A Cost Modeling Framework for Modular Battery Energy Storage Systems

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Abstract. This paper presents a cost modeling framework for battery systems. Based on findings in battery cost modeling literature, there is a need for scalable, systematic frameworks to model cost. The framework in this paper, which is developed with a systems approach in mind, incorporates parametric cost models that consider scaling in component rating, future cost prediction and economies of scale with a limited set of tunable parameters per component. This framework is employed to construct an instance of a novel battery architecture, the module level converter topology, in a scalable way using different classes for (sub-)systems and indivisible components, based on the desired power output and energy content of the system. By doing so, the system costs of the novel hybrid battery architecture are compared to a baseline battery topology in terms of cost decomposition. The prospects of this novel architecture are also mapped out in terms of production volume and future component costs.

Keywords: Cost modeling framework, Parametric cost model, HESS

1 Introduction

In the transportation sector electrification, modular battery systems and hybrid batteries have been identified as promising strategies to meet the critical requirements on energy, power density, lifetime and safety. Today, multiple promising topologies for battery hybridization can be identified. Missing however are systematic cost modeling approaches that can evaluate the total system capital cost with respect to key requirements such as battery capacity, voltage, and power output.

In the past decades, various cost models on batteries have been proposed. Overall, cost models presented in existing literature, based on their purposes, capture different elements in the battery industry on various fidelity levels. Fabian *et al.* grouped these models into four categories: intuitive models, analogous models, parametric models, and bottom-up models [1]. An intuitive model is largely based on expert insights and therefore requires little input data regarding the elements underlying the batteries [2, 3]. For this reason, these models have little reproducibility and their validity also decreases over time due to technological advancement and the change of macro-economic situations. Analogous models make projections by performing regression analyses on historical data. For instance, Penisa *et al*. [4] and Schneider *et al.* [5]

presented analogous models to project respectively the battery system costs and battery cell costs evolution in the future. However, due to the limited representation of the internal structure, it is challenging for analogous models to consider the evolution of different cost elements over time and the economy of scales. In order to consider more factors (such as technology advancement, dependency on critical materials, and economy of scales (EoS)), one should leverage a higher fidelity model – the so-called parametric model – where the cost elements are represented by cost functions characterizing the cost evolution as a function of time, size, and production [6,7,8]. One of the most comprehensive cost model in this spectrum is the BatPaC model developed by Argonne National Laboratory which comprises of a comprehensive battery system decomposition, critical design considerations (e.g., power, energy, voltage, etc), and other fixed investments costs and overhead costs [9]. Nevertheless, the high fidelity of the model, in combination with it being excel-based, reduce its scalability, transparency, and customizability. Hence, it is limited in performing analysis on the cost components and their evolution over time. In short, the fundamental difference between a parametric model and an analogous model is the use of equations on cost elements level. The most sophisticated cost models – the bottom-up models – add another layer of complexity by modeling the complete manufacturing process in a chronological manner. The cost is therefore estimated based on the cost incurred by each step in manufacturing [10,11,12].

To the best of the authors' knowledge, the cost modeling framework presented in this study is the first scalable, transparent, and modular parametric cost model that allows the user to analyze the cost evolution of selected cost elements against size, production, and technology advancements over time. In this regard, this paper presents a scalable, transparent, and modular battery system cost modeling framework that captures individual components and their dependency relationships and is capable of performing trend analysis of battery size, production upscaling and future cost.

The battery architecture for which the cost model is employed features a scalable module level converter (MLC) topology. Herein, the Hybrid Energy Storage System (HESS) capacity is determined by the number of parallel "strings", each of which is comprised of either high power (HP) or high energy (HE) cell technology. Each string contains several "modules" connected in series, which are fully managed battery packs that include a DCDC-converter.

2 Framework outline

This section will outline the developed framework, that is set up with a systems-approach in mind, allowing with minimal effort to construct a system-of-systems hierarchy of components at different levels. The object-oriented implementation of the first version is developed in Python due to its coding flexibility and the absence of computationally demanding calculations.

