

Chapter 2

Battery Management

Abstract The battery management in non-road HEV is exposed to higher requirements compared to on-road HEV, since higher power densities and load dynamics are usually demanded. For the control of HEV (see Chap. 4), a battery model comprising the nonlinear effects is required to be used in the controller itself as well as essentially within the battery management system. The state of charge of the battery is not measurable online, though, and needs to be estimated online during operation (Hametner and Jakubek 2013). In this chapter, a generic methodology is proposed comprising nonlinear system identification and optimal model-based design of experiments (DoE) of battery cells, which can be used for battery module modeling and accurate SoC estimation during operation.

Keywords Lithium ion batteries · Nonlinear system identification · Optimal model based design of experiments (DoE) · State observer

2.1 Introduction

2.1.1 Motivation

In many BMS, the open-circuit voltage (OCV) of the battery is used to estimate the SoC, which is feasible as long as the battery is not in use. During operation, the nonlinear behavior of the battery voltage comes into effect and big estimation errors occur if only the OCV is used to estimate the SoC (Hu and Yurkovich 2012). The integration of the battery current is another approach for SoC estimation, whose disadvantage is the drift due to the accumulation of current offsets when time increases. Dynamic SoC estimators (e.g., extended Kalman filter) are a powerful way to estimate the SoC, but require a precise dynamic battery model for accurate estimation (Plett 2004c). Precise battery models describe the nonlinear dynamic behavior of the battery cell terminal voltage accurately by considering nonlinear battery effects such as hysteresis, relaxation, and temperature effects. In general, due to the high

power densities in non-road HEV, the nonlinear effects of electrochemical batteries are increased (Gao et al. 2002), which complicates the modeling of the nonlinear battery effects (Unger et al. 2012a). Note that the used battery model needs to be real-time capable in order to be implemented in the BMS, which is in general a trade-off between accuracy and complexity.

2.1.2 Cell Chemistry-Dependent System Behavior of Batteries

The most known cell chemistry is the lead acid cell chemistry, which is used in almost every vehicle to start the engine. Beside of lead acid, there are many other cell chemistries such as lithium-iron-phosphate (LiFePO_4), lithium-polymer (LiPo), or nickel-metal hydride (Ni-MH). However, electrochemical batteries are strongly nonlinear systems, which depend nonlinearly on the SoC, temperature, and current, while additional effects such as relaxation and hysteresis are observable. In this context, relaxation refers to the slightly converging battery voltage at standby or steady-state current, while hysteresis refers to a phenomenon in relation to the cell polarization, which causes different shapes of the voltage values during charge/discharge of the battery. Inner chemical reactions may not be observed clearly in the voltage behavior since they occur randomly, but they are present and may have an influence on the voltage behavior. Lithium-ion batteries have a higher energy density compared to lead acid batteries and are therefore often used in mobile phones. Ni-MH chemistry has been used for traction batteries of HEV, but more and more traction batteries use the lithium-ion cells. This is not only caused by the higher energy density of lithium-ion cells but also by a smaller phenomenon referred to as “*memory effect*,” which reduces the capacity if the battery is not fully discharged before being charged again. A comparison of different battery cell chemistries in terms of energy and power capabilities is given in Fig. 2.1.

In general, traction batteries are built by coupling battery cells in serial and parallel connection in order to achieve a desired voltage level (series connection, since voltage add up) or battery capacity (parallel connection, since capacity add up). For the powertrain of non-road vehicles, the power capability of the traction battery is essential, due to which power-type battery cells are usually assembled in the battery module. Battery cells can be divided into power and energy cells, while power cells usually have higher power capabilities than the energy density maximized energy cells. The power capabilities of a battery cell can be expressed by the referred to as C-rate, which is a battery capacity-independent measure of the current intensity applied to a battery and is obtained by the quotient of current and battery cell capacity. In non-road vehicles, battery cells must be able to cope with possible C-rates above 20C, while electric vehicles mostly require larger energy contents. Due to this reason, power cells are generally used in non-road HEV.

Furthermore, depending on the cell chemistry, voltage levels and battery behaviors are different, while even the shape of the discharge curve within the same cell chemistry may vary (e.g., lithium-iron-phosphate and lithium-polymer). Also rele-

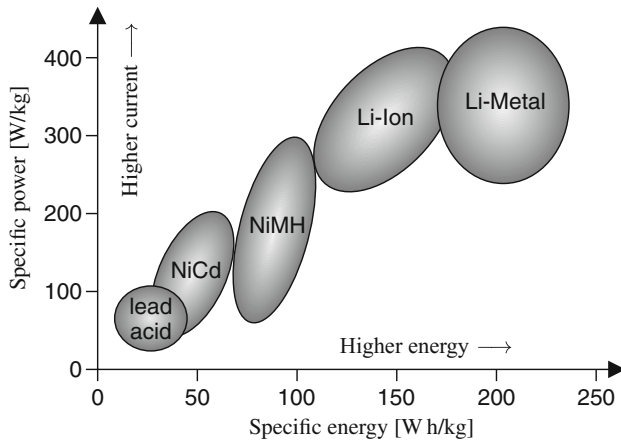


Fig. 2.1 Specific energy and power capabilities of different rechargeable battery cell chemistries

vant is the voltage level, which is significantly responsible for the overall energy flow and system requirements of the traction battery system. The type of the cell and the geometric structure (e.g., cylindrical, prismatic, ...) mostly define the temperature behavior of the cell. This can be seen at higher C-rates, where the temperature increases significantly and limits the ability of the battery cells to be used in the high dynamic environment of non-road vehicles. In this context, the energetic efficiency plays a major role for the temperature behavior of the cells and is especially essential in non-road applications. Note here that the energetic efficiency is nonlinearly depending on the history of the battery cell's usage, which is important for the more than 10 years intended product life of a non-road vehicle. For the lithium-ion chemistry, additionally higher safety requirements are relevant, because overcharging with higher voltage may lead to explosion or fire and must be avoided in any case.

2.1.3 Challenges in Dynamic Battery Model Identification

In order to use a battery model approach within non-road vehicles, it must be generically applicable to any battery cell chemistry. A general model structure is therefore required that considers nonlinear effects. The nonlinear relations between the voltage and temperature as well as the SoC are unknown in advance, and only physically measurable variables are available for parameter identification. In order to identify specific nonlinear effects, long test runs must be performed because the reaction times of batteries are slow. Time consuming and expensive measurements are unacceptable for non-road applications, since the sales volume of non-road machines is low. Data-based approaches are methodologies which only depend on the provided data. The advantage of data-based models is that the model is flexible to any cell

chemistry, while any model structure can be applied to consider the nonlinearities of the battery cells. On the other hand, the disadvantage is that an appropriate model structure needs to be found, and suitable data must be available for parameter identification. Nevertheless, an initial structure can be obtained from expert knowledge and included in the approach. The high dynamic requirement of non-road vehicles challenges especially the test equipment, because high current steps occur during operation. So far, high dynamics are not state of the art in the testing hardware of battery cells. Therefore, a major role corresponds to the design of experiments in order to achieve appropriate and reproducible measurements. The reproducibility of battery measurements depends on the excitation history of the battery, and appropriate procedures to clear the cell's short time history must be applied. Finding the appropriate procedure is challenging for battery cells, though, while the case is even more difficult for battery modules due to cell balancing. In order to gain maximum information from one test run, optimal design of experiments can be applied. Optimized test signals are able to achieve sufficient information content in the measurements, but since only the current is applied to the battery cell; in principle, a multi-dimensional optimization problem must be solved that consists of only one degree of freedom (DOF) and multiple effects to be tested.

2.1.4 State of the Art

The following sections review literature regarding battery cell modeling, design of experiments, battery module modeling, and SoC estimation.

2.1.4.1 Battery Cell Modeling

Three model approaches have been mainly used in the literature to model battery behavior:

1. Equivalent circuit models
2. Electrochemical battery models
3. Data-based battery models

In Fig. 2.2, the equivalent circuit model (ECM) approach is depicted schematically. Basic electric elements are used to describe the behavior of the terminal voltage, due to which physically interpretable parameters and real-time capability are achieved. Depending on the number of RC-circuits, different time constants are considered in the model. Only one RC-circuit accounting for nonlinear equilibrium potentials, rate and temperature dependencies, thermal effects, and response to transient power demand is used by Gao et al. (2002). A modified equivalent circuit model is used by Pattipati et al. (2010) to estimate SoC, state-of-health (SoH) and remaining useful life in the BMS. Due to the high power density appearing in the automotive industry,

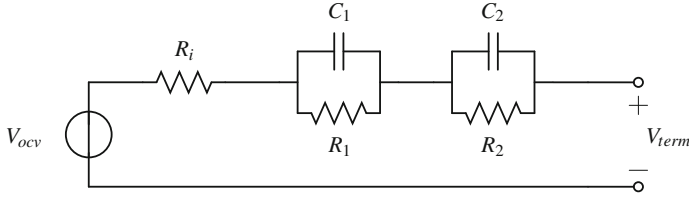


Fig. 2.2 Schematic overview of an equivalent circuit model (V_{term}) that consists of a constant voltage source (V_{ocv}), an inner resistance (R_i), and two RC-elements (R_1, C_1, R_2, C_2)

solution resistance, charge transfer resistance, and Warburg impedance cannot be neglected and must be considered within the ECM (Gomez et al. 2011).

Electrochemical battery models describe the electrochemical behavior of the battery by chemical reaction equations, which results in a physical model that is computationally intensive. The internal chemical states of the battery are simulated with high accuracy, and insight into the system is achieved (Klein et al. 2010), but in general the model is not real-time capable. Concentrated solution theory is used by Doyle et al. (1993) to describe lithium-ion battery cells. Klein et al. (2010) used partial differential-algebraic equations for state estimation, while a single particle model (SPM) is used by Santhanagopalan and White (2006) to estimate the SoC with an extended Kalman filter. However, the SPM model approach neglects the spatial variation of the states within the battery cell, which questions the validity for the operating region encountered for HEV (Chaturvedi et al. 2010).

