A lumped Electro-Thermal Model for Li-Ion cells in Electric Vehicle Application

Kamyar Makinejad\textsuperscript{1}, Sabine Arnold\textsuperscript{1}, Hassen Ennifar\textsuperscript{1}, Han Zhou\textsuperscript{1}, Suguna Thanagusundram\textsuperscript{1}, Andreas Jossen\textsuperscript{2}
\textsuperscript{1}TUM CREATE, Singapore, kamyar.makinejad@tum-create.edu.sg
\textsuperscript{2}Technische Universität München, (TUM), Munich, Germany; Institute for Electrical Energy Storage Systems (EES)

Abstract

A lumped temperature model of the large format high power Li-Ion cell is introduced in this paper. The model is able to meet the real time implementation requirements; hence it finds its application in Battery Management System (BMS) of an Electric Vehicle (EV).

The model is evaluated in Hardware in the Loop (HIL) setup to verify online estimation of cell surface and internal temperature estimation for an on-board EV application.

In this study, the cell is considered as a single homogeneous layer and the heat is generated in the centre point of the cell and flows in one direction towards the surface. For this modelling purpose, reversible and irreversible heat sources in the cell are considered. Irreversible heat source consists of the Joule heating effect due to internal resistance of the cell for instance, these values are then calculated with sufficient electrical cell model and evaluated both offline and in real time calculation. Reversible heat source is a result of entropy effect which can be negative or a positive value depending on the current flow direction in charging or discharging process of the cell. Other heat sources such as conductive heat transfer and convective heat transfer are also included into the model.

This paper introduces a reference case test used to calculate the required necessary coefficients both for parameterization of electrical model and thermal model. The battery setup in the laboratory for measuring the cell surface temperature as reference data as well as cell sandwich setup for evaluating the internal temperature of the cells is explained in detail. Fundamental equations to develop the thermal model are introduced and the model is evaluated in both offline and real time mode.

Keywords: Li-Ion cell, Equivalent circuit model, Thermal model, Battery management system, Hardware in the loop

1 Introduction

In EVs, the battery is the main energy provider which is responsible for the supply of all the electrical components. These components differ from each other in their energy requirements, thus a high dynamic range of energy is needed. This dynamic aspect becomes critical for high voltage implementation. When several cells are connected together in series and parallel, this forms the battery pack of an EV. Therefore, a reliable and accurate BMS is required to afford the adequate amount of power and energy for various applications in an EV. This leads to the necessity of keeping the batteries in optimal conditions, decreasing their losses and protecting them from potential damage such as overheating, overcharging and over discharging.

Since providing these optimal working conditions for the cells and gaining critical information about the cell real-time and future status such as amount of available energy, remaining life time and many other valuable information can’t be realized by direct measurement via physical sensors, developing models such as Equivalent Circuit Model (ECM), thermal model, ageing model and various algorithms for estimation of State of Charge (SOC), State of Health (SOH), State of Function (SOF) and many others as the heart of the BMS of an EV is necessary.
Error! Reference source not found. demonstrates the interaction between these models and algorithms in the form of a flowchart. Some parts of this flowchart are described more in detail in this work but not all as they were outside the scope of this paper.

In section 2, the experimental setup is explained and the required test data such as Voltage (V), Current (I) and Temperature (T) are logged via high speed data logger.

Section 3 describes the cell parameterization and cell voltage model, which is also known as ECM. SOC model is not explained in this paper but in the simulation it was running in parallel to the EMC and cell thermal model to generate the required parameter for the cell simulation as the parameters of the cell are all SOC dependant too.

In section 4, cell thermal model is demonstrated and the interaction with the EMC is explained. The outcome of the cell EMC, thermal model, SOC model, SOH model are up-scaled to create the overall battery pack model. The battery pack model is implementable on the target microcontroller or the BMS system.

Parameter adjustment shown in the flowchart is due to the fact that cell parameter will change over time for instance by ageing or other external conditions such as temperature variation, hence the new parameter should be considered for both ECM and thermal model.