A separation into classes is considered, to generalize functionality as much as possible. The two main classes are "System" and "AtomicComponent". Systems can own components, atomic components cannot. Fig. 1 shows the derived classes.

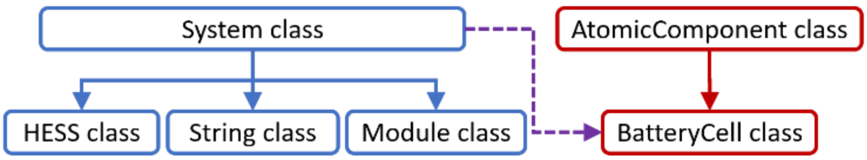

Fig. 1. Class hierarchy within the framework

The attributes and methods of the "System" class can be grouped into 3 themes: managing components, electrical properties and cost modeling functionalities, addressed in Section 3. The "AtomicComponents" class only includes rating and cost modeling attributes. The extended "BatteryCell" class includes the electrical properties as well.

A system is generated based on its requirements and a set of heuristics:

- The bus voltage and hybrid (HE/HP) capacities in ampere hours must be specified.
- The (fixed size) modules are placed in series to obtain the desired bus voltage.
- The ampere hour capacity of a module depends on the degree of downregulation by the DCDC-converter to match the desired bus voltage across all modules.

Whenever a HESS system instance is created, it creates for both HE and HP capacities a number of strings, which in turn allocate modules to the strings. At every system level a number of atomic components are also added (mostly from an Excel file). After this, the system is set up for queries, PBS generation or cost analyses.

3 Cost modeling

In Section 3.1, a single, fixed cost is attributed to each system component along with a cost category. This is extended with cost variability modeling in Section 3.2.

3.1 System cost construction per category

To compute system cost, each component has a cost and category. Given the scalable framework, total (sub-)system cost is easily constructed, as can be seen in Fig. 2.

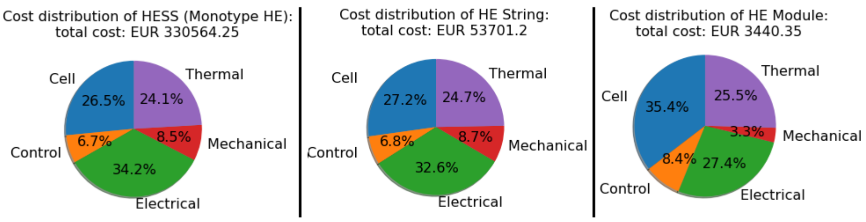

Fig. 2. Cost per category at HESS, string and module level

3.2 Parametric cost modeling

The fixed cost approach is extended to three cost dimensions, being:

1. Component scaling, i.e. increased cost due to e.g. higher component power rating
2. Future cost prediction, i.e. potential price declines due to technology resources, etc.
3. Economies of scale: higher discount due to higher production/sales volumes, etc.

For each of these a simple parametric model is proposed. The general equation is expressed by Equation 1. The fixed reference cost, $cost_{ref}$ from Section 3.1 represents the cost (1) at a given, normative rating (2) at the present (3) as a single item.

$$cost_{scaled} = cost_{ref} * f_{scaling}(R, f_{cs}) * f_{pred}\left(t_{yr}, \tau_{50}\right) * f_{EoS}(N, c_{eos}, f_{lvd}) \quad (1)$$

Component scaling cost model. The components rating ratio R compared to a reference rating affects its cost by Equation 2. A rounding function with 6 steps per decade is introduced to mimic the discreteness of product sizes (i.e. E6-scale for capacitors). Secondly, f_{cs} accounts for the price trend which typically introduces a discount for higher rated components (i.e. 10x the rating at only 6x-8x the price).

$$f_{scaling}(R, f_{cs}) = 10^{(1-f_{cs})\frac{ceil(6\log_{10}(R))}{6}} \quad (2)$$

Future cost prediction. Since price forecasting has limited accuracy, a simple single-parameter exponential represents the future cost factor is given by equation 3.:

$$f_{pred}\left(t_{yr}, \tau_{50}\right) = 2^{\frac{-t_{yr}}{\tau_{50}}} \quad (3)$$

Where t_{yr} is time in years and τ_{50} is the expected 50% time for each component. A negative τ_{50} can accommodate inflation if needed.

