State of Charge Estimation using Recurrent Neural Networks with Long Short-Term Memory for Lithium-Ion Batteries

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Abstract—**This paper presents an accurate state of charge (SOC) estimation algorithm using a recurrent neural network with long short-term memory (LSTM) for lithium-ion batteries (LIB) performing under real conditions. With its self-learning ability, this data-driven approach is able to model the highly non-linear behavior of LIB due to changes of environment and working conditions all along the battery lifetime. It is shown that the LSTM approach outperforms common physical-based models using Extended Kalman Filters (EKF) regarding accuracy and stability. To demonstrate this benefit for real-world applications, the provided network is trained and tested with data gathered from commercial industry applications in the domain of energy storage. The LSTM is evaluated and compared with an equivalent circuit model (ECM) using EKF under different working conditions. For dynamic loading profiles, the ECM-EKF achieves an error (RMSE) of 9.5% whereas the LSTM achieves an error (RMSE) of 5.0%.**

Keywords— lithium-ion battery, battery management system, state of charge estimation, artificial intelligence, recurrent neural network, long short-term memory, extended Kalman filter

I. Introduction

According to the Paris Agreement signed in 2016, 195 countries agreed to reduce their greenhouse gas emissions by at least 40 % until 2030 compared to 1990 [1]. In order to attain this objective, the usage of fossil fuels has to be drastically diminished wherefore the renewable energies are coming to the fore. For an efficient and sustainable utilization of renewable energy sources, reliable and safe energy storage is an indispensable prerequisite. The lithium-ion battery technology, with its high conversion efficiency provides an efficient solution as dynamic energy storage. In order to guarantee safety and high performance of a lithium-ion battery (LIB) for a long life-time, the LIB has to operate within electrical and thermal limits. This safe operating area (SOA) depends on the cell chemistry, the environment and working conditions as well as on the history of the battery. To ensure that LIBs operate within their SOA, a battery management system (BMS) is used to monitor battery parameters. Moreover, the BMS monitors the LIB to avoid over-charging, over-discharging and over-current scenarios depending on external operating conditions like temperature. The BMS has to precisely estimate the state of charge (SOC) to give an accurate estimation of the remaining available energy of the LIB for overall control units. This point is essential for a safe and economically viable usage of energy storage systems based on LIB [2].

The SOC of a LIB is defined as the residual charge of the battery and is given by the ratio of the residual capacity to the nominal, fully charged capacity of the battery [3]. Since the SOC is not directly measurable, it is crucial to use suitable algorithms for an accurate estimation. Traditionally, physical based SOC estimators are often limited due to their poor robustness regarding the highly non-linear dependence of the SOC on the changes of environment and working conditions during the operation of a LIB. Under laboratory conditions, data-driven approaches have demonstrated their potential to overcome these problems due to their high adaptability and self-learning ability [4].

In this work, an LSTM approach is used to determine the SOC of LIBs operating in industry applications. It is shown that this data-driven SOC estimator outperforms the physical based equivalent circuit model using EKF. This is especially the case for real-world conditions. Following the introduction, section II is covering the data generation and preprocessing. Subsequently, section III recapitulates the fundamentals of the SOC estimation. Afterwards, the results of the LSTM and EKF are presented and analyzed. Finally, the conclusion of this work and the outline for future research are given.

II. Data Generation and Preprocessing

Common lithium-ion based energy storage systems consist of one or several battery modules that in turn consist of multiple battery cells. The amount of the battery modules as well as the number of lithium-ion cells within each module mainly depends on the use case and the required energy and power. A comprehensible and reliable status monitoring of any energy storage system, independent of the containing chemistry and characteristics of the LIBs, requires a time discrete measurement of the voltage, current and temperature of each cell. The data measurements and logs for this publication were performed by the internally developed open source battery management system called foxBMS® [5].

Since foxBMS® has permanently measured for months depending on the dynamic real-world application, more than 1 TB data was collected. Due to the high amount of collected data, processing is a very computational intensive challenge. For a better insight and understanding of the data, an unsupervised learning algorithm, Gaussian Mean Mixture (GMM), is used to divide and cluster the preprocessed data. The resulting clustering of an exemplary dynamic profile of a LIB is provided by colored sections in Fig 1. The voltage and the C-rate of the LIB are plotted as well. The C-rate indicates the ratio of the current to the nominal capacity of the battery [3].