Data-based system identification is a powerful approach for modeling and estimation purposes. Model structure and order are easily adaptable, although in general, physical interpretability is not given (Klein et al. 2010). In a series of three papers, Plett (2004a, b, c) proposed a SoC estimator based on a data-based nonlinear state-space model and an extended Kalman filter. The current direction is considered in the model, and hysteresis as well as relaxation is also included by a “hysteresis state” and a low-pass filter on the current, respectively. The model is assumed to be cell chemistry independent. Neural networks for battery modeling have been used by Charkhgard and Farrokhi (2010) and stochastic fuzzy neural networks by Wang (1994), Wang and Chen (2005), and Jing et al. (1998). A stochastic fuzzy neural network is also used by Wang et al. (2009) for the purpose of modeling the nonlinear dynamics of current, temperature, and SoC, while Xu et al. (2012) used it for the purpose of SoC estimation.

Hametner and Jakubek (2013) obtained a nonlinear battery model due to a local model network, which composes of several local models that are linear in their model parameters and have a certain area of validity defined by validity functions (see e.g., Hametner and Jakubek 2007; Murray-Smith and Johansen 1997; Gregorcic and Lightbody 2007). The nonlinear interpolation of the local linear models (LLM) achieves a nonlinear model output, while the model is constructed by an iterative algorithm. Starting with one global linear model, in each iteration, a LLM is added to the network until a certain threshold is reached (partitioning). Depending on the

algorithm's strategy, the validity of the new LLM lies in a specific form in the partition space of the model. In order to identify the model parameters, any model approach requires measurements for parametrization. Battery cells are tested by applying a current excitation signal and recording the voltage response. Depending on the excitation signal, the testing device needs to fulfill certain requirements in terms of dynamics.

2.1.4.2 Design of Experiments

Simple constant discharge and charge cycles are used by Kroeze and Krein (2008) to identify the parameters of an ECM, while Gao et al. (2002), Chen and Rincon-Mora (2006), and Hentunen et al. (2011) used a discharge pulse excitation signal. Smith et al. (2010) also used a discharge pulse excitation signal for the model-based estimation of an electrochemical battery cell model. Charge and discharge modes within a pulse profile have been considered by Hu et al. (2011), Hu et al. (2009a), and Plett (2004b), in order to identify the parameters for more advanced ECMs (e.g., linear parameter-varying models). An asymmetrical current step profile, significantly more dynamic than the other excitation signals, has been used by Hu et al. (2009b) for the purpose of covering a wide range of SoC as well as a wide range of the current. The dynamic Federal Urban Driving Schedule (FUDS) is mostly used as a validation signal (see e.g., Smith and Wang 2006; Xu et al. 2012; Kroeze and Krein 2008; Sun et al. 2012a), but in non-road applications, the FUDS is rated as an example for low dynamics.

The design of experiments plays an important role, especially for data-based approaches, due to the decisive influence of the excitation signal on the parameter estimation (Unger et al. 2012a; Hametner and Jakubek 2013). In order to maximize the information content of measurements, model-based design of experiments can be used. The idea of model-based design of experiments is to use a prior process model (reference model) to maximize the information content of measurements in order to identify parameters with minimum variance (Pronzato 2008). A measure for the information content of an excitation signal can be obtained by the Fisher information matrix $\mathcal{I}$ (FIM), which gives the covariance for the parameters estimated from the excitation signal. Based on optimality criteria, the FIM is often used to optimize the excitation signal. Furthermore, depending on the accuracy of the reference model, constraints of the process can be considered in the excitation signal.

Static experiment design based on a local model network generation algorithm is proposed by Hartmann et al. (2011). Dynamic experiment design for multilayer perceptron networks is proposed by, e.g., Cohn (1996) and Deflorian and Klöpper (2009), where optimal inputs are chosen from a candidate set. Dynamic design of experiments based on multilayer perceptron networks is also centered by Stadlbauer et al. (2011a, b). These papers are used by Hametner et al. (2013b) to design non-linear dynamic experiments, which minimize the model variance of dynamic multilayer perceptron networks as well as local model networks. The influence of optimal model-based design of experiments on battery modeling, compared to dynamic exci-

tation signals from the literature, is investigated by Unger et al. (2012a). Model-based design of experiments using a linear dynamic model and predefined current levels is proposed by Hametner and Jakubek (2013) in order to achieve optimal SoC excitation and minimal measurement duration.

2.1.4.3 Battery Module Modeling

The modeling of battery modules is different compared to battery cells, since battery balancing needs to be considered (Bentley 1997). Furthermore, the internal resistance of the battery cell connections as well as the temperature effect on the internal resistance of the battery plays major roles in the overall voltage behavior. Lee et al. (2010) provided a comprehensive review of joining technologies and processes for automotive lithium-ion battery manufacturing and discussed advantages and disadvantages of the different joining technologies, while corresponding manufacturing issues are mentioned. Since the battery forms a critical part of the HEV powertrain, Sen and Kar (2009) present a battery pack model that analyzes the variation of internal resistance as a function of temperature in order to provide the possibilities to design a cost-effective and efficient battery management system. Watrin et al. (2011) proposed a multiphysical battery pack model along with a test procedure that must be followed to obtain the different model parameters. Based on a screening process that provides a selection of battery cells with similar electrochemical characteristics, in Kim et al. (2011), the accuracy of the SoC estimator is increased. Due to the screening process and a parameter comparison, the battery module model can be simplified into a unit-cell model that is multiplied with the number of series connected cells. A similar capacity and resistance screening process is used by Kim et al. (2012) to improve the voltage/SoC balancing of a lithium-ion series battery module. Dubarry et al. (2008) use an equivalent circuit technique commonly applied for electrochemical impedance characterizations to describe the behavior of battery cells. These battery cell models are furthermore used to express the behavior of a battery module, while the imbalance of the battery cells is addressed along other effects to improve the battery module model. Battery module model accuracy can be increased significantly if intrinsic cell-to-cell variations in capacity and internal resistance are considered (Dubarry et al. 2009). An estimation of the remaining available power of a battery module is presented in Plett (2004d).

2.1.4.4 State of Charge Estimation

Many state of charge estimation algorithms are based on the open-circuit voltage (Lee et al. 2008). Since the relationship between the OCV and SoC is not identical for all batteries, Lee et al. (2008) proposed a modified OCV–SoC relationship to increase the SoC estimation accuracy. Commonly, an equivalent circuit model is used in

combination with an extended Kalman filter (EKF) for the purpose of SoC estimation of batteries (see e.g., Do et al. 2009; Vasebi et al. 2007, 2008; Han et al. 2009; Bhangu et al. 2005), while Santhanagopalan and White (2006) use an electrochemical model. A sliding mode observer is applied by Kim (2006) to compensate the modeling errors of the used simple resistor–capacitor battery model. Neural networks (NNs) and EKF are used for modeling and SoC estimation by Charkhgard and Farrokhi (2010). Chen et al. (2011) used the same combination, but also developed a method to consider battery hysteresis effects. An adaptive unscented Kalman filtering method is proposed by Sun et al. (2011), which is further compared with an extended and an unscented Kalman filter. He et al. (2011) improved the dependence of the traditional filter algorithm on the battery model by an adaptive Kalman filter algorithm. An adaptive Luenberger observer for the SoC that uses an optimized model is built by Hu et al. (2010b). For the same purpose, a stochastic fuzzy neural network in combination with an extended Kalman filter for SoC estimation is proposed by Xu et al. (2012). Plett (2004b) based the SoC estimation also on an EKF, but used a state-space structure that considers the dynamic contributions due to open-circuit voltage, ohmic loss, and polarization time constants.

An alternative to the Kalman filter is the interacting multiple model (IMM) estimator, which has the ability to estimate the state of a dynamic system with several behavior models and to switch between them by corresponding rules (Mazor et al. 1998). The IMM is one of the most cost-effective hybrid state estimation schemes that can act as a self-adjusting variable-bandwidth filter, which is widely used for tracking maneuvering targets. Helm et al. (2012) used the IMM for a misfire detection that is based on two dedicated parametric Kalman filters. A fusion prediction-based interacting multiple model algorithms is used by Song et al. (2012). Another application of IMM is hypotheses merging (Blom and Bar-Shalom 1988). In the field of vehicle maneuvering, a fuzzy interacting multiple model unscented Kalman filter approach is presented by Jwo and Tseng (2009). Although the IMM approach could be applied for SoC estimation, so far, no papers are known in the literature discussing this topic.

Two different sliding mode observers for dynamic Takagi-Sugeno fuzzy systems are proposed by Bergsten et al. (2002). A nonlinear filter approach based on local linear models is proposed by Hametner and Jakubek (2013). Lendek et al. (2009) focused on the stability of cascaded fuzzy systems and observers.

2.1.5 Solution Approach

In this chapter, the methodologies are presented to achieve a precise battery cell terminal voltage model for non-road application, which can be applied to estimate the SoC of a battery module with high accuracy during operation.

The model is based on the data-based LMN approach, whose advantages are that expert knowledge can be considered, the computational effort is low, a random initialization of the parameters is avoided, and the LLMs can be interpreted as local linearization of the process (Hametner et al. 2012; Nelles 2001). Nelles and Isermann (1996) proposed the local linear model tree (LOLIMOT) construction algorithm, which is used to construct the LMN, while corresponding inputs are used to define the LMN structure. In order to consider the battery nonlinearities SoC, temperature and current as well as relaxation and hysteresis in the model, the inputs are adapted. In this context, a physically appropriate network is obtained by adapting the LOLIMOT algorithm to make use of a prepartitioned network and to prohibit splitting within specified dimensions of the network. The resulting battery cell model is applicable to different cell chemistries and real-time capable due to the low computational complexity.