Economies of scale (EoS) cost model. With higher volumes, price per component tends to drop. sometimes significantly. To match this, a sublinear trend is proposed

$$f_{EoS}(N, c_{eos}, f_{lvd}) = N^{-c_{eos}+c_{eos}e^{-f_{lvd}\sqrt{N}}} \quad (4)$$

The coefficient c_{eos} accounts for high-volume discount, although the discount margin flattens out. Resource scarcity is not modeled. The low volume discount factor f_{lvd} is added to better track low volume price trends. Fig. 3 features all three cost trends.

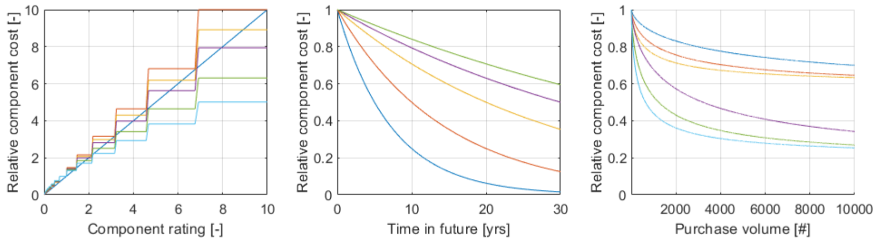

Fig. 3. The three cost functions for different parameter

4 Trend analysis

First, the MLC topology is compared with a baseline topology (i.e. single battery pack with large DCDC converter). Cost is impacted by differences in component count as well as component ratings. Price comparison in Table 1 reveals that for the current set of cost parameters, the MLC topology still ends up ~30% higher in cost than the baseline design, independent of system size (although upscaling from 1 to 5 MWh saves ~18% due to economy of scales for both topologies). Costly additional CPU's and intermodular connectors disadvantage the MLC topology. However, in contrast with baseline the MLC topology is hybrid-capable (allowing capacity savings).

For a second case, the cost for a 1 MWh HESS is projected into the future, also potential production upscaling is considered. Fig. 4 show the price prediction depending on volume for purchase now and in 10 years. Cost categories reveal lithium cells will continue to become cheaper over time and with production upscaling, which may affect cost composition of battery packs, as lithium may no longer dominate.

Table 1. Relative system cost in € per MWh compared to Baseline

Cost category	1MWh Baseline		1MWh MLC		5MWh Baseline		5MWh MLC	
Total cost	259k	(100%)	331k	(+27%)	1069k	(-18%)	1423k	(+10%)
Cells	88k	(100%)	88k	(+0%)	380k	(-13%)	380k	(-13%)
Control	1k	(100%)	22k	(+2121%)	2.6k	(-47%)	95k	(+1804%)
Electrical	72k	(100%)	113k	(+58%)	260k	(-27%)	482k	(+35%)
Mechanical	29k	(100%)	28k	(-3%)	123k	(-15%)	122k	(-16%)
Thermal	70k	(100%)	80k	(+13%)	303k	(-14%)	345k	(-2%)

