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Data-driven Approach for Battery Capacity Estimation Based on In-vehicle Driving Data and Incremental Capacity Analysis

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ABSTRACT

To ensure safety, performance and warranty of an electric vehicle, it is crucial to monitor the evolution of remaining capacity of NMC lithium-ion batteries. Estimators for the remaining capacity are often based on costly, complex and time consuming testing procedures under laboratory measurement conditions. Other methods like incremental capacity analysis require various load sequences at very low constant current rates. This is also not practical for real battery electric vehicle operation due to high and dynamic discharging rates caused by the customers individual driving behavior as well as high recharging rates.

To overcome these problems, we present a data-driven approach for battery capacity estimation in combination with incremental capacity analysis. The missing load sequences for the incremental capacity analysis are presented by the output of a recurrent neural network which describes the battery electric behavior from real in-vehicle data. Results show RMSE deviations of 1.77% to correctly estimate the remaining capacity over the whole vehicle life. This high accuracy is comparable to state of the art laboratory battery testing, but without the need of expensive experimental data. Instead only operational vehicle data can be used.

Keywords: Lithium-ion battery (LIB), remaining capacity, incremental capacity analysis (ICA), electric vehicle (EV), in-vehicle data, machine learning, long short term memory (LSTM)

1. INTRODUCTION

Decarbonizing transport is one of today's major challenges for the global automotive industry [1]. Electric vehicles (EVs) are a key technology to lower the greenhouse gas emissions. For that reason, leading automotive companies, such as Volkswagen, recently announced to increase their share in the EV market to up to 22 million in the next 10 years [2].

For the customer, as well as for battery development, state of health (SOH) monitoring becomes more and more important to ensure the necessary safety, performance and warranty of EVs. The SOH describes the aging state of a particular battery cell. Commonly used key parameters to describe the SOH in literature are the internal resistance and the remaining capacity [3]. The internal resistance describes the ohmic losses during load cycling. The remaining capacity is defined as the ratio of the maximum available capacity in the current state and the initial maximum capacity of a fresh battery [4]. These key parameters depend on the current battery performance and usually require extensive laboratory experiments for a precise determination, for instance characterization tests [5] and incremental capacity analysis (ICA). Using a battery model to simulate the electric battery response during such laboratory experiments would be a benefit for SOH monitoring and would reduce extensive battery testing.

In this paper we introduce a data-driven battery electric model to provide virtual battery tests in order to compute the remaining capacity at different SOHs of the battery. This battery electric model is based on recurrent neural networks and is explicitly trained on real in-vehicle driving data. We use ICA, while considering the customers driving behavior at the same time.

2. INCREMENTAL CAPACITY ANALYSIS

In literature, ICA is widely used due to its ability to detect and quantify battery aging mechanisms. ICA shows a strong correlation between the aging state (AS)

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of lithium-ion batteries (LIBs) and the characteristic shape of a measured incremental capacity (IC) curve [6]. The IC curve is determined by charging or discharging the battery at low constant current rates (c-rates) of 0.2C and calculated by the ratio of each IC with respect to the given battery voltage (dQ/dU). The characteristic peaks are the result of different phase-transition stages of Li-ions intercalation inside the electrode during cycling [7]. Li et al. [8] analyzed ICA characteristics of high energy NMC batteries at different ASs. Due to battery degradation mechanisms inside the cell, the electrochemical composition and structure of the battery cell will change through time and consequently the position and amplitude of the ICA-peaks [9]. Thereby, Li et al. identified a linear correlation between the position of the ICA-peaks [A,B,C] and the remaining capacity. We can also confirm the results of Li et al. by using our dataset which represents automotive NMC batteries. Figure 1 shows the IC curves and the shift of each ICA-peak [A,B,C] at different ASs of our data set. The linear correlation between the position of each ICA-peak position with respect to the remaining capacity is determined in Figure 2.

In order to generate meaningful results, ICA requires very low constant c-rates while the battery cell is charged or discharged over the whole state of charge (SOC). These particular load sequences are obsolete in real EV operation. The customers' demand of short recharging time (fast charging) requires high c-rates and the individual driving behavior is highly dynamic. Hence, the real in-vehicle data cannot be used off-hand for ICA.