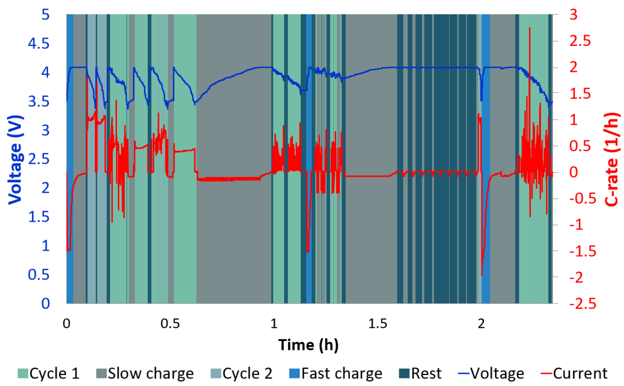

Fig. 1: Clustering of a dynamic load profile of a LIB.

Based on the clustering, the cumulated distribution of the most relevant operation phases (i.e., rest, discharge-, slow- and fast charge) can be evaluated. Using this information, it is verified if representative data is used as input for the SOC estimators. Fig. 2 illustrates the percentage of the four operating phases during exemplary dynamic cycle of the battery system.

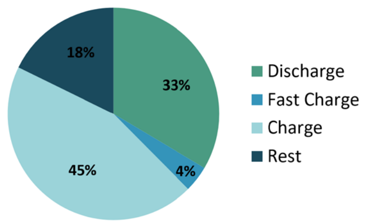

Fig. 2: Percentage of four different operating phases of a LIB during dynamic loading profiles.

The cell current, cell voltage and cell temperature are the input values for the SOC estimators considered in this work. This input is then mapped to the corresponding SOC. The reference SOC is calculated by the foxBMS using Coulomb Counting based on a shunt current sensor.

III. SOC Estimators

The Coulomb Counting approach is a straightforward method for predicting the SOC that uses current integration, meaning that the charge or discharge current is summed over time and then subtracted or added to the current SOC. However, this method has two drawbacks: the integrated value has to be initialized and the computed SOC shifts over time due to small integration errors. The initialization is usually processed with the open-circuit voltage (OCV): if the battery cell is at rest, there is a direct correspondence between the SOC and the battery voltage. However, this relation is not valid for the non-stationary case, i.e. during charging and discharging of the battery, including its relaxation period. This is because internal voltage losses occur during operation of the LIB. The voltage losses, also called overpotentials, arise due to the internal resistance as well as due to dynamic electrochemical reactions inside the battery. Even in the absence of current, the open-circuit voltage is not exactly measurable, due to relaxation phenomena. This renders the initialization impractical in a real application, as it is not wanted to immobilize the system to let the battery cell rest for SOC initialization.

A. Equivalent Circuit Models with Extended Kalman Filter

A way to overcome these issues is to use an equivalent-circuit model (ECM) combined with an Extended Kalman Filter (EKF). A typical ECM for modelling LIB is shown in Fig. 3.

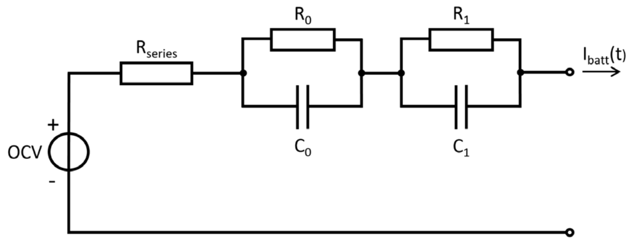

Fig. 3: Equivalent-circuit model used to describe the electrical behavior of a lithium-ion battery cell.

It contains a voltage source to model the OCV, a series resistance (R_{series}) to model the voltage drop when current is flowing and one (or several) RC-networks to model the dynamical behavior of the cell. Using the measured voltage of the battery cell, the EKF can correct the deviations due to an incorrect initialization and due to integration errors. An EKF is needed as the battery model is non-linear [6].