By using cell Equivalent Circuit Model (ECM) [1] and [2], one can easily realize that in general any successful and functional BMS should take advantage of cell ECM, ETM, SOC estimator and SOH estimator and many others. Since Simulink is suitable for offline data analysis, DS2202 HIL I/O board system used in this research from Dspace, enables us to read physical signals such as voltages, temperature and current in real time and by Analog to Digital Converter (ADC). These signals can be used in the compiled Simulink model in the ControlDesk. Then the cell voltage, temperature, SOC, SOH and other models can be run in real time for evaluation based on the desired test plan written for the battery cycler.

Figure 1: Flowchart of the investigation on the Li-Ion cell

2 Experimental

2.1 Test setup

High Energy Li-Ion Kokam pouch cell as shown in Figure 2 with the nominal capacity of 63 Ah and nominal voltage of 3.7 V is used for experiment. Figure 3 shows the test bench. High current battery cycler from Digatron industries with current ratings up to 300 A with additional parallel option of 4 circuits to reach 1200A, a 256 L Memmert thermal chamber capable of providing -40 °C to +120 °C, host computer and other equipment such as data loggers and precision current sensors are the part of this test bench. To evaluate the effectiveness of the algorithms, both new and aged cells cycled based on the flowchart shown in Figure 4 are considered. RTP in this flowchart stands for Reference Performance Test.
RTP is the first step in the design of the test for cell parameterization, which includes performing Hybrid Pulse Power Characterization (HPPC) test [3] as shown in Figure 5, repeats after every 100 ageing cycles under various conditions for instance different temperature level as shown in Figure 4. To have statistically reliable data, three cells were used for each test matrix and the parameterization result is the averaged value among these cells under each condition. By analysing separately the charge and discharge pulses, cell parameters can be calculated.

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The cycling ageing test will continue until the time which the cell discharge capacity reaches 80% of the initial discharge capacity at the time the cell was new. By definition when the cell discharge capacity is reduced by 20% the cell is considered at its End of Life (EOL) in EV application. Other method such as cell impedance monitoring is also being used to indicate if the cell is at EOL or is not able to deliver the required power for the specific application.
3 Cell Equivalent Circuit Model (ECM)

ECM is an electrical approach for representation of the internal/external behaviour of a cell. Other approaches are available for representation of the electrochemical internal/external behaviour of the cell which will be described in section 5. However the focus of this paper is mostly on the methods which are applicable on target low cost microcontrollers or the BMS of an EV [4]. It is noteworthy to mention that this high energy Li-Ion cell is being used to power TUM CREATE’s electric taxi called EVA which is developed for tropical weather in Singapore.

In this section, parameterization method of a Li-Ion Kokam cell is explained. This cell uses cathode material of Li[NMC]O₂ and the anode material of graphite found by X-Ray Diffraction (XRD) analysis and the electrolyte solvent of EC:EMC with LiPF₆ salt which is also studied by Botte et al. in terms of thermal stability by means of Differential Scanning Calorimeter (DSC) [5].

3.1 Cell parameterization

In Figure 7, the required cell ECM to provide inputs for cell thermal model to estimate internal/external temperature is presented. Analysis shows that this model is sufficient for accurate voltage simulation of the cell without the help of special controller or estimators such as Kalman Filter (KF) family. However it is noteworthy to mention that all the calculated parameters of the ECM model are SOC, Temperature and ageing dependant. The test matrix for the ageing test is extensively explained in [6].

Two conventional methods to determine any energy storage system parameters are either in frequency domain such as Electrochemical Impedance Spectroscopy (EIS) with sinusoidal excitation or with triangular excitation as discussed in [7] or in time domain such as Hybrid Pulse Power Characterization (HPPC) test. HPPC current profile is presented in Figure 5 and used to parameterize the High energy Kokam pouch cell. Cell parameterization can be performed both offline and online [4]. In our study, cell initial parameters are calculated in offline mode and later the parameter values are updated by minimizing the mean square error between the measured voltage and the simulated voltage. We refer to simulated voltage as $V_{\text{out}}$ shown in Figure 7.