Furthermore, optimal model-based design of experiments is utilized to achieve high dynamic excitation signals, which cover the entire SoC range during the measurements. Based on the Fisher information matrix $\mathcal{I}$, a scalar cost function $J(\mathcal{I})$ is used to optimize the excitation signal, while the battery cell is sufficiently excited and relaxation, hysteresis, as well as current and temperature effects are considered additionally. For this reason, the optimization is furthermore focused on real load ranges that are frequently used in operation (Unger et al. 2014). A gradient-based algorithm is used to solve the optimization problem, while battery constraints on current, voltage, and SoC are considered simultaneously. The obtained excitation signal reduces the identified model parameter variance and maximizes the information content of measurements.

Based on the optimal model-based DoE and the LMN approach, the battery module model can be built. A simple approach that multiplies the cell voltage with the number of cells in series connection is compared with the approach proposed by Kim et al. (2011), which considers the internal resistance of the battery cell connections as well as a voltage offset. The cell balancing is neglected, because in non-road vehicles, mostly a passive cell balancing strategy is used due to the appearing high energy conversions.

An accurate SoC estimation is then achieved for the battery module using the fuzzy observer approach as proposed by Hametner and Jakubek (2013). For a straight forward implementation, the battery module model must be transferred into a state-space representation with an augmented state vector that includes the SoC. At the end, different choices of process and measurement noise within the filter tuning show the trade-off between convergence and accuracy of the filter.

This chapter is organized as follows: First, the battery cell model is developed and an appropriate optimal model-based DoE is introduced for the developed battery cell model structure. Second, the temperature model approach is described. Third, different battery module model approaches that are based on the developed battery cell model are discussed. At the end, the SoC estimation for battery modules as well as for battery cells is discussed.

2.2 Data-Based Identification of Nonlinear Battery Cell Models

In this section, the generic methodology for nonlinear identification of high dynamic, current–voltage battery cell models is discussed. Nonlinear battery effects such as SoC, current, temperature, relaxation as well as hysteresis effects are considered by the model. First, the general architecture and structure of LMN is given, followed by the construction of the LMN using the LOLIMOT algorithm. Based on this, the final battery model is developed.

2.2.1 General Architecture and Structure of Local Model Networks

In principle, the local model network structure is built by local linear models that are only valid in a certain operation regime and interpolated to obtain the global nonlinear model output. An autoregressive with exogenous input model structure is chosen for the LLM, by what the regression vector $\boldsymbol{\varphi}$ follows with the global nonlinear model output $\hat{y}$, the global parameter vector $\boldsymbol{\theta}$, and the input variables u_l to

$$\begin{aligned}\boldsymbol{\varphi}(k, \boldsymbol{\theta}) &= [\bar{\mathbf{y}} \ \bar{\mathbf{u}}_1 \ \dots \ \bar{\mathbf{u}}_q \ 1]^T, \\ \bar{\mathbf{y}} &= [\hat{y}(k-1, \boldsymbol{\theta}) \ \dots \ \hat{y}(k-n, \boldsymbol{\theta})], \\ \bar{\mathbf{u}}_l &= [u_l(k-d) \ \dots \ u_l(k-d-m_l)], l = 1, \dots, q,\end{aligned}\quad (2.1)$$

with the actual time instant k , the output order n , the input order m_l of the l th of q input variables, and the dead time d . Following Nelles and Isermann (1996), the input variables u_l span the so-called input space $\mathcal{Q}$ of the model. The bias is considered by the one in Eq. (2.1). Note that Eq. (2.1) is denoted for MISO systems, but MIMO systems can be modeled as well (Nelles 2001).

One challenge in data-based modeling is the optimal choice of the model order of the inputs and outputs. In D’Agostino (1986), different methodologies such as goodness-of-fit (GOF) techniques are recommended to find the optimal model order. GOF, from the statistical point of view, is discussed by De Sá (2007). Akaike’s information criterion trades off goodness-of-fit and model complexity and is used by, e.g., Yuan et al. (2013) for the optimal order of an ARX-structured battery model. As presented by Jackey et al. (2013), another methodology is to analyze different selections of the model order and choose the best compromise between complexity and accuracy. To this end, the mean squared error (MSE) provides a basis to make a decision.

The chosen model order is applied to the M LLMs, where the i th model output $\hat{y}_i$ is obtained by

$$\hat{y}_i(k, \boldsymbol{\theta}) = \boldsymbol{\varphi}^T(k, \boldsymbol{\theta}) \boldsymbol{\vartheta}_i, \quad (2.2)$$

where $\boldsymbol{\theta} = [\boldsymbol{\vartheta}_1 \dots \boldsymbol{\vartheta}_M]^T$ denotes the global parameter vector, which consists of the local parameter vectors $\boldsymbol{\vartheta}_i$ of all M LLM. Weighted aggregation of $\hat{y}_i$ leads to the global nonlinear LMN output

$$\hat{y}(k, \boldsymbol{\theta}) = \sum_{i=1}^M \hat{y}_i(k, \boldsymbol{\theta}) \Phi_i(k), \quad (2.3)$$

where $\Phi_i(k)$ is the validity function of the i th LLM. Using a Kernel function $\mu_i(k, \mathbf{z})$, which can be any common function (e.g., uniform, triangle, ...) (Nelles 2001), the validity function follows by

$$\Phi_i(k) = \frac{\mu_i(k, \mathbf{z})}{\sum_{j=1}^M \mu_j(k, \mathbf{z})}, \quad (2.4)$$

where $\mathbf{z} = [z_1 \dots z_\phi]$ span the so-called partition space $\mathcal{Z}$ of the model using the ϕ partition variables (Gregorcic and Lightbody 2007). Note that the normalization results from the sum of all validity functions, which is required to be 1. Although input and partition variables may be used in the partition space $\mathcal{Z}$ and input space $\mathcal{Q}$ simultaneously, they are not mandatorily the same (Hoffmann and Nelles 2001).

2.2.2 Construction of LMN Using LOLIMOT

A LMN is usually constructed by algorithms, which iteratively add new LLM to the network. One such algorithm is the local linear model tree algorithm presented by Nelles (2001). LOLIMOT searches for the worst LLM by the quadratic error criterion and identifies the dimension in which a split of the model could achieve the best improvement for the global model output. The worst LLM is then axis-orthogonally split into two new models in the dimension with the best improvement (Nelles and Isermann 1996). Iteratively, the LMN grows until a certain threshold (here the maximal number of LLM M) is reached.

The parameters for the two new models are determined by weighted least squares (WLS). In case of numerical effects due to significant differences in the input, partition, and output variables, all signals used within the algorithm are normalized from 0 to 1 (Nelles 2001). Schematically, the LOLIMOT procedure for a two-dimensional partition space is depicted in Fig. 2.3. In every iteration, the quadratic evaluation criterion is used to find the worst LLM. The worst model is split into all possible dimensions, while the best alternative, identified likewise with the quadratic evaluation criterion, is chosen.

A characteristic of the LOLIMOT algorithm is the Kernel function $\mu_i(k, \mathbf{z})$, which is chosen to be Gaussian (Nelles 2001):

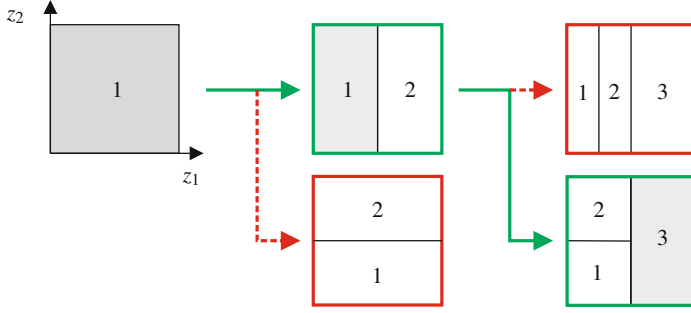


Fig. 2.3 Decision process of the LOLIMOT algorithm in a two-dimensional partition space

$$\mu_i(k, \mathbf{z}) = \exp\left(-\frac{1}{2}\left(\frac{(z_1(k) - c_{i1})^2}{\sigma_{i1}^2} + \dots + \frac{(z_\phi(k) - c_{i\phi})^2}{\sigma_{i\phi}^2}\right)\right). \quad (2.5)$$

Since the partition space $\mathcal{Z}$ is split axis-orthogonally, c_{ij} denotes the center point of the LLM and σ_{ij} is the corresponding individual standard deviation, which is approximated by

$$\sigma_{ij} = k_{\sigma,j} \Delta_{ij}. \quad (2.6)$$

The term Δ_{ij} corresponds to the spread of the LLM, while $k_{\sigma,j}$ is a user-defined sharpness factor that can be seen as an LLM overlapping factor that influences the smoothness of the nonlinear model output. Note that the optimal sharpness factor varies depending on the specific application as well as the partitioning dimensions.

Alternative construction algorithms have the same aim, but are different to LOLIMOT. Jakubek and Keuth (2006) used statistical criteria along with regularization to allow an arbitrary orientation and extent in the partition space of the constructed LMN. In Jakubek and Hametner (2009), a proper partitioning of the LMN is achieved by an expectation–maximization algorithm that makes use of a residual obtained from generalized total least squares parameter estimation. The advantage of LOLIMOT compared to mentioned alternatives is the low implementation complexity due to the axis-orthogonal orientation, for which reason LOLIMOT is used in this book.

