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A Study on Battery Model Parametrisation Problem – Application-Oriented Trade-offs between Accuracy and Simplicity

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Abstract: This study is focused on fast low-fidelity battery modelling for online applications. Because the battery parameters change due to variations of battery's states, the model may need to be updated during operation. This can be achieved through the use of an online parameter identification technique, making use of online current-voltage measurements. The parametrisation algorithm's speed is a crucial issue in such applications. This paper describes a study exploring the trade-offs between speed and accuracy, considering equivalent circuit models with different levels of complexity and different parameter-fitting algorithms. A visual investigation of the battery parametrisation problem is also proposed by obtaining battery model identification surfaces which help us to avoid unnecessary complexities. Three standard fitting algorithms are used to parametrise battery models using current-voltage measurements. For each level of complexity, the algorithms performances are evaluated using experimental data from a small NiMH battery pack. An application-oriented view on this trade-offs is discussed which demonstrates that the final target of the battery parametrisation problem can significantly affect the choice of the fitting algorithm and battery model structure.

Keywords: Battery Modelling, Parametrisation, Identification, Algorithm, Electric Vehicle.

1. INTRODUCTION

Hybrid electric vehicles (HEVs) are well-established in the market and electric vehicles (EVs) are growing in popularity. This trend is likely to sustain for the foreseeable future. Development of energy storage systems can be considered as the heart of vehicle electrification process. Battery modelling is a critical part of this technology development. They are a variety of battery model types in the literature which can be categorized into three groups: (i) mathematical models, (ii) electrochemical models, and (iii) electrical equivalent circuit network models, Fotouhi et al. (2016). Electrochemical battery models are the most accurate but also the most complex among all battery models. However, it is important to strike a balance between model complexity and accuracy so that the models can be embedded in microprocessors and provide accurate results in real-time, Pattipati et al. (2011). In other words, it is important to have models that are accurate enough, and not unnecessarily complicated. These reasons led researchers to investigate other modelling approaches like electrical circuit modelling or equivalent circuit network (ECN) modelling. Combining less complexity with good accuracy, ECN modelling is one of the most common battery modelling approaches especially for EV application.

ECN battery models are often parametrised using experimental data. Depending on the application, battery parametrisation is performed offline or online. In online applications, speed of the parametrisation process is crucial. An example of such applications is online battery state-of-charge (SOC) estimation as illustrated in Fig. 1. In this concept, parameters of battery model are estimated online in order to be used by an estimator to predict battery states, Fotouhi et al. (2015). System identification technique is used in this framework as one of the existing approaches for online model parametrisation of a time-varying system. ECN battery model parametrisation problem can be classified as an identification problem in which the model's structure is fixed while unknown parameters are determined using measured data. The goal is to find a model that its output has the least deviation from the measured data. In this case, the battery identification problem is an "optimisation problem" in which the parameters are optimised to get the least error in comparison to the test data.

There are relevant studies in the literature in which the system identification techniques are applied for battery parametrisation. Genetic algorithm (GA) is used for battery model identification, Hu et al. (2011a), by considering a complex model containing the ECN model parameters, SOC and temperature at the same time and an offline optimisation procedure is used to fit the model to experimental data. In a study by Brand et al. (2014), 31 and 45 parameters are considered for two battery equivalent circuit models which are parametrised using a multi-objective genetic algorithm. The main reason that GA method had been used in those studies was said to be its greater benefits compared to other methods when an analytic solution does not exist and when the number of unknown parameters are large, Brand et al. (2014). Particle swarm optimisation (PSO) is employed as another optimisation algorithm to identify battery parameters from measured test data for 12 different ECN model structures, Hu et al. (2012).

In almost all the previous studies, one or more battery models are parameterised and then the model's accuracy is discussed

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without focus on the parametrisation time. However, the speed of the battery model identification process can be crucial as well, particularly in online applications. This topic has been touched by Hu et al. (2011b) where a control-oriented approach was used for battery model identification using subspace method. Based on the previous results in the literature, it is clear that the battery model parametrisation's accuracy and speed depend on the model's structure and fitting algorithm both and a trade-off is needed between accuracy and simplicity. The main contribution of this study which distinguishes it from the previous works is an "application-oriented" view on this trade-off. In this study, new discussions are presented which prove that the final target (the final application) of the battery parametrisation problem can significantly affect the choice of fitting algorithm or model structure. This application-oriented point of view helps to prevent any unnecessary complexity while achieving the specified targets as simply as possible.