Other parameter in this figure is $V_{\text{OCV}}(\text{SOC, T, n})$ representing the open circuit voltage of the cell which is a function of SOC, temperature (T) and cycle number (n) and can be measured after sufficient rest time under no load ($I = 0$). To obtain the parameters of the cells, experiments are conducted at different conditions and age with charging and discharging cycles. In order to consider the temperature effect on the cell parameters, ageing tests were conducted at four different temperatures (15 °C, 25 °C, 40 °C and 60 °C) and all parameters are calculated based on these temperatures and at different SOC levels and ageing conditions. Parameter values at temperatures other than the mentioned controlled test temperatures are calculated by interpolation of the data. $R_1$ represents the series Ohmic resistance of the cell but good caution must be taken into account while connecting the cell since any poor connection to the cell will introduce additional resistances.

Charge transfer resistance and SEI resistances are considered both as $R_1$ and together with $C_1$ known as double layer capacitance the time constant $\tau_1$ is introduced ($\tau_1 = R_1 * C_1$ ).

Figure 6: Discharge capacity of the cell cycled at 25 °C

Figure 7: Equivalent circuit model used in simulation
3.1.1 Calculation of $V_{OCV}(SOC, T)$ for the model

By using the test profile shown in Figure 5, the OCV values can be measured by giving sufficient rest time to the cell after each charge/discharge pulses. The OCV-SOC characteristic of the Li-Ion cell is nonlinear, this nonlinearity is shown in Figure 8. Speaking about cell parameterization, capturing OCV data over different SOC is straightforward. It should be noted that enough relaxation time should be given to the cell. Temperature also has effect on OCV values, therefore cells are kept at a specific, evenly distributed temperatures inside the temperature chambers. Calculating OCV at different SOC values can be done by measuring the discharge capacity of the cell and stepwise charging or discharging the cell based on the specific fractures of the total capacity of the cell.

We considered capturing the OCV values at each 10% steps in SOC as the cell has steep OCV-SOC curve as described in detail in [4]. OCV values also depend on the temperature that the cell was cycled at. Figure 9 shows the OCV of the cell cycled at 25 ºC after from 0 cycle (new) to 1400 cycles. Results show that the OCV values of the cell are decreasing over ageing at same cycle ageing condition (e.g. same temperature and test profile), similar results repeats for the other cycling ageing condition at different temperature values. Ageing results are not presented in this paper. Subsection 3.1.2 analyses the ageing and temperature effect on the internal resistance of the cell.

![Figure 8: Fresh cell OCV vs SOC at 25 ºC](image)

![Figure 9: Averaged OCV of 3 cells cycled at 25 ºC](image)

3.1.2 Measurement of Discharge Capacity

Cell discharge capacity measurement via HPPC test profile at 25 ºC and 40 ºC up to 1400 cycles and at 15 ºC and 60 ºC up to 500 cycles is shown in figure 6. Cells cycles at 15 ºC and 60 ºC lost more than 20% of their initial discharge capacity after 600 cycles so the tests had to be terminated for these cells. Looking into the discharge capacity plot, it is revealed that at controlled temperature of 25 ºC, the irreversible capacity loss is 4.38 Ah in Figure 6. These data later are being used to create reference data for SOC estimation and also as reference data to evaluate State of Health (SOH) of the cell for comparison purposes with the simulation result.