2.2.3 Battery Cell Modeling Using LMN

So far, the methodology for battery modeling has been discussed. In the following, the procedure to apply the LMN to battery modeling is presented. Corresponding inputs and the structure for the LMN are presented in order to consider nonlinear battery effects and enhancements for the LOLIMOT algorithm to increase the physical

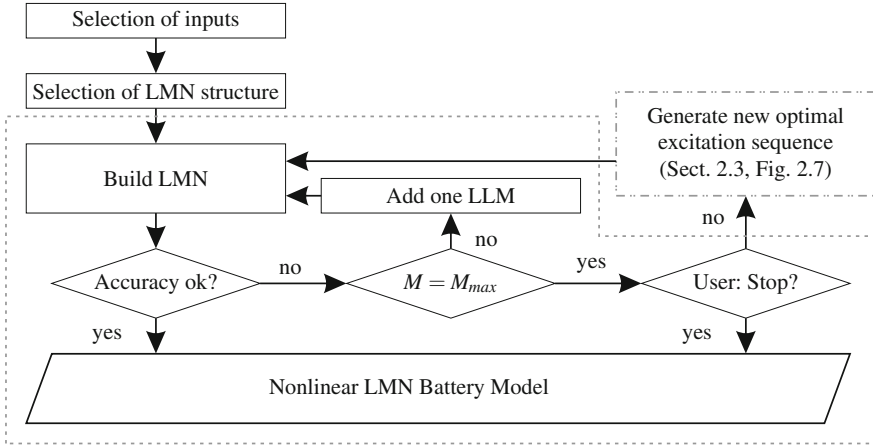


Fig. 2.4 Construction process flowchart for the battery model identification

meaning of the battery model. Figure 2.4 depicts an overview of the battery model construction process using a flowchart.

2.2.3.1 Corresponding LMN Inputs of Nonlinear Battery Cell Effects

Electrochemical batteries comprise physical and chemical nonlinear effects, which can be observed and explained in detail on the basis of Figs. 2.5 and 2.6.

Figure 2.5 depicts constant charge and discharge curves for different C-rates over the SoC. Cell *A* refers to a lithium-polymer chemistry, while Cell *B* represents a

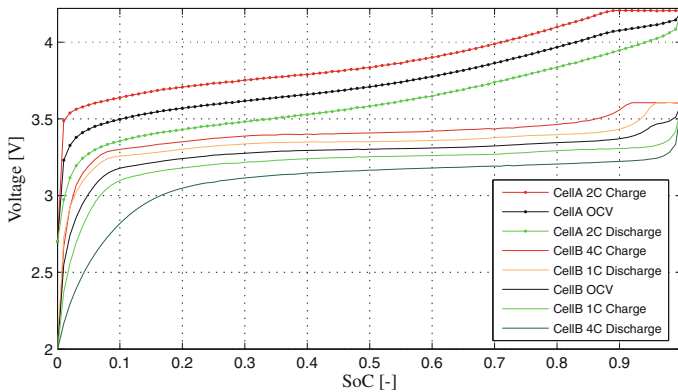


Fig. 2.5 Open-circuit voltages and different constant current discharge/charge curves from a lithium-polymer (Cell *A*) and a lithium-iron-phosphate (Cell *B*) cell

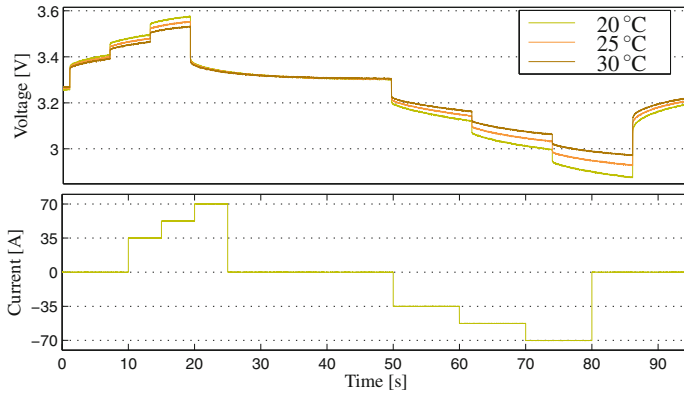


Fig. 2.6 Measurements of voltage responses obtained from a lithium-iron-phosphate cell (Cell **B**) during an applied current step sequence at different temperatures

lithium-iron-phosphate chemistry. In order to be able to plot the voltage curves over the SoC, the cell current is integrated (Sun et al. 2012a), while interpolation between the charge and discharge curve provided an estimate for the open-circuit voltage (Abu-Sharkh and Doerffel 2004).

In Fig. 2.6, a current step sequence at different temperatures measured for Cell **B** is shown. The nonlinear physical influence of current and temperature can be observed, but distinction must be made between physical and chemical effects. Physical effects are caused by any physical interaction such as an applied current and the resulting temperature increase, while chemical effects arise also without physical interaction such as hysteresis and relaxation. A dynamic change in the battery voltage is caused by the applied battery cell current, while the voltage drop is directly influenced by the temperature. Due to the lower/higher temperature, increased/decreased internal resistance of the battery cell is obtained and a bigger/smaller voltage drop is caused. Current as well as temperature are physically measurable online and can directly be considered in the model. Hence, the corresponding inputs u_{Current} and z_{Temp} are selected. The time constant of the temperature is significantly higher than the time constant of the current. Due to this reason, the current is included in the input space $\mathcal{Q}$, while the temperature is assumed to be static and is therefore included in the partition space $\mathcal{Z}$. Note that the small temperature gradients compared to gradients of the current underline the assumption.

The nonlinear influence of the SoC on the battery cell voltage is clearly shown in Fig. 2.5. Since the SoC cannot change dynamically or independently to the current, the SoC is considered as corresponding static input z_{SoC} with the value of the actual SoC. The value of the SoC is not measurable online and needs to be estimated in real batteries (see e.g., Hametner and Jakubek 2013; Plett 2004c). For simulation purposes, the current can be integrated to determine a value for the SoC. Note that in Sect. 2.6, the SoC estimation is discussed in detail.

Chemical effects are not directly measurable and need to be provided indirectly by corresponding inputs. The slightly to a steady-state value converging voltage at standby current in Fig. 2.6 is referred to as relaxation (Plett 2004b), although relaxation also acts during current phases (Bernardi and Go 2011). In Plett (2004b), a low-pass filter on the current, which follows certain requirements, is used to model the relaxation, whose time constant is significantly different to the one of the currents. Following Plett (2004b),

- after a long rest period and
- during constant current discharge/charge,

the relaxation state needs to converge to zero, which can be realized by the dynamic corresponding input

$$u_{\text{Relax}} = \text{filt}(\Delta u_{\text{Current}}). \quad (2.7)$$

Note that in order to force the filter $\text{filt}(\cdot)$ to have zero DC-gain, the change rate of the current $\Delta u_{\text{Current}}$ is used. For lithium-iron-phosphate as well as lithium-polymer chemistry, a third-order low-pass filter showed to be appropriate, whose relaxation time constant is approximated properly on the basis of the voltage converging speed at standby current after a current pulse has been applied to the battery cell (Unger et al. 2014).

Different shapes of the charge and discharge curve in Fig. 2.5 indicate the nonlinear chemical effect referred to as hysteresis (Tang et al. 2008). At standby current in Fig. 2.6, the effect is observable as well. In principle, the hysteresis effect separates the model into a charge and discharge model, which can be achieved using $\text{sign}(\cdot)$ of the current as a corresponding first-order hysteresis input z_{Hyst} that is kept at the last value, if the current is zero (Unger et al. 2014). As hysteresis is acting statically on the battery behavior, z_{Hyst} is included in $\mathcal{Z}$. Intercalation effects, conductivity of anode/electrolyte/cathode, concentration gradients, or other known chemical effects play a tangential role compared to the mentioned effects and are therefore neglected.

2.2.3.2 LMN Structure of Battery Cell Models

Distinction must further be made between dynamic and static influence on the cell voltage. Dynamic influence of the inputs needs to be considered in the dynamic LLM and must therefore be included in the input space $\mathcal{Q}$, while static influence is important for the partitioning and must therefore be included in the partition space $\mathcal{Z}$. This defines the structure of the LMN and leads to

$$\begin{aligned} \mathcal{Z} &= [z_1 \ z_2 \ z_3] \hat{=} [z_{\text{SoC}} \ z_{\text{Hyst}} \ z_{\text{Temp}}], \\ \mathcal{Q} &= [u_1 \ u_2 \ u_3] \hat{=} [z_{\text{SoC}} \ u_{\text{Current}} \ u_{\text{Relax}}]. \end{aligned} \quad (2.8)$$

To this end, the inclusion of the SoC z_{SoC} in the input space $\mathcal{Q}$ implies two advantages. On the one hand side, the continuous change of the voltage depending on the SoC is considered and on the other hand, the observability of the SoC within

the model is given, which is required by the SoC estimation with a fuzzy observer (c.f. Hametner and Jakubek 2013).

2.2.3.3 User-Defined Prepartitioning of the LMN Structure

In the iterative construction of the LMN, only the quadratic evaluation criterion decides whether to split a model or not. This may lead to physically inappropriate partitions that make a physical interpretation impossible. Due to this reason, LOLIMOT is enhanced to use initial partitions of $\mathcal{Z}$ instead of one global partition. The predefined physically appropriate partitions reduce the computational efforts, while all partitions can be kept physically appropriate if selected dimensions of the partition space are prohibited to be split (Unger et al. 2014). This influences the partitioning significantly and needs to be discussed in detail in the following.