For this purpose, the battery model parametrisation problem is analysed using a different visual approach firstly by plotting battery parametrisation surfaces. Although the surfaces seem simple, they contain quite useful information which is discussed and utilised in this study. Three standard fitting algorithms are used and analysed including gradient descent (GD), genetic algorithm (GA) and prediction error minimisation (PEM). There are many other algorithms in the literature and this paper does not aim at reviewing them. GA and PEM are selected just because they are two standard techniques in the literature. The GD algorithm is selected to demonstrate that simpler algorithms may also be applicable for battery parametrisation. For each level of complexity, the algorithms' performance is investigated using experimental data from a small NiMH battery pack. The results of this study are not limited to NiMH battery chemistry and the proposed contribution can be utilized in other applications as well.

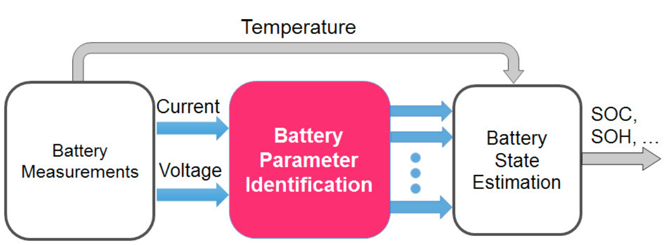

Fig. 1. Online battery state estimation based on parameter identification

2. BATTERY MODEL IDENTIFICATION

Generally, a system identification procedure consists of three main parts, Ljung (1987), (i) experiment design, (ii) model structure selection, and (iii) fitness criterion selection. The same parts are considered for battery model identification in this study. Different model structures and data fitting algorithms are used. The algorithms' computational effort and precision have been assessed using experimental data for different model structures.

2.1 Battery experiments

As a case study, a six-cell pack of NiMH batteries was tested using a low-cost test bench that was proposed by Propp et al. (2015). The NiMH battery pack was selected due to its simple and save handling as well as its convenient output voltage. Specifications of the battery pack are listed in Table 1. The experiment was conducted at 25°C by applying consecutive discharge current pulses to the battery and measuring the battery's terminal voltage. Data is saved in time domain with a sampling rate of one second. Fig. 2 illustrates the battery measurements during an experiment. The test started from fully charged state (8.5 V) and continued until the terminal voltage dropped below the cut-off voltage (6 V) which means depleted charge state. The discharge rate is 1C that is 2.4A and length of each pulse is 40 seconds with a relaxation time of 60 second in between.

Table 1. NiMH battery pack specifications

Parameter	*Value*
Rated capacity per cell	2400 mAh
No. of cells	6
Rated voltage	7.2 V
Full-Charged voltage	8.5 V
Cut-off voltage	6 V

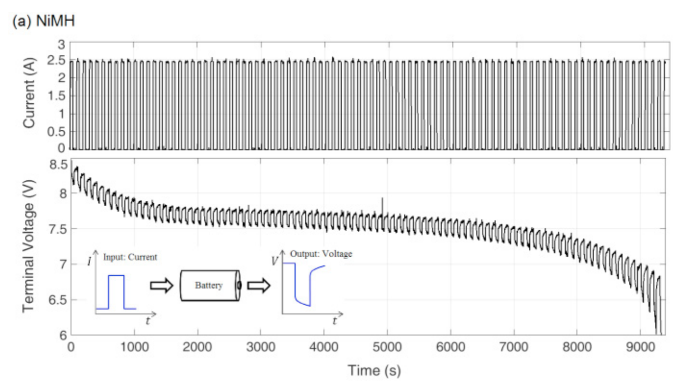

Fig. 2. Measurements during a discharge test by applying current (input) and measuring terminal voltage (output)

2.2 Battery model structures

Equivalent circuit network (ECN) battery model structures are used in this study. The ECN battery models are constructed by putting resistors, capacitors and voltage sources in a circuit. The simplest form of an ECN battery model is internal resistance model (*R model*). The *R model* includes an ideal voltage source (V_{OC}) and a resistance (R_O) as depicted in Fig. 3(a) in which V_t is the battery terminal voltage and I_L is the load current. Adding one RC network to the *R model* increases its accuracy by considering the battery polarisation characteristics as discussed by Salameh et al. (1992). This model, called Thevenin Model (1RC model), is illustrated in Fig. 3(b) in which V_t is cell's terminal voltage, V_{OC} is open circuit voltage (OCV), R_O is internal resistance, R_P and C_P are equivalent polarisation resistance and capacitance respec-