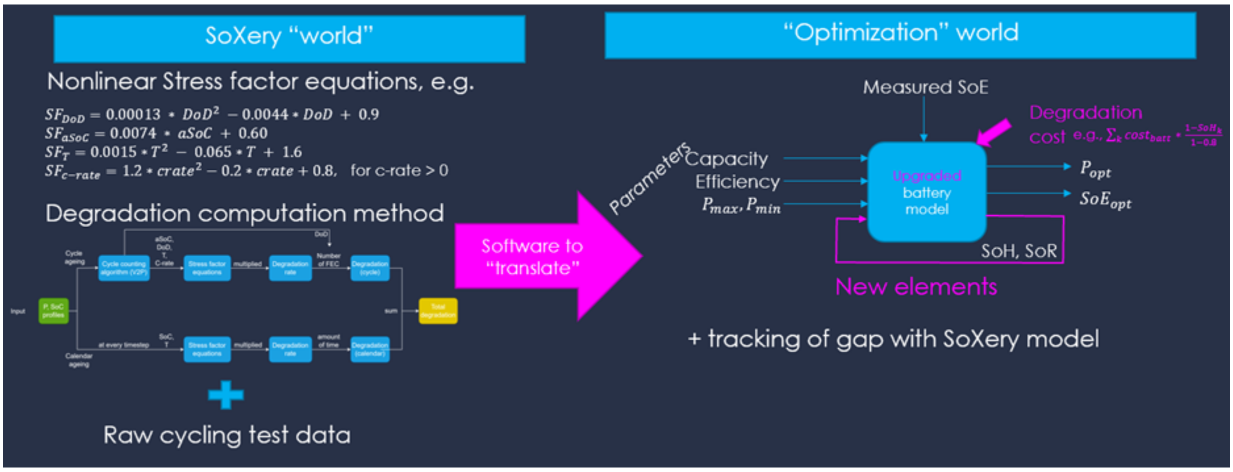
BATMAESTRO



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The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.

Zusammenfassung

Speichersysteme sind eine wichtige Voraussetzung für die Integration zunehmender Mengen erneuerbarer Energie. Für die Planung von Elektrizitätssystemen und den Betrieb elektrochemischer Speichersysteme werden Modelle benötigt, die sich für die Verwendung im Rahmen der mathematischen Optimierung eignen und die die wichtigsten Betriebsbeschränkungen von Batterien, wie etwa die Degradation, die zu einer Verringerung der verfügbaren Speicherkapazität führt, ausreichend genau erfassen. Im Rahmen dieses Projekts wurde ein Open-Source-Modell für Batterien entwickelt, das auf einem öffentlichen Simulationsmodell basiert, das durch experimentelle Daten gestützt wird. Dieses Modell ermöglicht es, mehrere Faktoren, die zur Degradation von Batterien beitragen, in Optimierungsrahmen auf der Grundlage nachvollziehbarer Daten angemessen zu berücksichtigen. Das Modell wurde einerseits durch den Nachweis von Fehlern bei der Degradationsvorhersage von weniger als 5 % über ein ganzes Jahr im Vergleich zu zuvor verfügbaren und validierten empirischen Modellen validiert. Andererseits wurde in simulierten Szenarien gezeigt, dass es zur Verbesserung der Lebensdauer und der wirtschaftlichen Leistung von Batterien in Arbitrage- und Eigenverbrauchsszenarien eingesetzt werden kann. Bei der Optimierung des Ladeprofils einer Batterie, die Arbitrage auf den Strompreisen betreibt, wurde beispielsweise festgestellt, dass die Lebensdauer der Batterie auf 12 Jahre verlängert werden kann, im Vergleich zu 5 Jahren, wenn nur die Standardlademenge und Ladezustandsgrenzen verwendet werden, was den Nettonutzen (einschließlich der jährlichen Kosten für den Batterieaustausch) von -1,2k auf +10kCHF/MWh/Jahr erhöht.

