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Electric vehicle battery management algorithm development using a HIL simulator incorporating three-phase machines and power electronics

A. Fotouhi, K. Propp, L. Samaranayake, D. J. Auger, S. Longo

Advanced Vehicle Engineering Centre, School of Aerospace, Transport and Manufacturing,
Cranfield University, UK
Email: a.fotouhi@cranfield.ac.uk; abfotouhi@gmail.com

Abstract: This paper describes a hardware-in-the-loop (HIL) test rig for the test and development of electric vehicle battery management and state-estimation algorithms in the presence of realistic real-world duty cycles. The rig includes two back-to-back connected brushless DC motors, the respective power electronic controllers, a target battery pack, a dSPACE real-time simulator, a thermal chamber and a PC for human-machine interface. The traction motor is commanded to track a reference velocity based on a drive cycle and the target battery pack provides the required power. Except the battery pack and the electric machine which are real, other parts of a vehicle powertrain system are modelled and used in the real-time simulator. A generic framework has been developed for real-time battery measurement, model identification and state estimation. Measurements of current and battery terminal voltage are used by an identification unit to extract parameters of an equivalent circuit network (ECN) model in real-time. Outputs of the identification unit are then used by an estimation unit which uses an artificial intelligent model trained to find the relationship between the battery parameters and state-of-charge (SOC). The results demonstrate that even with a high noise level in measured data, the proposed identification and estimation algorithms are able to work well in real-time.

Keywords: battery modelling, electric powertrain, hardware-in-the-loop test, state-of-charge estimation, identification.

1-Introduction

Development of electrical energy storage systems plays a significant role in the vehicle electrification process. Among the existing technologies in this area, batteries are the most widely used and still an area of constant development. Regardless of the state of development of various battery chemistries, it is important to be able to operate a battery pack in practical applications which needs building a fast low-fidelity model for a battery management system (BMS). In an EV, it is important to understand state-of-charge (SOC) or 'remaining capacity', which is vital for any kind of range prediction. EV range estimation, safe battery charge/discharge and optimal usage of batteries, all depend on efficient and accurate battery models. Different approaches can be used for cell modelling in which two main groups are electrochemical and equivalent electrical circuit models. Electrochemical battery models, with the ability of predicting electrochemical species and potential conservation distribution along the cell, are more accurate. On the other hand, equivalent circuit network (ECN) models are fast enough to be used in real-time applications. There are also other modelling approaches in the literature which are reviewed in [1]. Because of the low computational effort and relatively good precision, ECN models have been the subject of studies in a wide range specifically for automotive application [2].

Before applying a battery model or estimation algorithm in a real EV, a battery simulation environment is essential for testing the developed models and algorithms. In most conventional battery simulators, the duty cycle (or 'load profile') is obtained from simple models of the powertrain components: equivalent-circuit machine models are used, and the detail of power electronics is often neglected or treated as a simple efficiency map with ideal instantaneous switching. The rig described in this study avoids these limitations as real, physical components are used within the simulation: in addition to a small battery pack, a brushless DC (BLDC) machine driven by three-phase AC is used, together with its associated MOSFET-based power electronics. This type of machine is common in electric vehicles, and it would be hard to obtain a computational model that was sufficiently representative of real-world transient behaviour.

Using an ECN model, a fast system identification technique is applied to real-time parameterization of the battery pack, and the parameters are used for real-time state estimation. While such algorithms can be tested in simulation or through a conventional bench-test involving only batteries, using the proposed rig allows the testing of the algorithms in an environment that is more representative of real-world duty-cycles and thereby reduces the risk of failure at a later implementation stage.

2-Battery HIL Test Rig

2-1-HIL structure

The HIL test rig and its main components are shown in Figure 1. It includes two back-to-back connected electric machines, the respective power electronic controllers, a target battery pack (in this case, containing NiMH cells), a lead-acid battery pack to provide independent power sourcing and sinking, a dSPACE real-time simulator, a thermal chamber and a PC for human-machine interface. The test rig contains two BDLC machines of 5kW each. One of these – shown to the left in Figure 1 – is used to represent EV traction motor and the second machine is used to apply dynamic loads ('load' machine) representing the torques experienced in a vehicle-level duty cycle. The 'traction' machine is connected to the battery pack under test. The load machine is connected to a bi-directional power source consisting of a separate DC supply built from readily available lead-acid batteries.