Prohibiting a dimension to be split is only appropriate if a physical reason is given to limit the number of LLM within this dimension. At this point, expert knowledge can be included to improve the model accuracy. The hysteresis input z_{Hyst} refers to the corresponding cell polarization, which can only reach two different states. In this case, an initial split into charge as well as discharge mode and prohibiting to split within this dimension is advantageous. From Fig. 2.6, the temperature influence seems to be evenly distributed, and therefore three initial partitions are defined for the temperature input. Note that due to the split in the hysteresis dimension, a simultaneous split of charge and discharge mode cannot be achieved by definition, because of which partitioning is prohibited within the temperature dimension. The number of initial partitions follows to 6 and the partitioning DOF is limited to the SoC dimension.

2.3 Optimal Model-Based Design of Experiments

This section discusses the optimal model-based design of experiments for battery model identification. The goal of optimal model-based DoE is to obtain an excitation signal that minimizes the variance of the identified model parameters. To this end, the system dynamics of a battery cell must be sufficiently excited, while the entire SoC range is covered and relaxation as well as hysteresis effects are considered. The battery system behavior is obtained by applying a load current excitation signal U to the battery cell and recording the cell terminal voltage. In on-road applications, intermediate current steps show sufficient dynamics (Hu et al. 2009b), but in non-road applications higher dynamic excitation signals are required (Unger et al. 2012a).

For that purpose, a methodology is proposed to obtain optimal excitation signals for non-road application. In the following, first, an a priori available battery model and the Fisher information matrix $\mathcal{I}$ are used to formulate optimality criteria. Second, a constrained optimization problem is formulated to optimize an excitation signal under consideration of constraints and the nonlinear effects of a battery cell. Note that the information content is further improved by focusing the optimization especially

on load ranges frequently used in operation. Third, the optimization by means of a gradient-based algorithm is described in detail. At the end, some extensions are made to the obtained optimal excitation sequence to take into account the entire SoC operating range, relaxation, hysteresis, and constant current behavior.

2.3.1 Optimization Criteria Based on the Fisher Information Matrix

The Fisher information matrix $\mathcal{I}$ is a tool to measure the information content of measurements in terms of the covariance of the estimated model parameters. In order to increase the information content, the system inputs by means of the excitation signal $\mathbf{U}$ need to be modified (Hametner et al. 2013b). The calculation of $\mathcal{I}$ is based on the parameter sensitivity vector $\boldsymbol{\psi}(k)$, which is the partial derivative of the model output with respect to the model parameters. For the LMN approach as described in Sect. 2.2, $\boldsymbol{\psi}(k)$ follows by

$$\boldsymbol{\psi}(k) = \frac{\partial \hat{y}(k, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \Phi_1(k) \boldsymbol{\varphi}(k, \boldsymbol{\theta}) \\ \vdots \\ \Phi_M(k) \boldsymbol{\varphi}(k, \boldsymbol{\theta}) \end{bmatrix}, \quad k = 1, \dots, N, \quad (2.9)$$

where M denotes the number of LLM and $\Phi_i(k)$, $\boldsymbol{\varphi}(k, \boldsymbol{\theta})$, $\boldsymbol{\theta}$ as defined in Eqs. (2.4) and (2.1). A reference model is required for the optimization and can be obtained by two possibilities (Unger et al. 2014):

- A LMN model is available.
- A different model (no LMN model) or measurements are available.

A LMN with only one LLM describes a linear model of the battery and can be identified easily based on a priori available measurements. In this book, the easy approach of only a linear model is followed to show the significant influence of the methodology to the model quality. Note that a reference LMN can be identified by simulation data created by an available complex electrochemical model, alternatively.

The Fisher information matrix is defined by

$$\mathcal{I} = \frac{1}{\sigma^2} \sum_{k=1}^N \underbrace{\frac{\partial \hat{y}(k, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}}_{\boldsymbol{\psi}(k)} \frac{\partial \hat{y}(k, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}^T, \quad k = 1, \dots, N, \quad (2.10)$$

where σ is the variance of the measurement noise (Goodwin and Payne 1977). Denoting $\boldsymbol{\Psi}$ as

$$\boldsymbol{\Psi} = [\boldsymbol{\psi}^T(1) \dots \boldsymbol{\psi}^T(N)]^T, \quad (2.11)$$

the FIM can be expressed by

$$\mathcal{I} = \frac{1}{\sigma^2} \Psi^T \Psi. \quad (2.12)$$

Based on the obtained FIM, in the literature three common scalar criteria are known for the optimization of the excitation sequence. They are formulated as follows (Goodwin and Payne 1977):

$$\text{A-optimality: } J_A = \text{Tr}(\mathcal{I}^{-1}) \rightarrow \min_{\mathbf{U}} \quad (2.13)$$

$$\text{D-optimality: } J_D = \det(\mathcal{I}) \rightarrow \max_{\mathbf{U}} \quad (2.14)$$

$$\text{E-optimality: } J_E = \lambda_{\min}(\mathcal{I}) \rightarrow \max_{\mathbf{U}} \quad (2.15)$$

A-optimality minimizes the trace of the inverse of the Fisher information matrix, D-optimality corresponds to the maximization of the determinant of the FIM, and E-optimality is targeted to maximize the smallest eigenvalue of the FIM. The advantage of D-optimality is the higher sensitivity to single-parameter covariances compared to the A-optimality (Stadlbauer et al. 2011a).

Following the three common criteria Eqs. (2.13)–(2.15), Fig. 2.7 shows the process to obtain the optimal excitation signal $\mathbf{U}$.

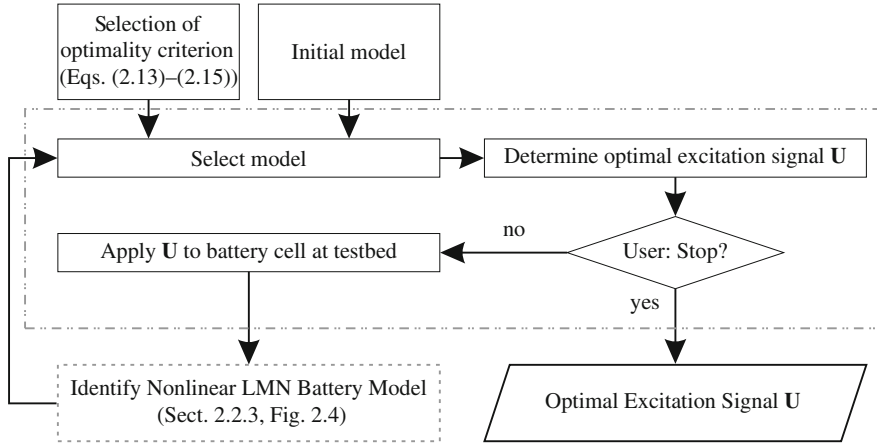


Fig. 2.7 Flowchart of the optimal design of experiments for battery models. The *dot* and *dash* line refer to the LMN identification as depicted in Fig. 2.4

2.3.2 Formulation of the Constrained Optimization Problem

The optimization aims primarily to achieve sufficient high dynamic currents within the excitation sequence, while constraints on current and battery cell voltage are considered. Note that the SoC is limited due to the physical capacity of the battery, which is automatically considered by voltage and current constraints. Constraints must be kept to avoid, among other things, physical damage, accelerated life-time reduction, electrolyte oxidation, fire, or explosion. Especially, the lithium-ion chemistry is sensitive to overcharge and over-voltage, respectively, which attracts the attention due to safety issues.

The current is furthermore constraint to ranges frequently used in operation to increase the information content especially in ranges used in real applications. Consequentially, two possibilities can be used for current constraints:

1. High dynamic excitation between physical minimum/maximum current.
2. High dynamic excitation between load ranges, frequently used in operation.

The first approach simply defines the current constraints at the physical minimum and maximum values, while the second approach defines the constraints using a real load cycle analysis that is realized as follows:

- step 1. Select a representative load cycle.
- step 2. Determine the distribution density of the load by a histogram with a defined number of intervals.
- step 3. Set the lower and the upper current constraints corresponding to the interval limits of the histogram.
- step 4. Define the durations within the corresponding constraint ranges by the corresponding distribution densities.
- step 5. Scale the constraints corresponding to the SoC.

Figures 2.8 and 2.9 show the load cycle analysis in more detail: A scaled real load cycle, for which the analysis is done, can be seen in the left subplot of Fig. 2.8. In the middle subplot, the corresponding histogram is depicted, while to the right, the current constraints for the depicted load cycle are shown.

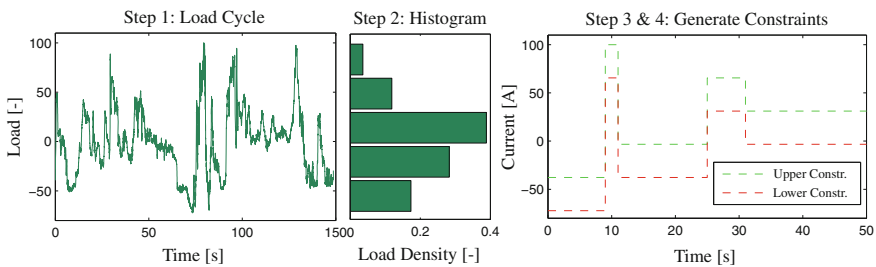
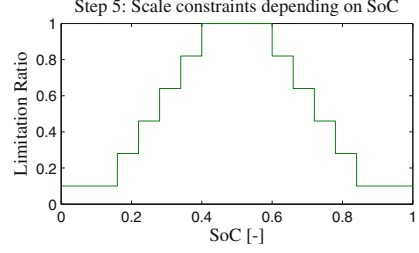


Fig. 2.8 Step 1–4 in the constraint construction used for the optimization of the excitation signal

Fig. 2.9 Step 5 in the constraints construction: SoC dependent limitation of the minimal/maximal battery current



In order to consider output constraints within the experiment design, the reference model must have sufficient accuracy. The used linear reference model is not able to provide such a precision, though, which implicates that voltage constraints must be included indirectly through the current. To this end, a limitation ratio for the current depending on the SoC is introduced. Figure 2.9 depicts the limitation ratio. Note that the reliability of the output constraints in general depends on the model accuracy and increases with each model update (Hametner et al. 2013a). Nevertheless, due to the maximal current constraints, the maximal deviation of the SoC from the starting SoC value is limited (Unger et al. 2014). The SoC limits therefore follow by an adequately chosen starting SoC value.