Résumé

Les systèmes de stockage constituent un outil important pour l'intégration de quantités croissantes d'énergie renouvelable. La planification du système électrique et l'exploitation des systèmes de stockage électrochimique nécessitent des modèles adaptés à l'optimisation mathématique qui saisissent avec suffisamment de précision les principales limites de fonctionnement des batteries, telles que la dégradation entraînant une réduction de la capacité de stockage disponible. Ce projet a conduit à la création d'un modèle open-source pour les batteries qui est construit sur un modèle de simulation public soutenu par des données expérimentales. Ce modèle permet de prendre en compte correctement les multiples facteurs contribuant à la dégradation des batteries dans des cadres d'optimisation basés sur des données traçables. Le modèle a été validé d'une part en démontrant des erreurs de prédiction de dégradation inférieures à 5% sur une année complète par rapport aux modèles empiriques précédemment disponibles et validés. D'autre part, il a été démontré dans des scénarios simulés qu'il peut être utilisé pour améliorer la durée de vie et les performances économiques des batteries dans des scénarios d'arbitrage et d'autoconsommation. Par exemple, lorsqu'il est utilisé pour optimiser le profil de charge d'une batterie effectuant un arbitrage sur les prix de l'électricité, il a été constaté que la durée de vie de la batterie pouvait être prolongée à 12 ans par rapport à 5 ans en utilisant uniquement le taux de charge standard et les limites de l'état de charge, ce qui porte le bénéfice net (y compris un coût annualisé pour le remplacement de la batterie) de -1,2k à +10kCHF/MWh/an.

Summary

Storage systems are an important enabler for the integration of increasing amounts of renewable energy. Electricity system planning and operation of electrochemical storage systems require models that are suitable for use within mathematical optimization that capture sufficiently accurately the main operating limitations of batteries, such as degradation resulting in a reduction of the available storage capacity. This project has led to the creation of an open-source model for batteries that is built upon a public simulation model supported by experimental data. This model allows to properly consider multiple

factors contributing to battery degradation in optimization frameworks based on traceable data. The model has been validated on the one hand by demonstrating errors in degradation prediction of less than 5% over a full year compared to previously available and validated empirical models based. On the other hand, it was demonstrated in simulated scenarios that it can be used to improve the lifetime and economic performance of batteries in arbitrage and self-consumption scenarios. For example, when utilized to optimize the charging profile of a battery performing arbitrage on electricity prices, it was found that the battery life could be extended to 12 years compared to 5 years when using only standard charging rate and state of charge limits, bringing the net benefit (including an annualized cost for battery replacement) from -1.2k to +10kCHF/MWh/year.

Contents

Abbreviations

SoC	State of charge
SoH	State of health
EoL	End of life
SoR	State of resistance
BESS	Battery energy storage system
MILP	Mixed-integer linear programming
SF	Stress factor
DR	Degradation rate
DoD	Depth of discharge
Crate	Charging rate

1 Introduction

1.1 Background information and current situation

Battery models are used in a wide range of applications, which require different levels of complexity and accuracy. Broadly speaking, model users include:

- Designers (of cells, battery packs, BESSs, etc) which use sophisticated, generally physics-based models.
- Planners (for entire national/regional power grids or complex energy systems/networks) which use models to run techno-economic analyses to select appropriate subsystem sizes, typically through the use of mathematical optimization of system parameters and scenario simulation (e.g., with tools such as TIMES),
- Operators (of buildings, energy systems or local grids) which choose operation strategies of energy assets. An emerging trend is the rise of the use of dynamic energy management strategies based on real-time mathematical optimization (also called predictive), to operate complex systems optimally according to some chosen criterion (e.g., cost, CO2 emission, etc.). The main advantage of this approach compared to traditional management strategy based on pre-determined operation rules, is the capacity to plan efficiently based on forecasts (of production, consumption and prices), while its drawback is the need for more computations and the availability of calibrated model to represent reality.

These applications require publicly available models of batteries that incorporate sufficient details to capture the operating limitations of batteries and phenomena such as battery degradation. The use of models in optimization contexts imposes strong limitations on the model size (# of parameters) and structure (e.g., linearity, convexity, etc.). In the context of planning, most established grid planning tools such as TIMES rely on linear models, as the underlying optimization problem is a mixed-integer linear program due to the availability of reliable solvers for this type of problem. So far, degradation is generally not considered satisfactorily: it is either disregarded, post-computed or treated in a very simplified way. In the context of operation, tools for predictive energy management (such as NRGMaestro™, see below) generally feature the same constraints of model linearity (with integer variables), although they may tolerate more complex models due to shorter optimization horizons and smaller systems under scope. In any case, considering degradation which is a highly nonlinear phenomenon requires some level of simplification.