During acceleration, the traction machine is in the first quadrant of its torque-speed characteristic curve and changes to the fourth quadrant during braking. In addition, during acceleration and uphill motion of the vehicle, the load machine acts as a generator, converting the shaft mechanical power to electrical power stored in the lead-acid battery. During deceleration and downhill motion of the vehicle, the load machine converts electrical power from the lead-acid battery to mechanical power in the shaft.

Figure 1: Battery HIL test rig and its components

2-2-Electric Machines and motor controllers

As mentioned above, 5 kW brushless DC (BLDC) machines are used in the battery test rig. A BLDC machine has a trapezoidal air gap flux distribution obtained through electronic commutation implemented through power electronics. In a three-phase ac machine of this type, a 'current controller' converts a 'torque reference' from an 'outer' speed controller to the respective current references for each of the three phase windings; to achieve this, the current controller outputs gate trigger signals to MOSFETs in the (hardware) motor controller block [3]. The current controller employs nonlinear hysteresis type current comparators, which are the most rugged analog controllers. The rotor position required for the correct commutation of the windings is obtained from Hall-effect position sensors in the stator. The same rotor position signals are used to calculate the rotor speed. Since the machine has eight permanent magnet poles, three Hall-effect sensors are placed in the stator, 15 mechanical degrees apart. In the speed calculation algorithm, any change in the Hall-effect sensor output (corresponding to a rotor pole movement) is detected and the time between two consecutive such changes is calculated. The inverse of this time multiplied by the angle rotated (15 degrees) gives the rotational speed of the machine.

2-3-Battery packs

Two battery packs are used in the test rig: the 'main' battery pack under test (connected to the traction machine) and a 'secondary' lead-acid pack (connected to the load machine). The secondary pack provides the load and is not the subject of study: the role of the EV traction battery is supplied by the main battery pack. The secondary pack consists of five 12 V lead-acid batteries connected in series, giving a nominal 60 V which matches the motor controller's voltage range. In this study, for the main battery pack under test, a NiMH battery chemistry has been selected as a first attempt while keeping this option to replace it with any other battery type in the same scale. The NiMH battery pack was built with the general aim to simplify development of the test rig but still being sufficiently representative of the automotive context. NiMH batteries have advantages in experimental development due to their high safety in charge and discharge and tolerance to abuse (overcharge and overdischarge), their good volumetric energy, power and thermal properties, and their simple and inexpensive charging and control circuits [4]. As an initial configuration, radio-controlled car cell packs (with six cells each) were used with their original charging power supplies, since they charge the packs similarly to a defined point. Here nine modules in series are used to create a nominal voltage (64.8 V) within the window of the motor controller. The layout of six NiMH cells per module, connected in series, is particularly close to automotive applications since it is also used in hybrid cars [5]. Table I summarizes the battery pack configuration for Honda Insight and Toyota Prius from [5], together the pack used here.

Table I: HIL battery pack configuration in comparison to two real EV battery packs

	Honda Insight	Toyota Prius	Test Rig Pack
Battery Type	NiMH	NiMH	NiMH
Nominal cell voltage	1.2 V	1.2 V	1.2 V
Rated capacity	6.5 Ah	6.5 Ah	5 Ah
Cells per module	6	6	6
Number of modules	20	38	9
Total voltage	144 V	273.6 V	64.8 V
Nominal energy storage	936 Wh	1778 Wh	324 Wh

2-4-EV simulation model

The parts of the vehicle not represented by the test rig are implemented in software simulation model in MATLAB and Simulink: this has been parameterized to represent the Nissan LEAF. As the components used in the test rig are not full size, appropriate scaling has been implemented to ensure that torques and speeds are appropriately matched to the components in use. The rig is used to simulate vehicle-level driving cycles such as the well-known urban dynamometer driving schedule (UDDS) [6], and because of the inclusion of physical components, it provides a good representative electrical load at battery level. Full details of the proposed EV model can be found in authors' previous study [7] so, it is not just repeated here.