By definition SOC represents the amount of the charge currently stored in the cell. Equation 1 shows how cell SOC is related to SOH.

$$SOC = \frac{Q_a}{Q_n}$$

Equation 1

$Q_a$ denotes the available charge of the cell, and $Q_n$ is the total charge of the cell. $Q_n$ is subject to the cell ageing and describes the relation between cell SOC and SOH. To realize the above formula as current is the rate of flow of charge and by renaming the charge to cell capacity we have:

$$SOC(t) = \frac{\int i(t)dt}{C_n} + SOC_0$$

Equation 2

However equation (2) or coulomb counting method is strongly dependent on current measurement accuracy plus accurate knowledge of the initial cell SOC.
A critical SOC definition is, Li-Ion deintercalation from anode material and placing in the cites of the cathode material during discharge, this process is considered as surface SOC. Whereas volumetric SOC is when the Li-Ions are places inside the porous cathode material during discharge. The entire process might lead to non-uniform SOC distribution.

Figure 10 shows the normalized discharge capacity of the cell measured at 1C rate discharge at 25 °C, as it can be understand from this normalized capacity test that cells cycled at 25 °C and 40 °C lost only 10% of their initial discharge capacity after 1400 cycles but the cells cycled at 60 °C lost 20% of their initial discharge capacity after about 400 cycles.

Figure 10: Normalized cell capacity measured at 1C rate discharge at 25 °C

3.1.3 Calculation of $R_i(SOC, T)$

The cell parameterization algorithm automatically calculates all necessary parameters over different temperature range and cycle life of several cells to create reference data, and enable us to study the ageing mechanism of the cell. Cell voltage simulation also depends on how accurate the cell parameters are captured and how well the model works. Figure 11 shows averaged internal resistance evolution of 3 cells cycled from 0 to 1400 cycles (standard procedure charge and discharge based on manufacturer standards) at 25°C, in this figure $R_i$ is plotted every 200 cycles. Similar data at different temperatures and at different cycle numbers are collected and analysed but not shown here. It is noteworthy to mention that the internal resistance mainly is a sum of unwanted wirings resistance, bulk metal resistance in the current collectors and terminals, active material resistance and electrolyte resistance.

$R_i$ values are calculated from the HPPC pulse data, this pulses are either charge or discharge pulses of at least 600 A. We consider the immediate change in the relaxed voltage value as the series resistance value, hence fast data logger is necessary to calculate the correct value of this series resistance. As it is obvious, the series resistance increase due to the ageing which results in reduction of power capability of the cell and more internal heat generation, the heat generation due to the series resistance is explained in section 4.

Figure 11: Averaged internal resistance evolution of 3 cells cycled at 25 °C

3.1.4 Calculation of $R_1(SOC, T)$ and $C_1(SOC, T)$

Figure 12 shows the variation of series resistance $R_i$ at different SOC with respect to 0, 200 and 400 cycles under four different temperatures (15 °C, 25 °C, 40 °C and 60 °C). For fresh cells (0 cycle) there is small differences in $R_i$ values at different temperatures, however for cells undergoing more than 200 cycles, the ones tested at 60°C had an apparent increase of series resistance. Figure 13 and 14 show the parameterized value of $R_1(SOC,T,n)$ and $C_1(SOC,T,n)$. Similar to OCV, these are SOC, temperature and cycle number dependant.
Subsection 3.1 describes the parameterization and parameters of the ECM model. This part will demonstrate the voltage simulation of the model suggested in Figure 7, however it is possible to estimate SOC, SOH and SOF with the gathered data, parameters and the proposed cell model, but this task is outside the scope of this paper and we only deal with the cell thermal model in section 4 and will show how a cell thermal model is developed over the basis of cell ECM model and is able to estimate both cell surface and internal temperature.

This ECM model however considers ageing of the cell as the parameters are calculated over few hundred cycles.

Ageing mechanism is a complex process occurring due to structural and chemical changes in the components of cell or the material used in the cell. It is characterised by deterioration of battery performance with time and usage. Cell ageing can be classified into calendar ageing and cycling ageing. In the present work we focus mainly on the cycle life ageing of the cells. Most literatures associate ageing mechanism with active material degradation, formation and growth of solid electrolyte interface (SEI) layers and electrolyte decomposition. However very recently, many studies show that ageing mechanism can be linked to separator degradation, chemistry, cell form and geometry, which cause non-uniform utilisation of active material and results in inhomogeneous ageing. In the present frame work we have only discussed the electrochemical part of cell ageing.