In the frame of the IEA ES TCP Task 32 project[1], the team at CSEM has already developed and open-source empirical simulation model for battery degradation, named SoXery [1], which can be used to simulate efficiently degradation of battery incurred through cycling and calendar ageing and capture the main contributing factors to ageing (temperature, depth of discharge, average state-of-charge and C-rates). SoXery is backed by experimental data of cell cycling tests. Despite being itself simplified and very efficient for fast simulation purposes, SoXery is not directly usable in MILP optimization contexts. Additionally, CSEM has developed the predictive energy manager NRGMaestro™, which also relies on MILP optimization for the operation of energy systems and has gathered experience in operating energy systems including batteries for behind-the-meter applications.

This combined expertise will allow us to bridge the gap from the existing simulation model towards a model that properly captures degradation and is directly usable in optimization contexts.

[1] https://iea-es.org/task-32/

1.2 Purpose of the project

The project aims to design a methodology to produce optimization-compatible models that capture the impact of battery charging and discharging on its ageing. By optimization-compatible models, we assume that models are described with mixed-integer linear equations (which is the most widely used approach to optimization, see 3.1) The methodology will be backed by experimental data and adapted to different battery chemistries and characteristics in line with previous modelling efforts that led to the publication of the SoXery battery simulation models.

The main target is the publication of the new battery models on an open-source repository with documentation so that they can be integrated in operations planning oriented optimization frameworks such as NRGMaestro™, and in planning tools such as TIMES.

The research questions underpinning this work are:

- What is the model complexity required to incorporate sufficient information about degradation in optimization tools?
- To which extent an "enhanced" model of battery does help to operate batteries in ways that extend battery life.

2 Procedures and methodology

The ultimate objective of the project is to derive, validate and disseminate a battery ageing model that can be described fully with mixed-integer linear equations and possesses could forecasting performance. This involves the following steps:

1. Review **state-of-the-art** of battery models with degradation modelling, as used in optimization contexts.
2. Select a **methodology** for deriving battery models from raw data and the available simulation model.
3. Implement a **prototype software** to generate models. This software processes data and pre-existing simulation models of battery into optimization-compatible models.
4. **Evaluate** the accuracy of new model and impact within operations' optimization in simulation scenarios. This involves the integration within optimization tools for operation and the evaluation of benefits of the new models compared to basic model without consideration of battery degradation. The background software from CSEM NRGMaestro™ will be used for this part.
5. **Disseminate the work**:
    - A publication has been accepted to the IEEE ISGT 2023 conference and will be presented there in October 2023.
    - An open-source implementation of the model has been released and can be found at https://github.com/csem/batmaestro
    - The results of the project have been presented to experts in the OPEN SESAME consortium during a project meeting in May 2023

3 Results and discussion

SoXery [1] is an open-source battery degradation simulation model, based on an empirical stress-based degradation model [2]. The degradation equations were developed on experimental tests on lithium-ion cells with a Lithium Nickel Manganese Cobalt (NMC) oxide. Soxery was developed in the frame of the IEA Open Source Energy Storage Models project [5].

The State-of-Health (SoH) of a battery at time *t* is defined as the ratio of the maximum capacity (in Ah) of a battery at time *t* to the maximum capacity of that battery at beginning of its life. As commonly done, the SoH decrease is modeled with two components: the calendar ageing D_cal that is happening continuously, and the cycle ageing D_cyc that occurs while the battery is cycled. The SoH after a period of time is forecasted as the integral of the sum of the cycle and calendar ageing.

SoXery offers a relatively complex method to calculate D_cal and D_cyc as a function of its cycling input power: each degradation component is based on a reference Degradation Rate (DR) multiplied by Stress Factor (SF) equations for every influencing parameter. Calendar ageing has a linear SF for SoC and exponential SF for temperature and is found by multiplying those two SF equations by the reference DR for calendar ageing and by the time elapsed. On the other hand, cycle ageing has nonlinear SFs for C-rate, SoC, DoD and temperature, where the average value is considered over the half-cycle. As a result, four nonlinear SF equations are calculated and multiplied by the reference charging or discharging DR, and by the DoD of the half-cycle *hc* considered.

$$D_{cyc} = DR_{ref} * DF_{Crate} * SF_{SoC} * SF_{DoD} * SF_{T} * DoD_{hc}$$

Similar equations apply for the calendar ageing and for the prediction of the state of resistance (SoR) increase. This type of model is not linear, due to the multiplication of all the stress factors and the breakdown of the charging profile into half-cycles: our goal has been to transform these equations into approximately equivalent ones that can be cast as a set of linear equations on continuous and discrete variables so that they are compatible with MILP optimization. To do so, the following assumptions have been made:

- A constant SF for temperature is calculated at 25°C. This is because the battery dynamic model considered in the optimization problem which we are currently able to handle currently does not include a thermal model to forecast the temperature of the cells,
- The cycle degradation is calculated at every time step (except for DoD as explained later), instead of each half-cycle. This is because extracting half-cycles in the optimization is complex and nonlinear. This makes no difference for linear SFs, but introduces errors for nonlinear ones.

