

## Evaluation of State of Charge Estimator Algorithms in Terms of Accuracy and Robustness

Lithium-ion batteries are increasingly being used in consumer electronics, Electric Vehicles (EVs) up to grid connected Energy Storage Systems (ESS) in the MWh range. The accurate State of Charge (SOC) estimation is essential to ensure a safe and reliable operation of lithium-ion batteries. In this project different SOC estimation algorithms for Battery Management Systems (BMSs) are compared regarding their accuracy and stability under dynamic load profiles as they occur in EVs.

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### Introduction

The main objective of this project is the implementation and evaluation of Kalman filter and Neural Network based SOC estimation algorithms for BMSs in EVs. The mean absolute error (MAE) of the estimation and the maximum absolute estimation error over the entire SOC range are used as evaluation criteria.

### Experimental Setup

For the evaluation of the SOC estimation algorithms, eight 18650 cells from LG and Sony with different SOH in the range of 100% - 80% are selected. The cells are placed in a temperature chamber and connected with a 4-wire cell holder to the cell tester as shown in Figure 1.

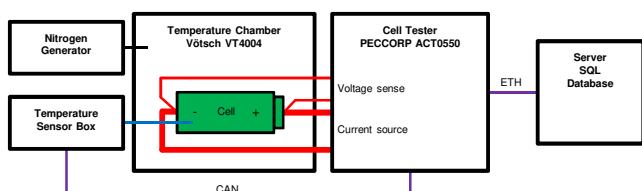


Figure 1: Overview of the test setup for one cell

The following tests are performed at 5°C, 25°C and 45°C ambient temperature:

- Open Circuit Voltage (OCV) with 0.05C and 0.03C
- Constant Current (CC) and Constant Resistance (CR) pulsed charge/discharge profiles
- Standardized Performance Tests (IEC 62660-1)
- Dynamometer Drive Schedules according to [1]: NYCC, UDDS, HWFET, USo6 and combinations

### Equivalent Circuit Cell Model

An equivalent cell model as shown in figure 2 is used to model the behavior of an electrochemical cell based on four main effects [2, p. 32]: The OCV, ohmic resistance, diffusion voltages and the voltage hysteresis. The model parameters are extracted using the least square method on the data of the OCV, pulsed and IEC 62660-1 tests.

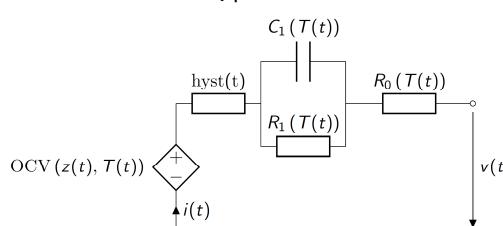


Figure 2: Equivalent Circuit Cell Model

### References

- [1] United States Environmental Protection Agency (EPA), "Dynamometer Drive Schedules", Online: <https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules>
- [2] G. L. Plett, Battery Management Systems, Volume II: Equivalent-Circuit Methods. Artech House, 2015, ISBN: 9781630810276
- [3] E. Chemali, "Intelligent State-of-Charge and State-of-Health Estimation Framework for Li-ion Batteries in Electrified Vehicles using Deep Learning Techniques", 2018, Online: <http://hdl.handle.net/11375/23021>

The validation data is recorded in the laboratory on various ambient temperatures by applying drive cycles to batteries of different age. The evaluation shows that the SOC estimation of state-of-the-art Kalman filters is accurate and stable, making them well suited for applications in EVs. The estimation of Neural Networks in the test configuration is unstable if untrained patterns occur. Thus, better training strategies must be developed to make them robust against unknown patterns.

### Kalman Filter SOC Estimation

The Kalman filter is an optimal state estimator for linear systems, it can be divided into two main parts. In the first part, the system state and error covariance is predicted. In the second part, the Kalman gain is calculated and based on measurements the state and error covariance is updated. Since the proposed cell model is nonlinear the SOC estimation is implemented on two nonlinear versions of the Kalman filter [2, p. 115]:

- Extended Kalman Filter (EKF) performs an analytical linearization of the cell model
- Sigma-Point Kalman Filter (SPKF) performs a statistical linearization of the cell model

To validate the EKF and SPKF methods, the Dynamometer Drive Schedules are disturbed by realistic sources of interference as seen in EVs (noise, offset and quantization errors). The figure 3 shows the worst estimation error in function of true SOC. Due to charges and discharges within the profile, the same SOC can appear several times. Table 1 shows the achieved estimation performance of the validation.