The ECM has to be calibrated, typically using optimization methods to fit experimentally measured voltage profiles. Since RC-models are empirical, it is awaited that they might not behave correctly outside of their calibration domain. Since the quality of the results depends on the adequacy of the model, the calibration effort can get high and a large amount of data can be needed to ensure that the model behaves correctly in all the situations that the battery system might encounter. Consequently, if a large amount of data is needed, a data-driven approach might be better suited, because it avoids the use of an empirical model.

B. Recurrent Neural Network with Long Short-Term Memory

Long-Short-Term Memory networks (LSTMs) are a type of Recurrent Neural Networks (RNNs) established in a wide range of time variant problems [7, 8, 9]. LSTMs as well as RNNs are specialized in processing time series to detect and memorize patterns, which are used to predict results at future time steps [9]. In contrast to the RNNs, which rely on simple feedback loops in their architecture to maintain the information in the memory [10], LSTMs have a separate cell state, which learns the management of the memory (such as its access and modification) in a more sophisticated manner. Implementations of LSTM cells are provided by all common machine learning frameworks. In the following, the LSTM module of Tensorflow [11], which is visualized in Fig. 4, is used and adapted for the battery use case. The module consists of one cell state and three gates that read and write the cell state.

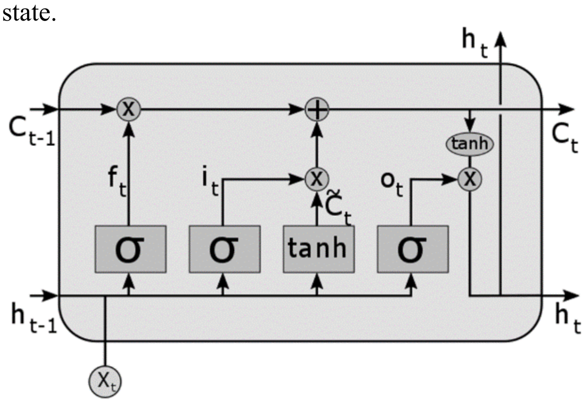

Fig. 4: Schematic setup of a long short-term memory cell.

The cell state is the memory lane of the network. Information that needs to be remembered is stored in the cell state vector and can be accessed by the LSTM at different time steps at later time. The three gates consist of neurons that are trained to decide which information should be forgotten, remembered and made available as output based on the previous output and current input. Since the input for the LSTM is a large amount of data, the network has to be fed sequentially. Therefore, the neural network is trained by feeding the time series sequentially. The deviation between the LSTM estimated SOC and the calculated reference SOC has to be determined. For this, a quadratic loss function is used that indicates the performance of the LSTM. The LSTMs ability to incorporate events from arbitrarily distant time steps into its prediction of future time steps is of great use for the SOC prediction, due to the superposition of short and long-term processes in real applications. While periods of fast charging and discharging take between several minutes up to hours, the degeneration and ageing of the cells is in the dimension of months or years. To yield a reliable model of the SOC, a large amount of data with a representative battery usage needs to be used for the training of the network [10]. Based on the clustered battery states in Fig. 1 and Fig. 2, the data input to the neural network can be adapted for modified use cases. Due to the highly parallel implementation of the LSTM, even with Graphics Processing Units (GPUs), multiple GBs of data can be processed at once. Moreover, based on established transfer learning strategies [12], trained LSTM models can be adapted to batteries using various cell chemistries.

IV. EXPERIMENTAL RESULTS

In the following section, the accuracy of the SOC estimation using LSTM and ECM-EKF is investigated for different operating scenarios. Using the information gained from the clustering, the same representative charge, discharge and rest patterns of 30 days are used for parameter fitting of the ECM-EKF as well as for training the LSTM. After training, the two SOC estimators are applied to different test data sets. The test data sets were not used for training or fitting parameters. The neural network used in this work consists of three layers with seven neurons each. A fully connected layer follows after the third layer and combines the output of the layers to one output neuron corresponding to the SOC value. Furthermore, the LSTM is trained by using the Adam's optimizer, which is an adaptive learning rate optimization algorithm that is specifically designed for deep learning applications [10]. The input for the LSTM contains the voltage, current and temperature of the LIB, whereas for the EKF only the measured voltage is used as input.