In tropical megacities like Singapore, the ambient temperature is quite high and the battery pack should be equipped with better cooling units. Many literature works show that high temperature has severe effect on battery lifetime due to accelerated ageing. Therefore the main function of the cooling units should keep the battery pack temperature at an optimal level to improve its performance and lifetime. To simulate the terminal voltage of the cell based on Figure 7:

\[ V_{\text{out}} = V_{\text{OCV}}(SOC, T, n) + V_{RLC1}(SOC, T, n) + \ldots + R_i(SOC, T, n) * I \]

Figure 15, the comparison of the simulation based on equation 3 and measured voltage with pulse test
inputs is demonstrated for both fresh and aged cell, the simulation model took advantage of model parameters and ECM as discussed in previous section. It is noteworthy to know that the ECM simulation model doesn’t take advantage of any corrective algorithms and methods such as Kalman Filter (KF) family at this stage. As mentioned, estimation of cell hidden parameters such as SOC, SOF and SOH is out of the scope of this paper and we only demonstrate modelling technique for terminal voltage and temperature estimation.

The cell is placed inside a temperature chamber and the ambient temperature is set to 25 °C. The following subsection demonstrates heat sources, test profile to get the parameters and the method to model this temperature rise and any other temperature variation on the cell surface as the result of different current profile inputs.

Figure 15: Comparison of measurement and simulation for input current profile shown in Figure 16

4 Cell thermal model

The objective of this work is to simulate the internal and external (by making cell sandwich) cell temperature and evaluate the simulation results with measured values by Dspace Hardware in the Loop (HIL) real time simulation as shown in Figure 16.

This section introduces a lumped thermal model that estimates both surface and internal temperature.

Similar to section 2, where a HPPC test profile was used to parameterize the cell to develop the ECM, a specific test profile was developed and implemented on the same cell to derive the parameters of the cell thermal model, see Figure 16. To collect reliable temperature data, several accurate and sensitive temperature sensors as shown in figure 2 are attached to the cell surface. The experimental setup is like before and shown in figures 2 and 3.

As it is shown in Figure 16, as the result of the current profile shown in the bottom, there is a considerable temperature rise on the surface of the cell, however the ambient temperature value doesn’t change much (shown in red colour) as the result of different current profile inputs.

Figure 16 Test setup for HIL implementation for real time implementation of cell models and algorithms

4.1 One Dimensional thermal analysis work and heat sources

This part describes the heat sources and thermal analysis of the Li-polymer Kokam 63 Ah pouch cell with the aid of two different softwares: Matlab Simulink and Comsol which is explained in section 5.

To start, we briefly speak about different heat sources in Li-Ion cell and the dominating ones responsible for the temperature rise of the cell.

Different heat sources to be considered to simulate the temperature model of the cell are as follows:

- Heat conduction
- Heat convection
- Heat Radiation
Temperature levels for Li-Ion cell environment in EV’s and HEV’s are assumed to be in between and, most of the heat generated by radiation is absorbed by the cell itself because it is composed from solid materials. Moreover the temperature range is so low that the amount of heat generated by radiation can be neglected for purpose of cell thermal analysis work.

4.2 Development of Equivalent Thermal Model (ETM) of Li-Ion cell

4.2.1 Heat Generation sources

For the thermal modelling of the Li-Ion cell, both reversible and irreversible heat generations sources are considered. The irreversible heat source consists of the Joule effect due to the internal resistances in the cell. Based on the electric model approach of the cell as shown in Figure 7, two main resistances are considered in this work: the polarization resistance \( R_1 \) and the Ohmic resistance \( R_i \). The equation for the heat generated at a central point in the cell is:

\[
Q_{\text{heat},\text{Joule}} = R_1 I^2 + R_i I^2
\]  

(4)

The reversible heat generation source consists of the entropy effect which can be negative or positive depending on respectively charging or discharging.