2-5-Real-time simulator

The BLDC machines receive motion signals corresponding to the vehicle dynamics implemented in the HIL using dSPACE system. It consists of a DS1006 processor with the dSPACE 2013b real-time operating system, DS2202 input-output card interfaced to the user through ControlDesk 5.1 proprietary software platform. The simulation files, developed in MATLAB/Simulink environment, are converted to readable codes for use in the dSPACE simulator using ControlDesk.

3- Real-Time Battery Model Identification and SOC Estimation

A generic framework has been developed for real-time battery measurement, model identification and state estimation as demonstrated in Figure 2. The measurements of current and voltage are used by the identification part to extract battery parameters in real-time. The outputs of the identification part (estimates of unknown parameters) are then used by the estimation unit which uses an artificial intelligent technique (described later in the paper) and is trained to find the relationship between the battery parameters and SOC. The effect of temperature is also taken into account however, the results of this study are presented for a fixed temperature. Number and type of the outputs of the identification part is not pre-determined: the number of parameters is chosen based on what is required for effective state estimation and can change with regard to the battery chemistry [8].

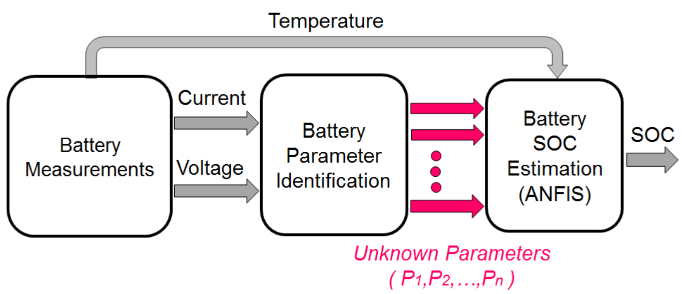

Figure 2: Battery measurement, identification and estimation in real-time

3-1-Battery measurements

The battery measurement consists of recording load current and terminal voltage during the tests. Temperature is controlled to be fixed at 25 °C during the experiments by using the thermal chamber depicted in Figure 1. Test data is stored with a sampling time of 0.1 second. The tests start from fully charged state and continue until the terminal voltage dropped below the cut-off voltage (i.e. 54 V for the NiMH pack) which means depleted charge state. The discharge rate depends on the power demand from the motor controller however, it is limited to 10 A to protect the battery pack. The setup uses a LEMTM 5V maximum output ±19.2 A current transducer (model number LTS 6NP) for accurate current measurements. The voltage output of the current transducer is fed to the analog-to-digital (AD) input of the dSPACE setup. The voltages are measured using simple resistive potential divider circuits. The divider resistors are selected such that the current through them is less than 0.1 mA and the output voltages are less than 10 V, which is a limit of dSPACE system.

3-2-Battery parameter identification

A system identification technique is used to find the battery parameters based on input-output battery measurements which are current and terminal voltage. Various ECN model structures and fitting algorithms can be used for this purpose depending on the required level of complexity and speed in each application. In the present case that the final target is the NiMH pack's SOC estimation, the results presented in [8] demonstrate that the battery pack's open-circuit-voltage (OCV) would be sufficient. Consequently, the only unknown parameter (referring to Figure 2) which should be obtained during the identification process is OCV here. For this purpose, an internal resistance model (R_{int} model) [1] is used which contains a voltage source and an ohmic resistance in series.