In this work we provide the missing ICA response by a data-driven battery electric model, which is explicitly trained on dynamic in-vehicle data and described in Section 3.

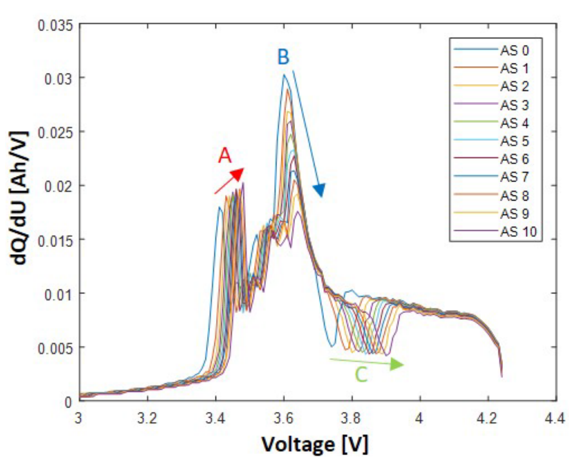

Fig 1: Incremental Capacity Analysis. Shift of position and amplitude of characteristic ICA-peaks [A B,C] at different aging states (AS 0-10) of automotive NMC battery

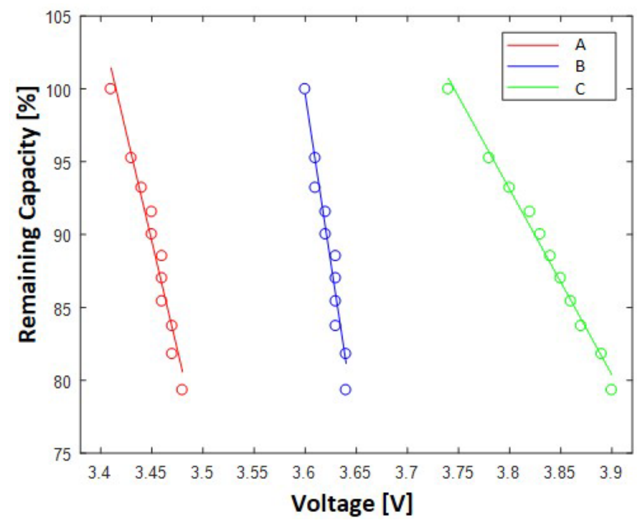

Fig 2: Shift of ICA-peaks [A,B,C] position with respect to the remaining capacity

3. METHODOLOGY

3.1 Battery electric model

The automotive battery data can be seen as a highly dynamic and very long multidimensional time series. In this context, this type of battery data has been successively tested in literature with recurrent neural networks, particularly with Long-Short Term Memory (LSTM) networks [10]. A LSTM network consists of multiple LSTM-cells and is explicitly designed to work on time series data [11]. LSTM-cells comprise additional gates compared to regular feed-forward neurons in order to allow information to persist over time. These cells not only compute the output h_t for a given input x_t, they also pass on cell information c_t, as shown in Figure 3. C_t represents the cell state and function as an embedding of previously seen information. At each time step the internal LSTM-gates modify c_t by determining whether to consider or forget past data and to which extend new data is affecting the new cell state. With this recurrent internal feedback-loop of information, the LSTM-cell is capable to capture multidimensional time dependencies inside long time series data [13].

The LSTM network is designed to learn the battery electric function. The battery electric function is defined

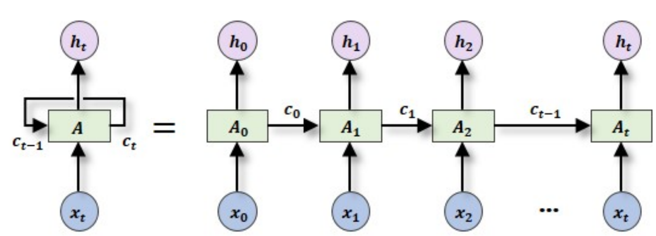

Fig 3: An unrolled LSTM neural network based on [12]

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to output the voltage response at a given electrical load (sequence of current $I(t)$, temperature $T(t)$, remaining battery charge $Q(t)$) [14] as an input. The utilized network hyperparameters, such as number of neurons (30), hidden layers (1), optimizer (*adam*), loss-function (*mean-squared-error*), learning rate (*0.001*), epochs (10) are determined using hyperparameter tuning techniques [15], which are out of scope in this paper.