Based on measurement of a 63 Ah Kokam cell the initial model parameters have been optimized with Recursive Least Square (RLS) method. The obtained results show that the estimated values of internal resistance, capacity, OCV and others provide valuable information about cell internal/external temperature and terminal voltages even if the physical sensors become faulty and go out of operation for any reason.

The heat generated by the entropy variation depends strongly on the OCV and therefore the SOC as shown in figure 17 for the mentioned cell. The equation for the reversible heat can be written as equation 6:

\[
Q_{\text{heat},\text{rev}} = -T \Delta S \frac{I}{nF}
\]  

(5)

In equation 5, \( F \) is the Faraday constant.

Thus, the total heat generated can be written as summation of Equation 4 and 5:

\[
Q_{\text{heat, total}} = Q_{\text{heat }, \text{Joule}} + Q_{\text{heat, rev}}
\]  

(6)

4.2.2 Heat Transfer Effects

1) Conductive Heat Transfer

\[
Q_{\text{cond}} = \frac{kA}{d} (T_i - T_{\text{cell}})
\]  

(7)
Where $k$ is the thermal conductivity, $A$ is the cross section area of the cell, $d$ is the cell thickness, $T_i$ is the cell estimated internal temperature and $T_{cell}$ is the temperature on the surface of the cell.

2) Convective Heat Transfer

$$Q_{conv} = hA(T_{cell} - T_{amb})$$ (8)

$h$ is the Heat transfer coefficient and $T_{amb}$ is the ambient temperature.

### 4.3 Mathematical formulation and parameterization of the cell thermal model

In the formula presented in Equation 9, $c_p$ is the specific heat capacity, $m$ is mass of the cell, initial value of each parameter is calculated in offline mode and presented in Table 1 and Table 2.

$$c_p m \frac{\partial T_i}{\partial t} = Q_{heat\text{total}} - \frac{kA}{d}(T_i - T_{cell})$$ (9)

We consider that the amount of heat flow absorbed by conduction effect is the same as the one absorbed by convection. We can write the following equation:

$$Q_{cond} = Q_{conv}$$ (10)

From this equation, we can derive the relation between $T_{amb}$ and $T_i$.

$$T_{cell} = \frac{kT_i + hdT_{amb}}{hd+k}$$ (11)

Parameters $k, h$ and $c_p$ will be identified by training the data with real measurements. All necessary parameters are brought in Table 1 and Table 2. Figure 18 demonstrates the comparison between cell measured temperature and cell modelled temperature as a result of the input current profile shown in Figure 16.

### Table 1: Physical Cell measurement

<table>
<thead>
<tr>
<th>Parameter</th>
<th>mass</th>
<th>cross section area</th>
<th>thickness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sign</td>
<td>M (kg)</td>
<td>A (m²)</td>
<td>d (m)</td>
</tr>
<tr>
<td>Value</td>
<td>1.52</td>
<td>0.262*0.257</td>
<td>0.0053</td>
</tr>
</tbody>
</table>

### Table 2: Cell calculated coefficients

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Thermal conductivity</th>
<th>Heat transfer coefficient</th>
<th>Specific heat capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sign</td>
<td>k W/(mK)</td>
<td>h W/(m²K)</td>
<td>c_p (J/kg/K)</td>
</tr>
<tr>
<td>Value</td>
<td>0.3627</td>
<td>38.9532</td>
<td>1.1044</td>
</tr>
</tbody>
</table>

![Figure 18 Measured and estimated temperature of the cell](image18.png)

Figure 18 Measured and estimated temperature of the cell

5 Temperature Distribution in the Cell

The ECM assumes the same temperature for the whole cell. In big high energy Li-Ion Cells, like the one investigated, the temperature is likely to vary locally. At the same time it is difficult to determine the spatial temperature distribution within the cell [8]. However multidimensional finite element models (FEM) provide valuable assumptions of the temperature gradients and local heat generation or dissipation inside a single battery cell or cell layer. FEM are not suitable for BMs application, as they do not provide real time data. Nevertheless they facilitate a better understanding of the physiochemical processes in
the battery cell as these models are explained in greater detail.