In Fig. 5 the SOC, voltage, C-rate and temperature of a LIB are plotted for an exemplary dynamic battery cycle that is used as a test data set. After a constant current discharge and a rest phase, a phase follows where the battery is dynamically discharged as shown by the profile of the SOC. Subsequently, a short resting phase and a constant current – constant voltage (CC-CV) charging phase are ensuing. Finally, during two dynamic operating phases separated with two resting periods, the LIB is again discharged.

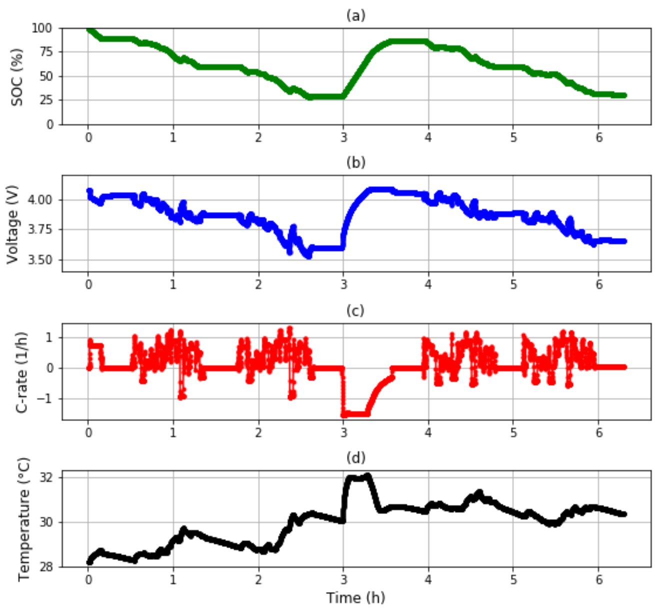

Fig. 5: a) SOC b) voltage c) C-rate and d) temperature of a lithium-ion battery during dynamic charge and discharge cycles.

In Fig. 6, Fig. 7 and Fig. 8 the SOC profiles calculated with LSTM (green) and ECM-EKF (red) are provided. The SOC determined with Coulomb Counting (black) serves as reference. Due to the drawbacks of the Coulomb Counting approach mentioned in section III, time-consuming recalibrations were done during the measurements, in order to provide a reliable reference SOC.

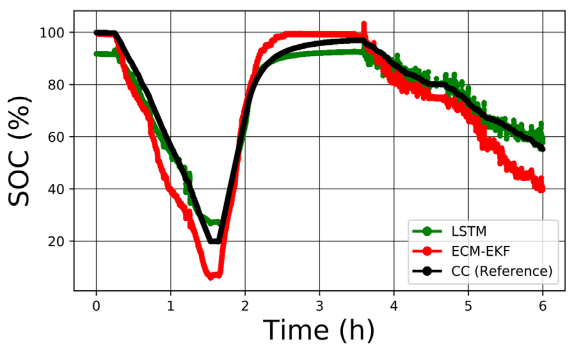

Fig. 6: SOC Estimation by LSTM, ECM-EKF with CC as reference for a load profile.

Fig. 6 shows the SOC estimations for a test cycle where only the second half of the profile contains a dynamic operating phase. Starting with a correct initialization, the estimation by ECM-EKF gets worse during discharging the battery. While the LSTM starts with a wrong initialization, the SOC estimation for the following first part of the load profile is very accurate. During the dynamic discharging, both methods are differing from the reference SOC. However, whereas the SOC computed with ECM-EKF moves away from the reference, the SOC profile estimated by the LSTM oscillates around the reference SOC.

In Fig. 7, the SOC profiles are plotted for another dynamic discharging profile. The ECM-EKF and LSTM are behaving similarly compared to the previous test shown in Fig. 6.

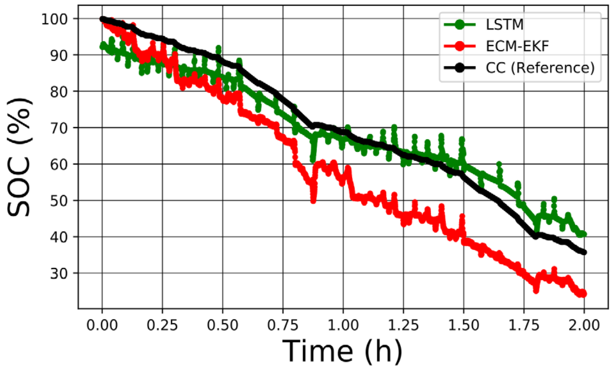

Fig. 7: SOC Estimation by RNN-LSTM, ECM-EKF with Coulomb Counting as reference for a dynamic discharging cycle.