As a result, calendar ageing depends on the SoC only, which has a linear SF, making it compatible with the MILP optimization framework:

The cycle ageing is more complex as it depends on the C-rate, SoC and DoD. We observe that the C-rate is the dominant factor for degradation. Therefore, we have developed two models with different levels of complexity and accuracy: a simplified model SoH model has first been developed accounting only for the C-rate in cycle ageing; and a more complex one that considers all SFs. The cycle ageing DR (in \%SoH loss per Half Equivalent Cycle (HEC)) is converted to %SoH loss per hour by multiplying by the C-rate (in HEC per hour), shown in Figure 1. By integrating over time, we get the cycle ageing DR for the simplified model.

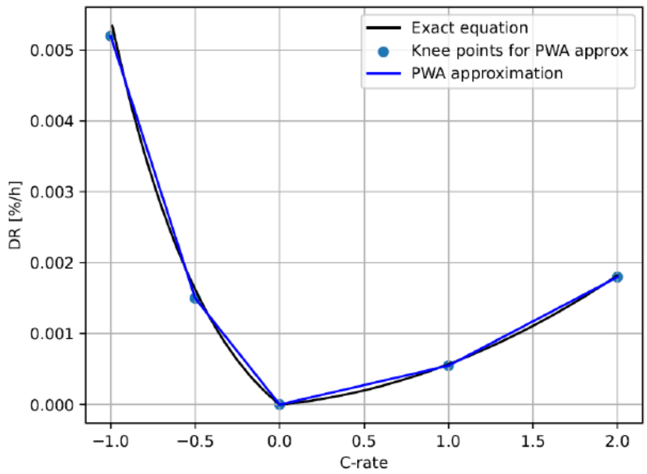

Figure 1: Degradation rate for SoH cycle ageing and piecewise affine approximation

The negative and positive C-rates represent charging and discharging, respectively. This simple model assumes that the SoC and DoD do not influence the cycle ageing, yielding SF values of 1 for those factors.

For the more complex SoH model, the cycle SF for SoC is a linear function and it is considered at each time step. This gives rise to a bilinear term that must be transformed to approximate linear equations. Similarly, the DoD SF needs to be piecewise linearized, but another approximation was introduced to avoid considering only the DoD of each time step, which would always be small if time steps are short: we have considered in the optimization the maximum SoC range over the horizon of optimization to approximate the DoD. This is not perfect as there can be multiple cycles of different DoDs over the optimization horizon, but typically not many for a horizon of one to a few days, as will used for our receding-horizon control application.

This results in the following equation for the complex cycle ageing degradation at the end of the horizon of *N* time-steps:

$$D_{cyc}^{complex}(N) = \sum_{t} DR_{cyc,ref} * SF_{Crate} * Crate(t) * SF_{SoC} * DF_{DoD_{max}} * dt$$

As this is multilinear, we have tailored the piece-wise McCormick relaxation to this use case. This technique allows to apply the well-known convex McCormick relaxation for bilinear terms on different portion of the variables space controlled by the introduction of new discrete variables. Our formulation was adapted from the formulation [NF-12] found in the reference [3], where we partition the variables. Note that this approach allows a controlled level of accuracy through a higher or lower number of subintervals for the relaxation. Full details of the derivation will be found in our publication referenced in section 9.

Based on the above, we have considered three alternate battery models in a simulation study with the goal of studying the effect of considering degradation in an optimization problem. The three models considered are:

- A0: ignoring the degradation in the optimization, and limiting the battery operating range: maximum 0.5C for charging and SoC between 10% and 90%.
- A1: simple SoH model, including exact calendar ageing and only C-rate dependent cycle ageing
- A2: complex SoH model, including SoC and DoD in the cycle ageing calculations, and relax through the tight McCormick relaxation approach