The electrochemical-thermal COMSOL models employ the Porous Electrode Theory and the Concentrated Solution Theory introduced by Newman and Tideman [9] and Doyle et al. [10]. The cell behaviour is characterized by its reaction kinetics, charge transfer and its internal material transport including diffusion reactions. For the single layer model (Figure 20) this is coupled to the energy balance to simulate the thermal behaviour [11]. For a lumped analysis of the entire cell stack (Figure 19), the single layer properties are averaged over the entire layer to create a heat rate estimation at different boundary temperatures and times of the cycling process. This estimation is then fed into a purely thermal cell stack model described by unsteady heat conduction.

\[ \rho c_p \frac{dT}{dt} = -k \nabla^2 T + Q \]  

(12)

Simulations show temperature gradients do exist within the high energy Li-Ion pouch cell for EV applications. However they remain rather small. Figure 19 shows the temperature distribution in the 63 Ah high energy Li-Ion Kokam pouch cell in the cross-section of the cell stack within the symmetry plane (yz-plane) during a 1C charge/discharge cycle a) discharging and b) charging. For evaluation of the estimated internal temperature, a cell sandwich experiment is proposed, where temperature sensor is placed between two pouch cells surfaces

Conclusion

This paper presents a novel coupled electrical and thermal model for large format Li-ion cell in terms of interaction between models and considering temperature effect for tropical weather condition for countries like Singapore and also cycling ageing of the cell. 3 new cells were selected for each test matrix to have statistically reliable data and also generating comprehensive and enough amounts of reliable reference data for comparison purposes between measurements and Simulations. The electrical model is known as ECM model and the parameterization technique is explained in detail. ECM model is evaluated real time by HIL system and is implementable on target microcontroller or BMs system. Thermal model uses inputs of ECM model to generate temperature simulation of the cell and feedbacks the simulated temperature data into the ECM model. As cycling ageing and temperature effects are considered and were implemented in both ECM and thermal model of the cell, this coupled model is suitable to be up-scaled into battery pack model and be used in BMS. Moreover the internal temperature of the cell can also be estimated by the thermal model. For evaluation of the estimated internal temperature, a cell sandwich experiment is proposed, where temperature sensor is placed between two pouch cells surfaces
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References


Authors

Kamyar Makinejad earned his M.Sc. degree from Leibniz University of Hanover, Germany in 2011. He is currently working as Research Associate in TUM CREATE, Singapore and pursing his PhD with the Technical University of Munich, Germany. His research interest is battery diagnostics, modelling, state determination and BMS in EV applications.

Sabine Arnold studied Electrical Engineering and Information Technology at Karlsruhe Institute for Technology (KIT), Germany. Her research within TUM CREATE focuses on battery modelling on cell level. Here, she is especially interested in 3D, multiphysic models, which allow safety simulation.

Hassen Ennifar earned his B.Sc. in electrical engineering and information from Nanyang Technological
University, currently his is a master student at Technische Universität München, Germany.

Han Zhou obtained her bachelor degree in Material Science and Engineering from Nanjing University, China, and master degree in Material Science from Université de Picardie Jules Verne, Amiens, France. Currently she is working in TUM CREATE on thermal management of battery pack.

Suguna Thanagasundram earned her B.Eng. in electrical and electronic engineering from National University of Singapore. She completed her MSc and PhD degrees from the University of Leicester UK in 2003 and 2007 respectively. She is currently a Research Fellow in TUM CREATE in Singapore, working in the area of electrical storage systems.

Andreas Jossen earned his doctorate, dealing with "Management of photovoltaic plants using energy storage systems" at University of Stuttgart. From 1994 he was group leader for different battery related topics with ZSW, Ulm. Since 2010 he is full professor at the Institute for Electrical Energy Storage Technology, TUM.