After selecting the battery model structure, the unknown parameters should be found during the identification process. The parameter vector (θ) is determined so that the prediction error (ε) is minimized, defined as follows [9]:

$$\varepsilon(t_k,\theta) = y(t_k) - \hat{y}(t_k \,|\, t_{k-1};\theta) \tag{1}$$

where $y(t_k)$ is the measurement data at time *k* and $\hat{y}(t_k \,|\, t_{k-1};\theta)$ is the model's prediction at time *k* using the parameters θ. A fitness function like the root mean square error (RMSE) can be used in this optimization problem;

$$RMSE = \left[\frac{1}{N} \sum_{k=1}^{N} \left| \varepsilon(t_k,\theta) \right|^2 \right]^{\frac{1}{2}} \tag{2}$$

In this case, the battery model's parameters are optimized so that the least difference between the measured terminal voltage and the model's output is achieved so we have:

$$RMSE = \frac{1}{\sqrt{n}} \left(\sum_{i=1}^{n} (V_{t,i} - \hat{V}_{t,i})^2 \right)^{0.5} \tag{3}$$

where V_t and $\hat{V}_t$ are measured and estimated values of the battery terminal voltage respectively. Using R_{int} model, the estimated value can be obtained as follows;

$$\hat{V}_t = V_{OC} - R_O.I \tag{4}$$

The model has just two variable parameters (V_{OC} and R_O), so RMSE is considered as a function (*f*) of these parameters. Because the minimum value of RMSE is desired, the corresponding optimum values of the parameters can be obtained by putting the gradient equal to zero as discussed in [9] that gets the following closed-form formulas.

$$R_O = \left(\frac{\sum_{i=1}^{n} V_{t,i} I_i}{\sum_{i=1}^{n} I_i} - \frac{\sum_{i=1}^{n} V_{t,i}}{n} \right) \Bigg/ \left(\frac{\sum_{i=1}^{n} I_i}{n} - \frac{\sum_{i=1}^{n} I_i^2}{\sum_{i=1}^{n} I_i} \right) \tag{5}$$

$$V_{OC} = R_O \cdot \frac{\sum_{i=1}^{n} I_i^2}{\sum_{i=1}^{n} I_i} + \frac{\sum_{i=1}^{n} V_{t,i} I_i}{\sum_{i=1}^{n} I_i} \tag{6}$$

These V_{OC} and R_O are the optimum battery model parameters that give us the least RMSE. Some points that should be considered when using the proposed formula are:

1) The analytical solution is obtained for the R_{int} model and is not valid for other ECN models.
2) The formula can be used for any battery type (not limiting to NiMH battery).
3) It gives the average values of V_{OC} and R_O by using charge and discharge data at the same time.

3-3-Battery SOC estimation

An adaptive neuro-fuzzy inference system (ANFIS) is trained to learn the relationship between the battery pack's OCV and SOC. By this way, ANFIS can perform as an estimator which uses OCV as the input to predict SOC as the output in real-time as presented in Figure 3. As a reference for validation of the estimations, coulomb-counting (CC) is usually used. CC is a theoretical method which cannot be used in practice because of its restrictions however; it is a good benchmark for checking other techniques [10]. In CC, battery SOC is obtained by integrating the current over time. Assuming SOC_0 as the initial SOC at time t_0, the battery pack's SOC at time *t* is:

$$SOC = SOC_0 - \left(\int_{t_0}^{t} \frac{\eta\, i(\tau)}{C_t} d\tau \right), \quad 0 < SOC < 1 \tag{7}$$

where $i(t)$ is the current (A) (assumed positive for discharging and negative for charging). η is the battery's coulombic efficiency (dimensionless) and C_t is the total capacity (As). In this representation, the SOC value is a number between 0 and 1 with 0 indicating a fully depleted state and 1 representing a fully charged state.

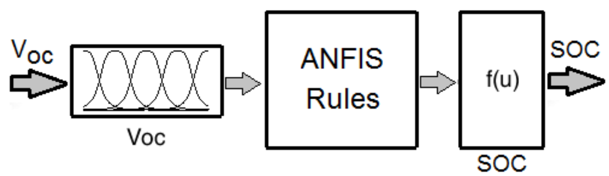

Figure 3: ANFIS structure used for NiMH pack's SOC estimation

4- Results Analysis

In a case study, a 64.8 V NiMH battery pack was tested using the rig and the proposed algorithms were tested in real-time. Urban dynamometer driving schedule (UDDS) [6] was used as the input of the tests. The tests were performed at 25 °C, starting from fully charged state and continued until the terminal voltage dropped below 54 V (cut-off voltage of the NiMH pack). The driver model followed the driving cycle by generating acceleration and deceleration commands. Rotational speed of the electric motors was measured and a velocity tracking error was calculated in real-time. The reference velocity and measured velocity are illustrated in Figure 4, demonstrating a good tracking performance. Variations of battery pack's current and voltage are also depicted in Figure 4. As shown in this figure, the measurements are very noisy, challenging for the identification and estimation algorithms.