On the basis of these constraints, a formulation of the optimization problem can be obtained. Following Pronzato (2008), the D-optimality criterion has higher sensitivity to single-parameter covariances and is more invariable to re-parametrization of the model than the A-optimality. Due to this reason, the D-optimality criterion is used to formulate the optimization problem:

$$\begin{aligned} \text{D-optimality: } & \max_{\mathbf{U}} \det(\mathcal{I}) \\ \text{s.t. } & \begin{cases} U_{\min}(k) \leq U(k) \leq U_{\max}(k), & k = 1, \dots, N \\ \mathbf{U} \in \mathbb{R}^{N \times 1} \end{cases}, \end{aligned} \quad (2.16)$$

where $U = u_{\text{Current}}$ corresponds to the current input. Note that relaxation input and SoC are directly dependent on the current, which is therefore the only degree of freedom within the optimization.

2.3.3 Constrained Optimization

The constraints require to solve the stated optimization problem iteratively. One approach with low computational efforts and sufficient performance is the gradient descent method. The derivative of the design criterion with respect to the input $U(r)$ for all observations N composes the gradient $\mathbf{g} = [g(1) \dots g(N)]^T$. In order to obtain the single gradients, the trace of the product of the derivative of the determinant of

the FIM with respect to the parameter sensitivity matrix Ψ and the derivative of Ψ with respect to $U(r)$ need to be built, which is computationally intensive (Stadlbauer et al. 2011a). Nevertheless, the r th observation follows by

$$\frac{dJ_D(\Psi)}{dU(r)} = \text{Tr} \left(\frac{dJ_D(\Psi)}{d\Psi^T} \frac{d\Psi}{dU(r)} \right), \quad (2.17)$$

where for the D-optimality, the first term is obtained by (cf. Magnus and Neudecker 1988)

$$\frac{dJ_D(\Psi)}{d\Psi^T} = 2J_D(\Psi)\Psi[\Psi^T\Psi]^{-1}. \quad (2.18)$$

Note that the inversion of the FIM appears in Eq. (2.18), due to which the FIM is required to be a regular matrix with full rank (Hametner et al. 2013b).

The second term in Eq. (2.17) is obtained by the single derivatives of the parameter sensitivity vectors with respect to the model input, which are based on the derivative of the regressor $\varphi(k, \theta)$ as defined in Eq. (2.1) with respect to the input $U(r)$. Denoting the derivative of $\varphi(k, \theta)$ by

$$\frac{d\varphi^T(k, \theta)}{dU(r)} = \left[\frac{d\hat{y}(k-1, \theta)}{dU(r)} \dots \frac{d\hat{y}(k-n, \theta)}{dU(r)} \quad \delta_{1l}\delta_{(k-1)r} \dots \delta_{pl}\delta_{(k-m_l)r} \quad 0 \right], \quad k > r, \quad (2.19)$$

where δ_{ij} is the Kronecker delta function and l corresponds to the current input of the LMN battery model. The former model output with respect to the input $U(r)$ is recursively calculated and follows to

$$\begin{aligned} \frac{d\hat{y}(k, \theta)}{dU(r)} &= \frac{\partial \hat{y}(k, \theta)}{\partial \hat{y}(k-1, \theta)} \cdot \underbrace{\frac{d\hat{y}(k-1, \theta)}{dU(r)}}_{\text{recursive calculation}} \\ &+ \frac{\partial \hat{y}(k, \theta)}{\partial \hat{y}(k-n, \theta)} \frac{d\hat{y}(k-n, \theta)}{dU(r)} + \frac{\partial \hat{y}(k, \theta)}{\partial U(r)}, \quad k > r. \end{aligned} \quad (2.20)$$

Based on Eqs. (2.19) and (2.20), the derivative of the parameter sensitivity vector with respect to the model input is obtained by

$$\frac{d\Psi(k)}{dU(r)} = \begin{bmatrix} \Phi_1(k) \frac{d\varphi(k, \theta)}{dU(r)} \\ \vdots \\ \Phi_M(k) \frac{d\varphi(k, \theta)}{dU(r)} \end{bmatrix} + \begin{bmatrix} \varphi(k, \theta) \frac{d\Phi_1(k)}{dU(r)} \\ \vdots \\ \varphi(k, \theta) \frac{d\Phi_M(k)}{dU(r)} \end{bmatrix}, \quad k > r, \quad (2.21)$$

while the compact notation of Eq. (2.21) yields the second term of Eq. (2.17)

$$\frac{d\boldsymbol{\Psi}}{dU(r)} = \left[\frac{d\boldsymbol{\Psi}^T(1)}{dU(r)} \cdots \frac{d\boldsymbol{\Psi}^T(N)}{dU(r)} \right]^T. \quad (2.22)$$

Using Eqs. (2.18) and (2.22), the gradient $\mathbf{g}$ can be used in the gradient descent method to update the excitation sequence. Considering the current constraints along with an adaptively adjusted step size η , the update follows by

$$\begin{aligned} \mathbf{U}^{(v+1)} &= \mathbf{U}^{(v)} + \eta \cdot \mathbf{g}^{(v)}, \quad v = 0, 1, 2, \dots \\ \text{s.t. } &\begin{cases} \mathbf{U}_{min} \leq \mathbf{U}^{(v+1)} \leq \mathbf{U}_{max} \\ \mathbf{U} \in \mathbb{R}^{N \times 1} \end{cases}, \end{aligned} \quad (2.23)$$

which process is repeated until no further improvement is achieved.

Note that the voltage constraints are included indirectly, and therefore a nonlinear constrained optimization problem is avoided. Nevertheless, several alternative approaches are known, which include the output constraints directly in the formulation of the optimization problem: The (quadratic) difference between the gradient of the design criterion and the excitation signal increment is minimized by Stadlbauer et al. (2011a), while the feasible area is approached simultaneously. In order to realize the constrained optimization, Hametner et al. (2013b) applied Lagrangian multipliers. Sequential quadratic programming (see e.g., Luenberger and Ye 2008) and numerical multi-objective optimization (see e.g., Seyr and Jakubek 2007) are further approaches.

2.3.4 Extensions on the Excitation Sequence

The previous sections discussed the optimization of the excitation sequence, while constraints are considered. For the purpose of especially including the battery-specific nonlinear effects, the optimized excitation sequence is extended in the following.

Constant discharge/charge currents with following standby currents are able to reveal the voltage behavior caused by relaxation and to discharge/charge the battery to a desired SoC value. Constant discharge/charge current pulses with subsequent standby current are therefore added in front of/after the optimized sequence. Following the limitation ratio (see Fig. 2.9), the values of the constant currents are obtained, while the duration of the pulses is related to the longest time constant of the system. Sufficient information about relaxation requires the duration of the standby current to be at least a multiple of the duration of the constant current. An analysis of Fig. 2.6 leads to a duration ratio of at least 6 for an abated voltage degradation at standby current. Due to this reason, a duration ratio of 8 is suggested and used in this book.

The final excitation signal is obtained by merging the extended high dynamic sequences for evenly distributed SoC values across the entire SoC range of interest (Unger et al. 2014). Any SoC deviations from the desired SoC are carefully compensated by varying the durations of the constant currents, in order to achieve information across the entire SoC range. Note that the SoC range of interest for different non-road applications differs from each other and therefore may vary.

2.4 Temperature Model of Battery Cells

In order to provide a simulation model, the battery temperature needs to be modeled as well. At high charge and discharge currents, the cell temperature increases significantly and may raise above allowable limits (Onda et al. 2006). Hu et al. (2010a) proposed an accurate battery thermal model using a Foster network, which extracts capacitance and resistance from computational fluid dynamics (CFD) results. A simplified mathematical model is presented by Jeon and Baek (2011) that considers heat generations due to joule heating and entropy change, respectively. Sun et al. (2012b) developed a three-dimensional thermal model to gain a better understanding of the thermal battery cell behavior in a battery module. The more advanced approach considers the battery nonuniform heat generation rate, the battery temperature distribution as well as battery temperature variation across the module in order to predict the temperature behavior during simulated driving cycles. A lumped-parameter thermal model based on a differential equation is developed in Forgez et al. (2010), whose approach is used in this book. Based on the cell thermal capacity c_p and the heat transfer coefficient h_{out} , the temperature behavior of a battery cell can be expressed by

$$c_p \frac{d\vartheta_{cell}}{dt} = h_{out} (\vartheta_{amb} - \vartheta_{cell}) + I_{cell}^2 R_{int}, \quad (2.24)$$

where ϑ_{amb} is the ambient temperature, ϑ_{cell} is the cell temperature, R_{int} is the internal resistance of the cell model, and I_{cell} is the cell current. The battery type (energy or power cell) influences the temperature behavior essentially, since the losses produce heat, which is dissipated through the battery cell. In general, energy cells have a different design, due to which the heat transfer resistance is higher. Nevertheless, as can be seen in Eq. (2.24), the internal resistance R_{int} is required and needs to be exported from the LMN battery cell. Due to the nonlinear behavior of the battery cell, R_{int} depends on the actual state of the battery cell, though.

