Interpretable data-driven battery model based on tensor trains

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Abstract: The global energy transition increasingly relies on renewable energy sources and the use of batteries for electrical energy storage. Efficient battery utilization necessitates accurate state estimation algorithms and appropriate control mechanisms. This paper presents and evaluates a data-driven approach for estimating a battery's dynamic model using tensor trains, that efficiently reconstruct complex multidimensional systems with respect to time and memory, enabling the development of adaptive models capable of capturing real-time variations in system parameters. In this study, the proposed method is applied to reconstruct a dynamic battery model from operational data and is tested upon a solid-state lithium-ion battery cell. The method's explanatory capabilities are demonstrated through the extraction of key parameters such as open circuit voltage and impedance in the form of relaxation times distribution. The accuracy is further validated against the results of conventional battery characterization tests. Owing to its intrinsic scalability and low computational cost, this method holds potential for integration into artificial intelligence-driven battery management systems, enhancing battery longevity and safety while optimizing time-intensive battery characterization processes.

Keywords: mathematical models, machine learning, tensor trains, batteries.

1. INTRODUCTION

Batteries start to play a crucial role in the global energy system, enabling renewable energy integration and supporting electrification of transport. Grid-level storage demands scalability, durability, and cost-effectiveness, while electric vehicles prioritize safety, price, and energy density. Aviation requires the highest standards for safety and efficiency, which current battery technology struggles to meet (Bills et.al.).

Battery Management Systems (BMS) monitor battery performance, estimating key metrics like State of Charge (SOC) and State of Health (SOH) to improve safety and durability. These systems use mathematical models or machine learning techniques to optimize battery behaviour, and can be enhanced through real-time data and control. In aviation, rigorous certification standards are assumed to be partially addressed through solid-state batteries and advanced safety designs. Predictive BMS tools are also essential to meet the safety margins, requiring accuracy and adaptability.

This research introduces a real-time model estimation algorithm based on low-rank data decomposition based on tensor trains (TT), which efficiently estimates SOC as well as physically relevant parameters without time-consuming battery characterization tests for a preliminary tuning (Pattipati et.al.). Experiments with lithium-ion solid-state batteries are used to validate the method, demonstrating high accuracy and negligible sub-second training time. The model's ability to explain physical battery behaviour is vital for safety-critical applications, showing its potential in enhancing battery management across various sectors.

2. METHODS

TT are widely used in machine learning as allow to efficiently process sparse high-dimentional data (Oseledets). In the present work we use TT to build two models: battery dynamic mode, that includes an open cirquit voltage (OCV) and impedance, depending on the relative state of charge (SoC), and SoC as a function of observables, that include in the present case voltage drop on the battery current collecors, load and the battery temperature. The first one can be used for predictive modelling and safety status assessments, while the later provides an adaptable battery state estimation tool for the BMS.

Temperature, voltage (for the state estimation) or SoC (for the dynamic model estimation) are represented using a series of Chebyshev polynomials of the order up to 8. The load, or a current, is recalculated into a number of “smoothed” functions to use a relaxation times distribution method (Heinzmann et.al.). In order to build a model, 3 rank-3 or 2 tensors are randomly generated on the initial phase, corresponding to temperature, load and voltage/SoC. Scalar product of inputs with the tensors, and further convolution of tensors with each other allows to calculate the output, that correspond either to SoC (state estimation) or to voltage (dynamical model). Each tensor is calculated using Ridge regression method (Marquardt et.al.) with quadratic reqularization assuming the environment is frozen. Experiments demonstrate, that 2-5 sweeps over the tensors, each taking <1ms on a single-core 3GHz CPU, is enough to get a converged solution. Bonds dimensions of up to 3 is

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enough to get the reconstruction accuracy within ~1% average and ~5% maximum error.