Identification and estimation results are also presented in Figure 5 including ohmic resistance and OCV as discussed in section 3.2 and battery SOC estimation using ANFIS explained in section 3.3. Identification was repeated every 0.1% change in SOC and a time window of 2 minutes ago was used to extract the parameters. One of the main advantages of the proposed identification formula is its high speed that makes it suitable for real-time applications. SOC estimation was performed using the last 20 identifications which means every 2% change in SOC in this case. The reason of using a number of identifications (20 times in this case) for every estimation attempt is to make it more robust against the identification fluctuations. As shown in Figure 5, identification performance is affected by the discharge rate where a continuous high rate of discharge can confuse the algorithm to detect the parameters. Since SOC estimation accuracy directly depends on the identification precision, this confusion is observed for a short time in the estimation results as well. All in all, the algorithms perform well against the high level of noise (caused by using low-cost sensors) which is designed by purpose to test the algorithms in the worst scenario.

5-Conclusions

A generic framework was explained and tested for real-time battery model identification and state estimation. Battery ohmic resistance and open-circuit voltage were obtained in real-time using current and voltage measurements. The main feature of the proposed identification algorithm is its simplicity and speed that makes it suitable to be embedded on battery management boards. Another advantage of the proposed framework is its flexibility that makes it usable for other applications like state-of-health estimation and other battery types too. Performance of the proposed algorithms was tested using a HIL test rig, representing a scaled-down electric vehicle powertrain system. Using such a HIL test rig for battery management algorithm development, is a quite useful approach to evaluate the proposed algorithms in a more realistic scenario by considering the effects of noise and uncertainties.