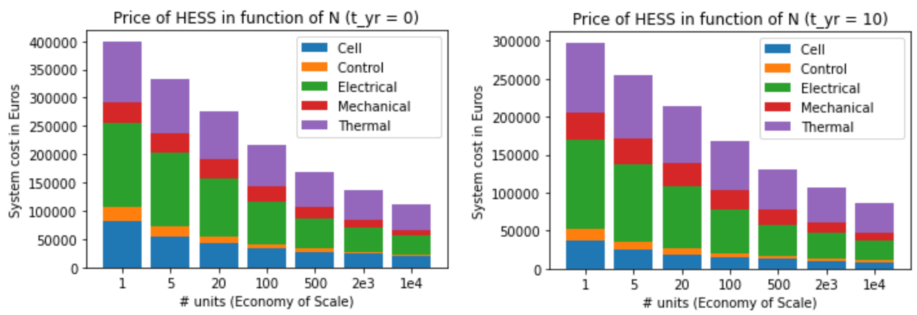

Fig. 4. System cost depending on production volume in present (left) and 10 years (right)

5 Conclusion

A scalable, parametric cost modeling framework has been presented, which was applied to hybrid batteries for vessel applications. This allowed assessment of future viability of modular battery topologies at sea. Further development paths may include further generalization of the framework to arbitrary battery architectures and detailing of data-based cost parameters to improve the predictive power of the framework.

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References

1. Duffner, F., Wentker, M., Greenwood, M., & Leker, J. (2020). Battery cost modeling: A review and directions for future research. Renewable and Sustainable Energy Reviews, 127, 109872.
2. Mongird, K., Viswanathan, V., Balducci, P., Alam, J., Fotedar, V., Koritarov, V., & Hadjerioua, B. (2020). An evaluation of energy storage cost and performance characteristics. Energies, 13(13), 3307.
3. Few, S., Schmidt, O., Offer, G. J., Brandon, N., Nelson, J., & Gambhir, A. (2018). Prospective improvements in cost and cycle life of off-grid lithium-ion battery packs: An analysis informed by expert elicitations. Energy Policy, 114, 578-590.
4. Penisa, X. N., Castro, M. T., Pascasio, J. D. A., Esparcia Jr, E. A., Schmidt, O., & Ocon, J. D. (2020). Projecting the price of lithium-ion NMC battery packs using a multifactor learning curve model. Energies, 13(20), 5276.
5. Schneider, S. F., Bauer, C., Novák, P., & Berg, E. J. (2019). A modeling framework to assess specific energy, costs and environmental impacts of Li-ion and Na-ion batteries. Sustainable Energy & Fuels, 3(11), 3061-3070.
6. Wentker, M., Greenwood, M., & Leker, J. (2019). A bottom-up approach to lithium-ion battery cost modeling with a focus on cathode active materials. Energies, 12(3), 504.
7. Beuse, M., Steffen, B., & Schmidt, T. S. (2020). Projecting the competition between energy-storage technologies in the electricity sector. Joule, 4(10), 2162-2184.
8. Wang, F., Deng, Y., & Yuan, C. (2020). Design and cost modeling of high capacity lithium ion batteries for electric vehicles through a techno-economic analysis approach. Procedia Manufacturing, 49, 24-31.
9. Nelson, P. A., Ahmed, S., Gallagher, K. G., & Dees, D. W. (2019). Modeling the performance and cost of lithium-ion batteries for electric-drive vehicles (No. ANL/CSE-19/2). Argonne National Lab.(ANL), Argonne, IL (United States).
10. Duffner, F., Mauler, L., Wentker, M., Leker, J., & Winter, M. (2021). Large-scale automotive battery cell manufacturing: Analyzing strategic and operational effects on manufacturing costs. International Journal of Production Economics, 232, 107982.
11. Orangi, S., & Strømman, A. H. (2022). A Techno-Economic Model for Benchmarking the Production Cost of Lithium-Ion Battery Cells. Batteries, 8(8), 83.
12. Schnell, J., Knörzer, H., Imbsweiler, A. J., & Reinhart, G. (2020). Solid versus liquid—a bottom-up calculation model to analyze the manufacturing cost of future high-energy batteries. Energy Technology, 8(3), 1901237.
13. Author, F., Author, S., Author, T.: Book title. 2nd edn. Publisher, Location (1999).
14. Author, F.: Contribution title. In: 9th International Proceedings on Proceedings, pp. 1–2. Publisher, Location (2010).
15. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.