3. RESULTS

Experiments were conducted on 30 Ah lithium-ion solid-state cells with a voltage window from 2.75 to 4.2 V. The specific energy is 270 Wh/kg and 560 Wh/L. The batteries have a durability of 500 cycles with 80% capacity retention at 3C, and a maximum operation current of 7C. The cells use NMC cathodes, graphite anodes, and a solid-state electrolyte, though the exact formulation is undisclosed. Experiments are performed in climatic chambers with fixed temperatures.

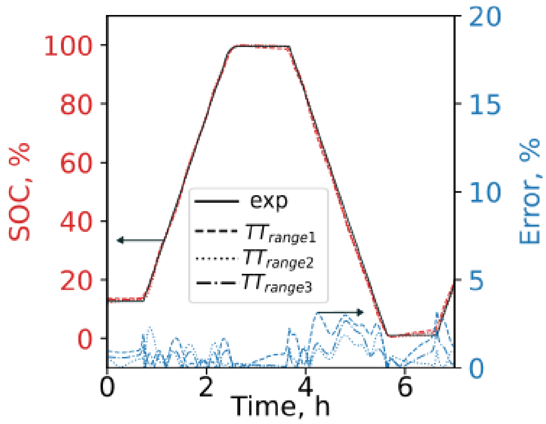

Fig. 1. Experimental SoC (left axis) for charge-discharge cycle (solid line) and reconstructed SoC using TT for 3 training data ranges, and corresponding error (right axis).

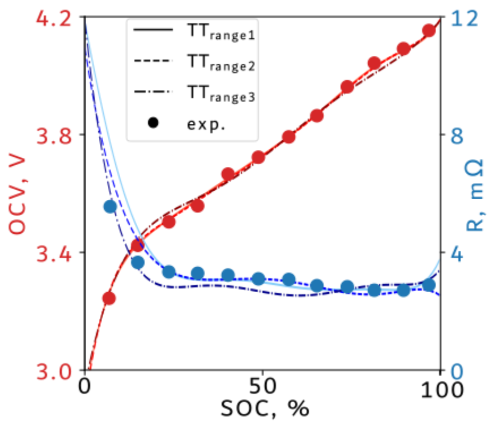

Fig. 2. OCV and resistance from characterization tests (dots) and extracted from TT for 3 training data ranges.

Standard battery characterizatiopn tests were conducted with different temperatures to obtain reference OCV and resistance values. Cycling tests, mimicking the battery operation in EV/HEA are performed to assess the method performance, with data collected every second.

The developed method is first used as a state estimation tool. SoC is typically calculated as the cumulative sum of charge passed through the battery, normalized by its capacity, and scaled so that SoC values range from 0 to 1, corresponding to the voltage vindow limits. For the model training, a charge conservation is used. This method calculates the change in capacity between two time stamps by integrating the current passed through the battery over that time period. The model allows to calculate observables into the latent spase variable (SoC), with the error within 5% on the whole testing dataset (one cycle is plotted at Fig.1). Therefore, potentially the method can substitude such widely used methods as KF, that require preliminary characterization tests data, that are obtained on the beginning of the battery's lifetime and change during a long-term operation thus dicreasing the state estimation accuracy.

Secondly, the method is applied to reconstruct a dynamic battery model. Here, SoC is assumed to be available along with load and temperature, while the voltage is the output value. The relaxation times distribution method allows to explicitly parse the trained TT to extract OCV and resistance functions vs. temperature and SoC (Fig.2). Note, that these functions correspond to the current battery "health" status and can be treated as synthetic characterization tests.

4. CONCLUSIONS

The safe and efficient use of batteries requires monitoring and control systems. Algorithms should be fast, adaptable, and representative. TT algorithm solves battery state estimation and dynamic model reconstruction problems. The state estimation algorithm is used in BMS to optimize battery loading, thermal management, and remaining capacity calculation. Dynamic model also allows extracting battery properties important for the health status calculation and early fault prediction. The proposed method does not require characterization data obtained under controlled conditions with predefined loads. The algorithm uses operational data on voltage, temperature and load to train in near-real time. The algorithm can be used in safety-critical applications, such as aviation, and in fully adaptive BMS. It can optimize or eliminate the need for time-consuming battery characterization tests.

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