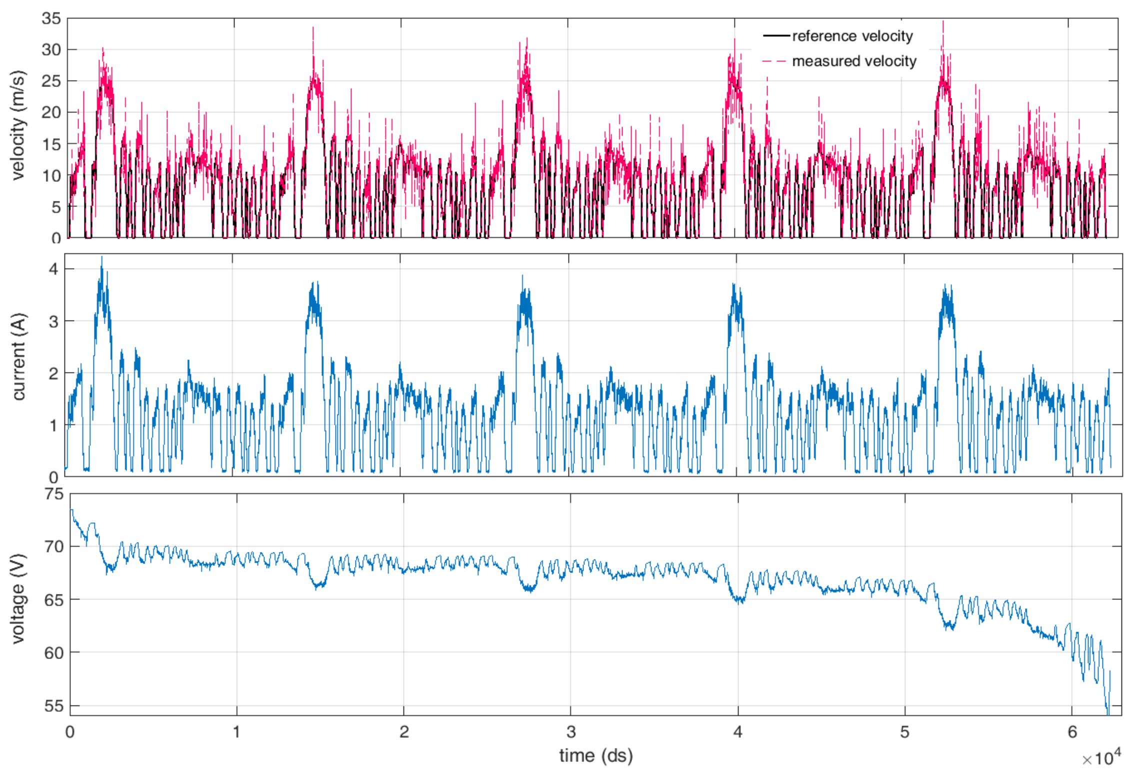

Figure 4: velocity and battery measurements during UDDS test

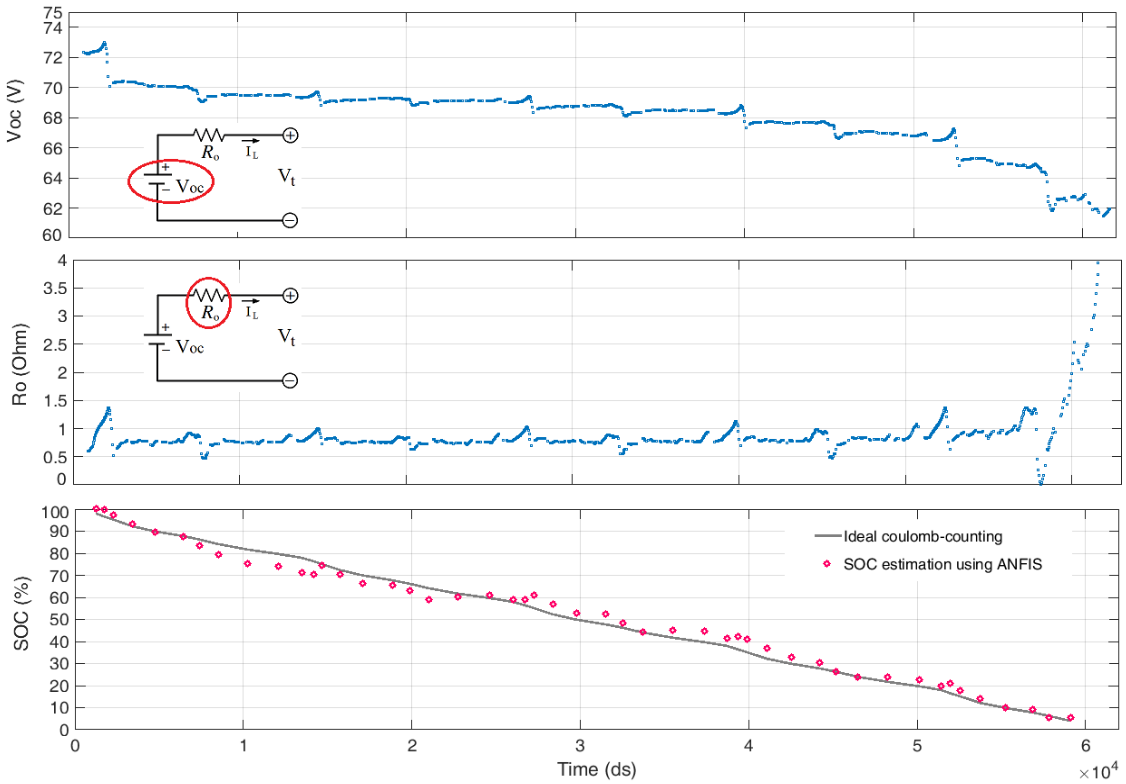

Figure 5: real-time battery parameter identification and SOC estimation during UDDS test

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