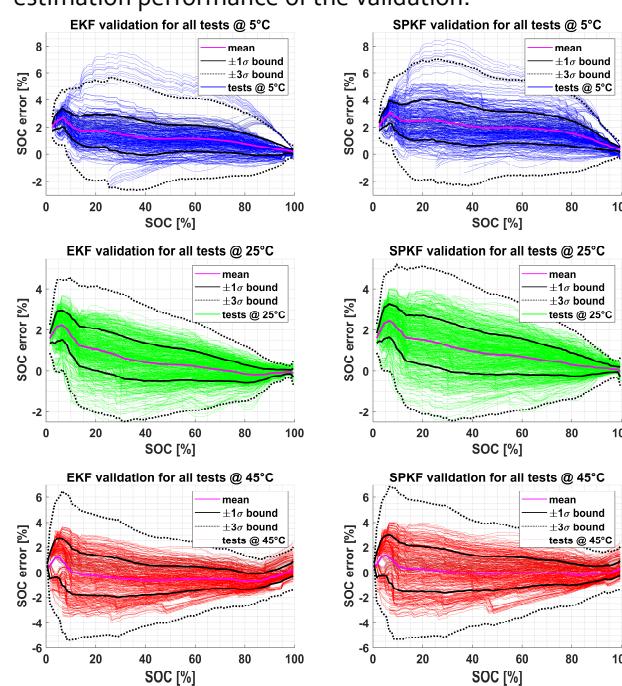


Figure 3: Plot of worst Kalman filter based SOC estimation in function of true SOC for different drive cycles at 5, 25 and 45°C

Method	Evaluation	all Temperatures		
		5°C	25°C	45°C
EKF	MAE [%]	0.96	1.23	0.77
	max abs error [%]	7.55	7.55	3.71
	SD [%]	0.84	1.02	0.71
SPKF	MAE [%]	1.27	1.88	1.03
	max abs error [%]	8.45	8.45	4.06
	SD [%]	1.06	1.27	0.88

Table 1: Performance of the Kalman filter based SOC estimation

### Neural Network SOC Estimation

Neural Network based SOC estimation is a new method with limited experience for practical applications. The Figure 4 shows a Convolutional Neural Network (CNN) based approach, where the measured cell voltage, current and temperature is directly mapped to SOC. This eliminates the time-consuming part of cell modelling that is required for the Kalman filter.

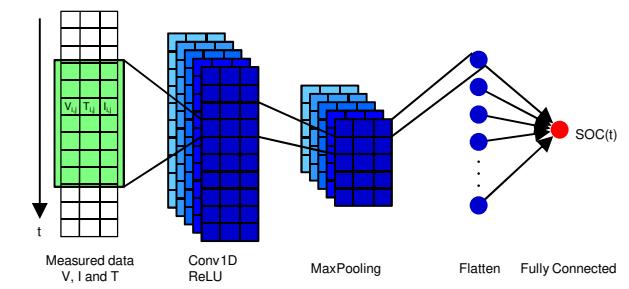


Figure 4: Direct mapping of measured voltage, current and temperature to SOC based on a Convolutional Neural Network

The CNN is trained for regression based on the recorded and disturbed drive cycles. The figure 5 shows the k-fold cross validation where similar cycles for each fold are excluded from the train and test set. It turns out that the USo6 cycle leads to incorrect estimates due to higher current peaks, which do not occur in the other cycles.

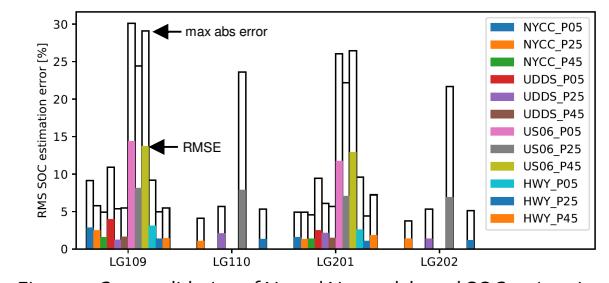


Figure 5: Cross validation of Neural Network based SOC estimation

### Conclusions

The evaluation shows that state-of-the-art Kalman filters can estimate the SOC with an accuracy of 0.96% MAE and a maximum absolute error of 7.55% over a temperature range of 5°C – 45°C. They are therefore suitable for use in EVs. Neural Networks in the tested setup exhibited low robustness when untrained patterns occur in the measurements. Their maximum estimation error can reach up to 30%. An improved training strategy is necessary to make the estimation of Neural Networks more stable. An accurate estimate of the SOC prolongs the life of the battery and enables a safe and reliable operation.

### Partners



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