In this context, the interpretability of the LMN battery model should be discussed in more detail. Due to the physically appropriate partitioning of the LMN, the steady-state gain of the LLM can be interpreted as the local internal resistance of the particular LLM. Note that the calculated steady-state gain is normalized and needs to be transformed first before it can be interpreted as physical value. In Fig. 2.10 in the upper two subplots, the identified internal resistances for Cell **A** and Cell **B**, respectively, are shown for different temperatures. Since the partition space is three-dimensional,

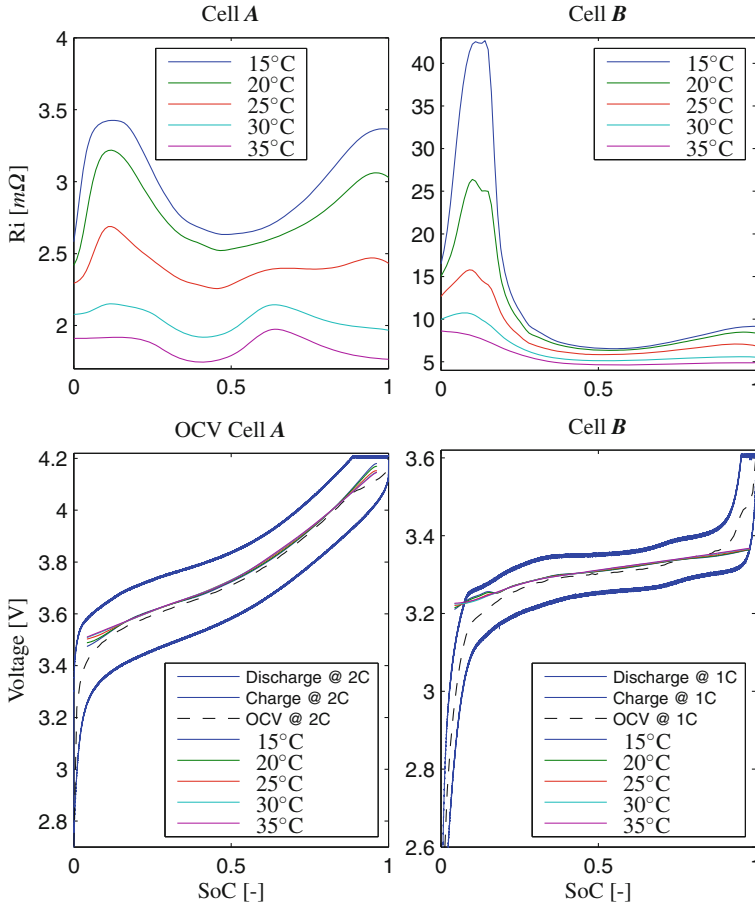


Fig. 2.10 Interpretability of LMN battery model parameters shown at Cell A and Cell B. The current dimension is held at $I_{cell} = -40$ A

the current is held at $I_{cell} = -40$ A to be able to depict a two-dimensional representation of the parameters. The lower two subplots show the identified open-circuit voltages in comparison with an OCV that is obtained from an interpolation of the charge and discharge curves at 2C. As can be seen, the OCV is precisely identified, though the excitation signal has been highly dynamic and included only few standby phases during the measurements. Based on this interpretation, look-up tables for the internal resistance R_{int} and the OCV V_0 can be exported from the LMN and used in Eq. (2.24).

2.5 Battery Module Model Design

Battery module models are required for the simulation of powertrain concepts in hybrid electric vehicles as well as for the implementation in battery simulators, which emulate the real battery behavior at the test bed. Real-time capability is especially necessary for the implementation in battery simulators. Nevertheless, battery modules consist of multiple battery cells connected in series and parallel connections, which results in a required monitoring system that observes the voltage and SoC balance between the battery cells to avoid physical damage. The balancing strategy needs to be included in a battery model, as long as there is an effect during operation. Due to this reason, cell balancing in battery modules is reviewed in the following, before the design of the LMN-based battery module model is discussed.

2.5.1 Battery Cell Balancing in Battery Modules

Battery balancing refers to the equalization of the state of charge of the battery cells within a battery module to avoid overcharge, which might cause physical damage and safety issues due to explosion and fire. Cao et al. (2008) present the theory behind balancing methods for battery systems within the past 20 years and group their nature of balancing. In general, two different balancing techniques are known (Andrea 2010):

1. Active balancing
2. Passive balancing

Active balancing draws the energy from the most charged cell and transfers the energy through DC–DC converters to the least charged cells. For example, Lee and Cheng (2005) proposed an active balancing algorithm for lithium battery modules. Passive systems waste energy from the most charged cell as heat, until the cell charges are equalized. To this end, the balancing strategy needs to be considered in the battery module model, if cell balancing is carried out during operation and has an influence on the voltage behavior.

In this book, a battery module with implemented passive balancing system is used. Thus, balancing is neglected in the proposed model approach. Nevertheless, different balancing strategies and their implementation in battery models are discussed in, e.g., Bentley (1997), Daowd et al. (2011), and Weicker (2013).

2.5.2 LMN-Based Battery Module Design

In non-road vehicles, the voltage level of battery modules is usually high, because the current capabilities of electrochemical batteries for high power demands are

generally limited. Thus often super capacitors are used due to their significantly larger power capabilities. Nevertheless, the higher energy densities of batteries make them an equal alternative. During the design process of hybrid electric powertrains, the planned battery module may not be physically available. This complicates the design of battery module models, since a sufficient parametrization is difficult. To this end, four different approaches of battery module model approaches Σ_i are discussed in the following in order to show the influence of different considered effects.

Battery cell measurements are easier to realize, and therefore a battery module model that is based on battery cell models is desired and advantageous. The proposed methodology in the previous sections provides LMN battery cell models that can easily be obtained by cell measurements, but does not consider the additional internal resistance of battery modules resulting from the cell connections. Nevertheless, the internal resistance is unknown in advance, and therefore a first obvious model approach is

$$V_{module, \Sigma_1} = n_{cells} \cdot V_{cell}, \quad (2.25)$$

where n_{cells} is the number of series connected cells and V_{cell} refers to the battery cell voltage. The battery cell voltage V_{cell} can be obtained by the LMN battery cell model using the battery cell current

$$I_{cell} = \frac{I_{module}}{p_{cells}}, \quad (2.26)$$

where p_{cells} is the number of parallel connected cells, and I_{module} is the battery module current. Note that the internal resistances of the battery cell connections are not considered in this simple approach and may limit the accuracy. Therefore, however, no information is required about the internal resistance of a battery module.

Considering the internal resistance of the battery module in V_{module, Σ_1} leads to model Σ_2

$$V_{module, \Sigma_2} = n_{cells} \cdot V_{cell} - R_{int, \Sigma_2} \cdot I_{module}, \quad (2.27)$$

where R_{int, Σ_2} refers to the internal module resistance. Battery cells usually vary in nominal cell voltage, which can be considered by an offset voltage. Module model approach Σ_3 follows therefore to

$$V_{module, \Sigma_3} = n_{cells} \cdot V_{cell} - R_{int, \Sigma_3} \cdot I_{module} + V_{offset, \Sigma_3}, \quad (2.28)$$

where the offset voltage V_{offset, Σ_3} also considers measurement sensor offsets and any other additional influences on the module voltage. Electrical resistances are usually linear elements, but a current-dependent adaptation of the internal resistance and offset, respectively, has been shown as advantageous. This can be caused by, e.g., inaccuracies in the battery cells, different ages of the installed battery cells, or the battery cell used to identify the battery cell model. Nevertheless, the resulting model can be denoted by

$$V_{module, \Sigma_4} = n_{cells} \cdot V_{cell} - R_{int, \Sigma_4}^{\pm} \cdot I_{module} + V_{offset, \Sigma_4}^{\pm} \quad (2.29)$$

with

$$R_{int, \Sigma_4}^{\pm} = \begin{cases} R_{int, \Sigma_4}^{+} & \text{if } I_{module} > 0 \\ R_{int, \Sigma_4}^{-} & \text{if } I_{module} \leq 0 \end{cases}, \quad V_{offset, \Sigma_4}^{\pm} = \begin{cases} V_{offset, \Sigma_4}^{+} & \text{if } I_{module} > 0 \\ V_{offset, \Sigma_4}^{-} & \text{if } I_{module} \leq 0 \end{cases}. \quad (2.30)$$

Battery module measurements can then be used to identify the module parameters R_{int, Σ_i} and V_{offset, Σ_i} , respectively.

2.6 State of Charge Estimation

State estimation is required, if system states are not measurable. An observer is used to estimate the unmeasurable states based on the measurable states and a dynamic model of the process. In this context, the observability of the system must be given, which is the case if the observability matrix $\mathcal{O}$

$$\mathcal{O} = [\mathbf{C}^T(\mathbf{CA})^T(\mathbf{CA}^2)^T \dots (\mathbf{CA}^{n_{states}-1})^T]^T, \quad (2.31)$$

where n_{states} denotes the number of states in the state-space system with state matrix $\mathbf{A}$ and output matrix $\mathbf{C}$, has full rank.