Two simulation scenarios have been studied with two use cases for batteries over a one year period. The first one considers an arbitrage scenario on electricity prices. The price data used was from 2021. Although this is generally not very profitable for batteries it is an interesting scenario as it involves high cycling of the battery and complex decision to be made which is suitable for an optimization framework. The second is a more traditional PV + battery scenario where the battery is used to increase self-consumption. Here we report only results for the first scenario as results were very comparable between the two studies. Full details of the second scenario is available in an extended report [4]

We show in the results of the study in the following table

Table 1: Comparison of model performance within MPC for arbitrage scenario

Arbitrage 1 year	Real SoH loss [%/year]	Battery life-time [years]	Relative difference for SoH	Time per run [s]
A0: No degradation	4.2	5	-	0.1
A1: Simple SoH	1.7	12	1.2 %	0.2
A2: Complex SoH	1.7	12	<0.1 %	5

The real SoH loss is calculated *a posteriori* based on the optimized SoC and C-rate profiles with the original SoXery model. This is assumed to be the ground truth in terms of degradation. The battery end-of-Life (EoL) is assumed when the battery reaches a SoH of 80%. Finally, the computing time reflects the complexity of using each degradation model in the optimization.

Table 2: Economical benefits in arbitrage scenario

Arbitrage results [EUR/MWh/year]	Arbitrage gain	Real cost of degradation	Total real benefit
A0: No degradation	27,750	28,950	-1,200
A1: Simplest SoH	18,250	12,000	6,250
A2: Complex SoH	20,300	10,300	10,000

The economical results, reported in Table 2 and given in EUR per MWh of battery installed per year, are broken down in two parts. First, the arbitrage gain is calculated as the gain from selling energy from the battery to the grid, minus the cost of the energy bought from the grid. Also, an equivalent cost of degradation is computed by assuming that the batteries need to be replaced at EoL, and attributing a fraction of the replacement cost proportional to SoH loss over that year (this is consistent with the cost of degradation incorporated in the optimization). Finally, the total real benefit is the difference between the arbitrage gain and the equivalent degradation cost.

The total real benefit is negative in option A0 (if degradation is only limited with hard constraints) meaning that the degradation cost exceeds the benefit from using a battery for arbitrage. The simple SoH model of option A1 is quite accurate (1.2% difference with exact degradation equations) and allows to significantly reduce the SoH loss per year and extends the battery life to 12 years. As a result, the benefit has a positive value of 6,250 EUR/MWh/year, making arbitrage beneficial over the battery lifetime. The complex SoH proposed in A2 allows to reduce further the degradation cost and yields a higher benefit, allowing up to 10,000 EUR/MWh/year, while exhibiting a manageable computing time per run of 5 seconds. Overall, we conclude that both A1 and A2 options are viable, and which one is to be used depends on the desired trade-off between performance and computational load in a given application.

4 Conclusions

We have demonstrated in this work that including degradation in a predictive energy management strategy allows to account accurately for the hidden cost of degradation, therefore boosting the economic viability and lifetime of batteries in an arbitrage scenario. It has also been demonstrated that it is possible to manage a tradeoff between accuracy, computational load and optimality with different levels of degradation model accuracy, leading up to savings of up to 10,000 EUR/MWh/year.

5 Outlook and next steps

The results reached are promising. It shows explicitly modelling the degradation due to charging profiles on battery life allows to increase battery life and economical benefits when managing battery charging through a mathematical optimization strategy such as MPC.

What is more, we have shown that nonlinear degradation model wich may a priori be hard to use in optimization contexts can be transformed accurately to models amenable to mixed-integer linear optimization, a very popular framework for energy systems design optimization and management. This can be done at a moderate cost in terms of complexity and in a way that allows to control the accuracy-complexity tradeoff of the model.

Future work can include further investigation of the McCormick relaxation with multivariate partitioning or other technical refinement in the formulation, but should most importantly consider more realistic case studies with other grid services such as frequency control. Additionally, the main assumption underpinning this work is the availability of a pre-existing ageing model for the battery, which often is unavailable. To reach wide applicability of the results of this project, further work in building such degradation models from live measured data from battery packs is required.

6 Publications

A publication has been presented at the IEEE ISGT Europe 2023 in Grenoble, France in October 2023:

Method to Embed Behavioral Battery Model in Predictive Energy Management Systems, A. Sutter, T. T. Gorecki and S. S. Bhoir

Open-access link : https://yoda.csem.ch/items/d080c968-da94-47c4-83a4-bf28b87bac4f

In addition, an open-source implementation in Python of scripts to generate the optimization-compatible version of the model with examples has been published at the following repository: https://github.com/csem/batmaestro

7 References

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