3.2 Experimental Setup

The battery used for this experimental setup is a high energy NMC 622 LIB. In order to investigate the evolving capacity loss over time, the LIB is stressed to different AS ($t = \{0,1,2,\ldots,10\}$). At each AS the LIB is tested according to the work-flow in Figure 4:

1) A laboratory characterization test (CT) with a full discharge cycle at constant current (1C) and temperature (23°C) is performed to calculate the exact remaining capacity via Coulomb-Counting.
2) An IC curve over a full discharge cycle at constant current (0.2C) and temperature (23°C) is performed to determine the peaks' position and compute their correlation to the exact remaining capacity, as previously shown in Figure 2.
3) The LIB is discharged 15 times with different automotive drive cycles to generate an aging state specific trainings data set $DS_{AS(t)}$. This data set is used for LSTM network training to learn the battery electric function at this particular AS. Once the battery function is learned we simulate virtual battery tests (CT, ICA) in order to compute the remaining capacity.
4) Afterwards the LIB is stressed to the next AS(t+1) and the work-flow is repeated until the remaining capacity drops below 80%.

4. RESULTS AND DISCUSSION

Based on the work-flow shown in Figure 4, the remaining capacity can be determined in four different ways. Either we run real and extensive laboratory experiments (CT, ICA) or we use the real in-vehicle data at a particular AS to train a LSTM battery model and run virtual experiments (LSTM-CT, LSTM-ICA).

The resulting capacity degradation through the different AS are shown in Figure 5. The laboratory CT is considered to be the ground truth value and is further set as the baseline for the other experiments. By running a laboratory ICA we achieve a root-mean-square-error (RMSE) of 0.6% compared to the ground truth value. This deviation is within the state of the art error

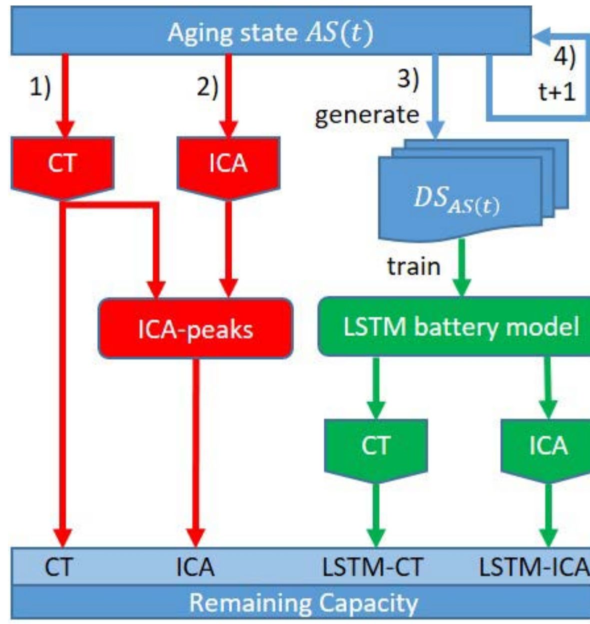

Fig 4: Work-flow. Battery testing at each aging state (AS). Laboratory (red) and virtual LSTM experiments (green)

deviation for conventional experimental setups of around 1% [16]. The simulated LSTM-ICA achieves almost the same accuracy compared to the laboratory ICA test with a RMSE deviation of 1.77%. Whereas the virtual characterization test (LSTM-CT) performs the worst with an average RMSE of 7.06%.

