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A novel methodology for non-linear system identification of battery cells used in non-road hybrid electric vehicles

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HIGHLIGHTS

- A generic methodology for battery cell terminal voltage modeling is presented.
- Model based experiment design is introduced for optimal battery cell testing.
- The optimal excitation signals cover the entire operating ranges of non-road HEVs.
- The framework is purely data-based and regards relaxation and hysteresis effects.
- Measurements validate the methodology applicable to different cell chemistries.

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ABSTRACT

An accurate state of charge (SoC) estimation of a traction battery in hybrid electric non-road vehicles, which possess higher dynamics and power densities than on-road vehicles, requires a precise battery cell terminal voltage model. This paper presents a novel methodology for non-linear system identification of battery cells to obtain precise battery models. The methodology comprises the architecture of local model networks (LMN) and optimal model based design of experiments (DoE). Three main novelties are proposed: 1) Optimal model based DoE, which aims to high dynamically excite the battery cells at load ranges frequently used in operation. 2) The integration of corresponding inputs in the LMN to regard the non-linearities SoC, relaxation, hysteresis as well as temperature effects. 3) Enhancements to the local linear model tree (LOLIMOT) construction algorithm, to achieve a physical appropriate interpretation of the LMN. The framework is applicable for different battery cell chemistries and different temperatures, and is real time capable, which is shown on an industrial PC. The accuracy of the obtained non-linear battery model is demonstrated on cells with different chemistries and temperatures. The results show significant improvement due to optimal experiment design and integration of the battery non-linearities within the LMN structure.

1. Introduction

A novel generic methodology for non-linear system identification and optimal model based design of experiments (DoE) of battery cells are proposed in this paper.

The control strategy of hybrid electric vehicles (HEV) is essentially dependent on the state of charge (SoC) of the used traction battery. The state of charge of the battery is not measurable on-line, which requires an estimate of the actual SoC during operation [1]. The estimation of the SoC is placed in the battery management system (BMS) and is often only based on the open circuit voltage of the battery. This leads to big estimation errors, since the non-linear behavior of the battery voltage at operation is not regarded with this approach [2]. Another approach is to integrate the battery current. Disadvantageously, current offsets are accumulated, which may lead to estimation errors after some time. The third possibility is to use SoC estimators (e.g. extended Kalman filter), which require a model of the battery that can be implemented in the BMS in real time. The model is an integral part of the BMS and describes the non-linear dynamic behavior of the battery cell terminal voltage. The SoC estimation accuracy can be improved only if a precise non-linear battery cell model is used in the SoC estimator [3].

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Non-road hybrid electric vehicles and machinery (e.g. construction site vehicles, mining vehicles, …), compared to on-road vehicles, usually demand higher power densities and load dynamics, which makes the modeling of the batteries more complicated [4]. The non-linear battery effects (e.g. hysteresis, relaxation, temperature effects, …) of electrochemical batteries are increased due to the high power densities [5].

In this paper, a non-linear data-based battery model is proposed, which can be used for the purpose of accurate SoC estimation in *non-road* vehicles. Optimal model based DoE is utilized to optimize the excitation signals for battery measurements. The optimal excitation signals are used for the model parameter identification to increase the accuracy at high dynamic demands. Furthermore, due to the experiment design and data-based structure, the model can be obtained for different battery cell chemistries within a reasonable time period.

State-of-the-art battery models and DoE are reviewed in the following. The solution approach and the contributions of the paper are summarized at the end of this section.

1.1. State-of-the-art

In the literature three main types of battery model approaches are mentioned:

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

Equivalent circuit models (ECM), as depicted in Fig. 1 exemplarily, use basic electric elements in order to model a battery cell. The main intention is to parameterize the model using physically interpretable values. Gao et al. [5] used an ECM with one RC circuit, that accounts for non-linear equilibrium potentials, rate- and temperature-dependencies, thermal effects and response to transient power demand. Pattipati et al. [6] used a modified equivalent circuit model for SoC, state-of-health (SoH) and remaining useful life estimation in the BMS. The high power density application in automotive industry requires to consider the behavior of the impedance elements (such as solution resistance, charge transfer resistance, and Warburg impedance) in a simple ECM (see Gomez et al. [7]).