After a correct initialization, the SOC computed with ECM-EKF differs from the reference profile, while the SOC curve determined by LSTM oscillates around the reference solution. In Fig. 8, another dynamic discharging and charging cycle is considered. For this test set, the SOC estimation provided by the LSTM oscillates again around the reference. However, in contrast to the test sets showed before, the ECM-EKF does not drift away from the reference SOC. Despite of this, the LSTM performs again better than the ECM-EKF.

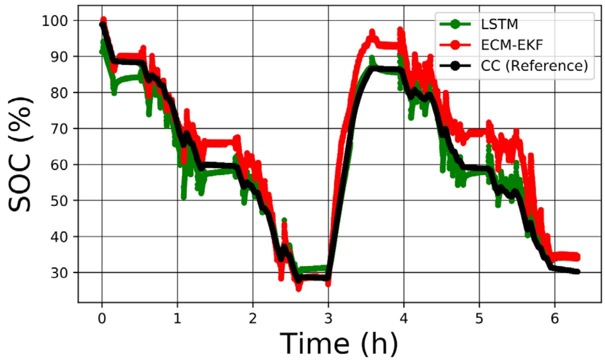

Fig. 8: SOC Estimation by RNN-LSTM, ECM-EKF with Coulomb Counting as reference for a dynamic load profile.

In order to quantify the results, three different integral error measurements are used: Root Mean Square Error (RMSE), Mean Average Error (MAE) and Maximum Average Error (MaxAE). In Table 1, the integral errors are shown for the two SOC estimation methods over all test data sets.

Models	**Error Benchmarks**		
	RMSE	***MAE***	***MaxAE***
ECM-EKF	9.5%	8.5%	19.3%
LSTM	5.0%	4.1%	12.8%

Table 1: Integral error measurements for the ECM-EKF and LSTM: Root Mean Square Error (RMSE), Mean Average Error (MAE) and Maximum Average Error (MaxAE).

The LSTM achieves an RMSE of 5.0% whereas the ECM-EKF achieves only an RMSE of 9.5%. Furthermore, independent of the used error measurement, the error obtained by LSTM is lower than the error obtained with the ECM-EKF. The LSTM estimate behaves consistently for various types of data sets, whereas the ECM-EKF performance strongly varies depending on the data set it is applied too. The results can get very poor in some cases. The reason for this is that the ECM-EKF adopts badly for changing environments and working conditions. During collecting data of over one year, these conditions change drastically. Even though the parameter fitting for the ECM-EKF is done for a representative data set, not every single combination of environment and working conditions is taken into account. As a result, the ECM-EKF does not work for profiles corresponding to conditions that were not exactly present in the training data set. The ECM-EKF has to be recalibrated in order to achieve a correct estimation. Here the high adaptability and self-learning ability from neural networks are coming to the fore, especially for real-world data with dynamically changing framework conditions. The LSTM not only outperforms the ECM-EKF, it provides a more reliable SOC estimation even for a fast changing environment and working conditions.

V. Conclusion

Physically motivated models like ECM-EKF and data driven approaches like LSTMs enable the prediction of the time varying states of LIBs for energy storage systems. The usage of battery data from real world profiles in this paper, compared to data generated under laboratory conditions, yields to a significantly higher deviation between the predicted SOC and reference values for both methods. It emerges that the data-based LSTM outperforms the physically motivated model by halving the averaged deviation to the reference in all cases, reached a 5% RMS error, even though the number and height of the error peaks have been barely reduced. Considering the growing amount of data gathered in all domains of energy storage, it is awaited that the accuracy of the LSTM approach will significantly increase. Compared to the sequential data processing needed to calibrate the ECM model in ECM-EKFs, the data driven approaches can be performed on GPU clusters, which enable the processing of multiple data sets containing the entire life-time of a battery system in several hours, allowing a better description of the LIB dynamics.

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