This behavior can be explained by analyzing the automotive training data. It is important to note, that data-driven models are only able to capture patterns and dependencies inside data set used for training [17]. Transferring this to the automotive context means, that the proposed LSTM battery model simply learns the electric behavior inside the restricted state space of the trained electric load situation $DS_{AS(t)}$. It thereby has no

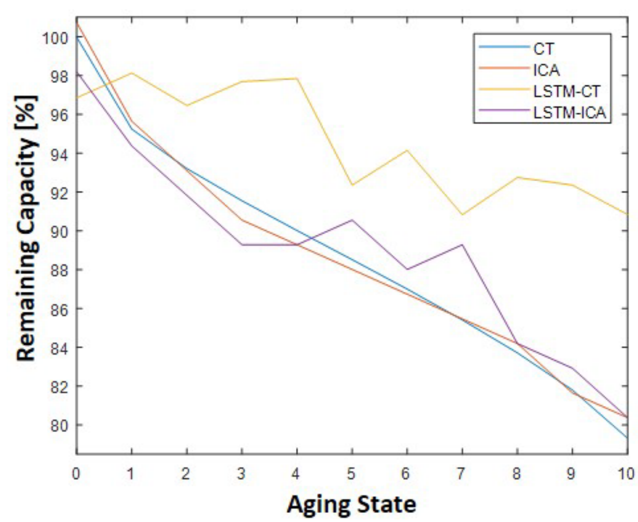

Fig 5: Remaining capacity. Laboratory experiments (CT,ICA) and virtual battery test (LSTM-CT,LSTM-ICA)

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knowledge about the real CT, the remaining capacity and neither the real performed ICA. Figure 6 shows such exemplary state space of a regular EV-customer behavior while driving. Summarizing all driving situations with respect to the c-rate and the SOC, we can observe that the customer is predominantly driving with moderate c-rates below 1C and inside SOC regions above 40%. This driving behavior does not cover the state space of the virtual experiments, why they had to be adjusted.

In terms of the LSTM-ICA, we determine the ICA-peak-[C] in order to calculate the remaining capacity. According to Figure 2, the ICA-peak-[C] is at around 3.8V (similar to 65% SOC) and thereby inside the trained state space. In terms of the CT, we have to extrapolate the virtual experiment. While discharging the battery to only 50% SOC, the charge throughput is calculated via Coulomb-Counting. The overall remaining capacity is determined by extrapolating the charge throughput to a full cycle. This method involves high errors due to the extrapolation as well as to deviations during the exact SOC estimation. The exact SOC estimation suffers from low open-circuit-voltage gradients in middle SOC regions combined with regular voltage measurement tolerance.

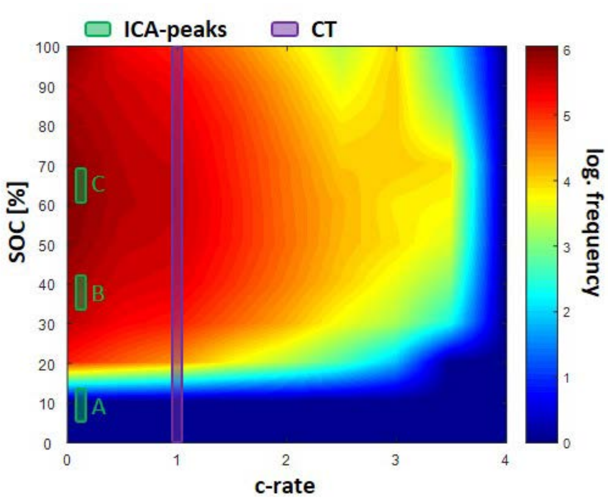

Fig 6: Logarithmic frequency distribution of exemplary state space of regular EV-customer driving behavior

5. CONCLUSION

The SOH estimation in the automotive context still appears to be a challenging task in EV development. Hence, data-driven methods to determine the remaining capacity only by using real in-vehicle driving data are a benefit for battery state monitoring and development.

In this work, we introduced a LSTM based battery electric model to learn the battery electric behavior from real in-vehicle data only. Consequently, we use the LSTM battery model to perform virtual experiments in order to compute the remaining capacity at different SOH of the battery. Considering the driving behavior of EV-customers, the battery model achieved state of the art RMSE deviation of 1.77% by performing ICA compared to conventional real laboratory experiments.

This method shows great potential, once the battery electric function is properly learned. In future work we will apply this method to different battery tests, such as internal resistance tests and will investigate the behavior of the combination of multiple battery cells.

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