Electrochemical battery models pursue to physically model the electrochemical behavior of the battery. These models are able to simulate the chemical states of a battery accurately and to give insight into the system itself [8], while the disadvantage is that they are computationally intensive. Doyle et al. [9] modeled a lithium battery cell by using concentrated solution theory. Partial differential-algebraic equations are used by Klein et al. [8] for state estimation. Santhanagopalan et al. [10] used a single particle model (SPM) for SoC estimation with an extended Kalman filter. However,

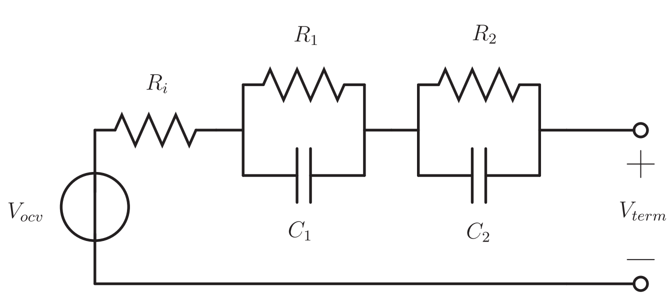

Fig. 1. Equivalent circuit model with two RC-elements.

due to non-consideration of spatial variation of the states in the battery cell, the success of the SPM model, especially at high currents or long duration pulses, might not be valid for the operating region encountered for HEV [11].

Data-based models are a useful way for modeling and estimation purposes, although in general, the model parameters are not physically interpretable [8]. Plett [12,13,3], used a data-based non-linear state space model for extended Kalman filter SoC estimation. The model takes different current directions into account and regards a "hysteresis state" as well as the relaxation using a low pass filter on the current. Battery cell chemistry independence of the model is assumed. Charkhgard et al. [14] applied neural networks to battery modeling. Based on a stochastic fuzzy neural network [15,16,17], Wang et al. [18] modeled the non-linear dynamics of current, temperature and SoC to the battery voltage. Xu et al. [19] used the same model for SoC estimation. Hametner et al. [1] applied a local model network (LMN) to battery modeling. A LMN is composed 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. Refs. [20,21,22]). The model output is non-linear, due to the non-linear interpolation of the local linear models (LLM). The LMN is constructed by an iterative algorithm, which starts with one global linear model and adds a LLM to the network in every iteration until a certain threshold is reached (partitioning). The validity of the new LLM lies in a specific form in the partition space of the model and depends on the algorithm's strategy.

All of the mentioned battery models require measurements to parameterize the model parameters. The measurements are obtained by applying a current excitation signal to a battery cell and recording the voltage response. Kroeze et al. [23] used simple constant discharge and charge cycles for the identification of an ECM, while Gao et al. [5], Chen et al. [24] and Hentunen et al. [25] made use of a discharge pulse excitation signal for the same purpose. A discharge pulse excitation signal is also used in Ref. [26] for a model-based estimation of an electrochemical battery cell model. More advanced ECM (e.g. linear parameter varying models) are identified in Refs. [27,28,13] using a pulse profile, regarding charge and discharge mode. Hu et al. [29] employs an asymmetrical current step profile, in order to cover a wide range of SoC as well as a wide current range. This profile is more dynamic compared to the other excitation signals. An example for low dynamics in non-road applications is the dynamic Federal Urban Driving Schedule (FUDS), which is used in many papers as validation signal (see e.g. Refs. [30,19,23,31]).

Depending on the model approach, the design of the experiment plays an important role since the excitation signal has a decisive influence on the parameter estimation, especially for data-based model approaches [4,1]. Model based design of experiments can be used to create optimal excitation signals: The goal is that, based on a prior model of the process (reference model), the information obtained from measurements is maximized and parameters can be estimated with minimum variance [32]. In this context, the Fisher information matrix $\mathcal{I}$ (FIM), a way to measure the information content of a signal, is often used for optimization of an excitation signal. Furthermore, constraints of the process can be regarded, provided that the reference model is sufficiently accurate.

In Ref. [33], a local model network based generation algorithm for static experiment design is proposed. Dynamic experiment design for multilayer perceptron networks by choosing optimal inputs from a candidate set is proposed in e.g. Refs. [34,35]. Stadlbauer et al. [36,37] focused on the dynamic design of experiments based on multilayer perceptron networks. Based on these papers, Hametner et al. [38] proposed a design approach for non-linear dynamic experiments, which is targeted to minimize the model