The linear Kalman filter is an efficient recursive filter that is able to observe the internal states of a linear dynamic system by measurements corrupted with noise. It is of advantage that the filter is based on time-invariant models, which significantly reduces the computational complexity. In general, nonlinear processes are more challenging, since nonlinear estimation approaches need to be applied. A well-known nonlinear estimator is the extended Kalman filter, which is based on the local Jacobian of a nonlinear model and is therefore more complex than a linear Kalman filter. Note that the filter gain as well as the data-dependent local linearization of the EKF cannot be precalculated, which is disadvantageous for real-time application (Plett 2004b; Vasebi et al. 2007). The interacting multiple models' approach achieves a nonlinear estimation by running separate linear Kalman filters and switching between the filters based on a detection scheme using the validity probability of the underlying models (Mazor et al. 1998; Helm et al. 2012). Another similar nonlinear estimator, which is ideal in combination with LMN models, is the fuzzy observer (Chen et al. 1998; Senthil et al. 2006). Since each LLM of the LMN corresponds to an linear time-invariant dynamic system, the linear Kalman filter theory can be applied, and the global filter output can be obtained by weighted aggregation of the local filters (Simon 2003). Furthermore, stability of the fuzzy observer can be shown based on Lyapunov stability theory and is discussed in, e.g., Mayr et al. (2011b) and Tanaka et al. (1998). The fuzzy observer approach is therefore used in this book.

In the following, the general architecture of the SoC estimation scheme is presented before the development of the fuzzy SoC observer. Note that the SoC estimation approach is applicable for cell and module SoC estimation, respectively, and is therefore developed for the general case.

2.6.1 General Architecture of the SoC Observer Scheme

The estimation of the SoC of a battery can be obtained by two practical principles. First, measuring the open-circuit voltage leads to an accurate estimate of the SoC if the battery has been in standby mode for a sufficiently long period of time, but cannot be used during operation. The second possibility is to integrate the current, which can be denoted by

$$\text{SoC}(t) = \text{SoC}_{init} + \frac{1}{Q_{c,batt}} \int_0^t \eta_{batt,cou}(I_{batt}(v)) I_{batt}(v) dv, \quad (2.32)$$

where SoC_{init} is the initial SoC, $Q_{c,batt}$ is the battery capacity, and $\eta_{batt,cou}$ is the charge efficiency. Note that $\eta_{batt,cou}$ is usually 0.99 and can be neglected for the purpose of observer based SoC estimation. Nevertheless, the integration of the current leads to an acceptable initial SoC value that can be used in an advanced SoC observer scheme.

Following Hametner and Jakubek (2013), the estimation of the SoC can be done by automated nonlinear observer design using a fuzzy observer. In this context, the relative SoC estimation given by Eq. (2.32) should be included in the observer scheme. For that purpose, Eq. (2.32) is represented in the discrete formulation

$$\text{SoC}(k) = \text{SoC}(k-1) + \frac{t_{s,bms}}{Q_{c,batt}} I_{batt}(k), \quad (2.33)$$

where $t_{s,bms}$ corresponds to the sampling time. An overview of the observer scheme is depicted in Fig. 2.11 exemplarily. As can be seen in the figure, the SoC is corrected by the observer, which obtains the simulated battery voltage by the LMN battery model discussed in Sect. 2.2. Any drift of the SoC due to extended operational time is compensated, since the SoC estimator is able to act during operation. Note that the estimation accuracy is mainly dependent on the battery model accuracy. In the next subsection, the SoC fuzzy observer is developed in detail.

2.6.2 SoC Fuzzy Observer Design

The automated nonlinear observer design requires the nonlinear LMN in state-space (SS) representation (Senthil et al. 2006), the state vector of which needs to be

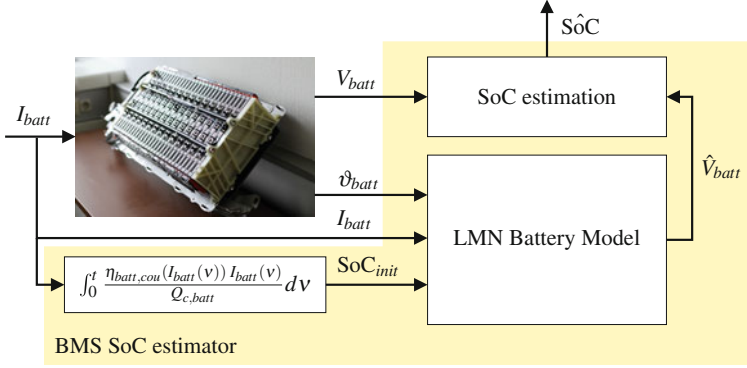


Fig. 2.11 SoC fuzzy observer scheme

augmented in order to consider the initial SoC from the current integration in the fuzzy observer. A correct transformation of the LLM (c.f. Eq. (2.2)) into the SS representation can be achieved by including the past outputs y and the previous state of charge $\text{SoC}(k-1)$ in the augmented state vector $\mathbf{x}_{aug}$, which follows to

$$\mathbf{x}_{aug}(k) = [y(k-1) \ y(k-2) \ \dots \ y(k-n) \ \text{SoC}(k-1)]^T. \quad (2.34)$$

The parameter vector of the i th LLM can be denoted by

$$\boldsymbol{\vartheta}_i = [a_{1,i} \ \dots \ a_{n,i} \ b_{11,i} \ \dots \ b_{lm_i,i} \ \dots \ b_{qm_i,i} \ b_{0,i}], \quad (2.35)$$

where $a_{\cdot,i}$ and $b_{\cdot,i}$ denote the output and input parameters, respectively, while $b_{11,i} = b_{\text{SoC},i}$ corresponds to the order-one SoC input parameter used in the LMN design (cf. Eq. (2.8)). Note that the LMN design described in Sect. 2.2.3 already includes the SoC as input variable, in order to be able to use the identified parameter for the augmented state variable in the design of the linear Kalman filters. Using these parameters, the state matrix $\mathbf{A}_i$ can be established by

$$\mathbf{A}_i = \begin{bmatrix} a_{1,i} & a_{2,i} & \dots & a_{n,i} & b_{\text{SoC},i} \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix} \quad (2.36)$$

and the input matrix $\mathbf{B}_i$ follows by

$$\mathbf{B}_i = \begin{bmatrix} b_{21,i} & \cdots & b_{lm_i,i} & \cdots & b_{qm_q,i} & b_{0,i} \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ \frac{t_{s,bms}}{Q_{c,batt}} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad (2.37)$$

where $b_{0,i}$ corresponds to the local affine term (bias term). Note that the corresponding parameter of the SoC input $b_{11,i} = b_{\text{SoC},i}$ is excluded from $\mathbf{B}_i$ since it is already considered in $\mathbf{A}_i$. The augmented input vector for the augmented observer SS model follows then to

$$\mathbf{u}_{aug}(k) = [u_1(k) \ u_1(k-1) \ \cdots \ u_q(k-m_q) \ 1]^T, \quad (2.38)$$

where u_i corresponds to the actual and past elements of the model inputs. At this point it is important to mention that the integrator needs to be adapted if a normalization of the LMN is used. In case of scaled parameters, the integrator increment can be transformed by a corresponding additional term in the last row and column of the matrix $\mathbf{B}_i$.

Using Eqs. (2.34)–(2.38), the augmented state equation

$$\mathbf{x}_{aug}(k) = \sum_{i=1}^M \Phi_i(k-1) \{ \mathbf{A}_i \mathbf{x}_{aug}(k-1) + \mathbf{B}_i \mathbf{u}_{aug}(k) \} \quad (2.39)$$

leads to the global model output

$$y(k) = \mathbf{C} \mathbf{x}_{aug}(k) \quad (2.40)$$

with

$$\mathbf{C} = \mathbf{C}_i = [1 \ 0 \ \dots \ 0 \ 0]. \quad (2.41)$$

Based on these equations, the local steady-state Kalman filters can be designed for each local linear model, while the global filter is obtained by weighted aggregation of the individual local estimates. The state estimate $\hat{\mathbf{x}}_{aug}$ of the global filter can be determined based on the gain matrix $\mathbf{K}_i$ by

$$\hat{\mathbf{x}}_{aug}(k) = \sum_{i=1}^M \Phi_i(k-1) \{ \mathbf{x}_{aug,i}^*(k) + \mathbf{K}_i [y(k) - \hat{y}(k)] \}, \quad (2.42)$$

with

$$\mathbf{x}_{aug,i}^*(k) = \mathbf{A}_i \hat{\mathbf{x}}_{aug}(k-1) + \mathbf{B}_i \mathbf{u}_{aug}(k), \quad (2.43)$$

where

$$\hat{y}(k) = \sum_{i=1}^M \phi_i(k-1) \mathbf{C} \mathbf{x}_{aug,i}^*(k). \quad (2.44)$$

The gain matrix $\mathbf{K}_i$ is calculated by

$$\mathbf{K}_i = \mathbf{A}_i \mathbf{P}_i^T \mathbf{C}^T (\mathbf{C} \mathbf{P}_i^T \mathbf{C}^T + \mathbf{R}^T)^{-1}, \quad (2.45)$$

where $\mathbf{P}_i$ refers to the solution of the discrete-time algebraic Riccati equation (DARE)

$$\mathbf{A}_i \mathbf{P}_i \mathbf{A}_i^T - \mathbf{P}_i - \mathbf{A}_i \mathbf{P}_i \mathbf{C}^T (\mathbf{C} \mathbf{P}_i \mathbf{C}^T + \mathbf{R})^{-1} \mathbf{C} \mathbf{P}_i \mathbf{A}_i^T + \mathbf{Q} = 0. \quad (2.46)$$

In Eq. (2.46), the matrices $\mathbf{R}$ and $\mathbf{Q}$ reflect the covariance matrices of the measurement and process noise, respectively. The Kalman filter theory assumes $\mathbf{R}$, $\mathbf{Q}$ to be known, but often the covariance matrices are unknown and $\mathbf{R}$ and $\mathbf{Q}$ are used as tuning parameters (Hametner and Jakubek 2013). For the application of SoC estimation in batteries, the terminal voltage measurement noise $\mathbf{R}$ can be found by experiments. The process noise $\mathbf{Q}$, similar to Vasebi et al. (2007), is used to tune the filter and no correlation between the different elements in $\mathbf{Q}$ is assumed.

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