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# Electric Vehicle Battery Parameter Identification and SOC Observability Analysis: NiMH and Li-S Case Studies

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## Abstract

In this study, a framework is proposed for battery model identification to be applied in electric vehicle energy storage systems. The main advantage of the proposed approach is having capability to handle different battery chemistries. Two case studies are investigated: nickel-metal hydride (NiMH), which is a mature battery technology, and Lithium-Sulphur (Li-S), a promising next-generation technology. Equivalent circuit battery model parametrisation is performed in both cases using the Prediction-Error Minimization (PEM) algorithm applied to experimental data. The use of identified parameters for battery state-of-charge (SOC) estimation is then discussed. It is demonstrated that the set of parameters needed can change with a different battery chemistry. In the case of NiMH, the battery's open circuit voltage (OCV) is adequate for SOC estimation. However, Li-S battery SOC estimation can be challenging due to the chemistry's unique features and the SOC cannot be estimated from the OCV-SOC curve alone because of its flat gradient. An observability analysis demonstrates that Li-S battery SOC is not observable using the common state-space representations in the literature. Finally, the problem's solution is discussed using the proposed framework.

## 1 Introduction

Road vehicles are becoming increasingly electrified. One of the most significant issues of the development of electric vehicles (EVs) is energy storage technology. Batteries, as the most common type of energy storage systems, may have different electrochemical features depending on their exact chemistry, and they may need to be managed in different ways. In the literature, many battery chemistries have been investigated and used for automotive applications: lead-acid, nickel-metal hydride (NiMH), and lithium-ion (Li-ion) are just a few examples. There is much research on improved battery technologies with many aims such as increasing battery capacity, lower cost and greater safety. Among these new battery technologies, lithium-sulphur (Li-S) is a promising technology, with a suggested specific energy up to 650 Wh/kg. This offers the potential for increased energy storage capacity without an increase in weight, and in applications where weight rather than space is the limiting factor, this offers a potential way to increase an EV's range. Good explanations of the electrochemical reactions taking place inside a Li-S battery can be found in the literature [1]-[3] and are not duplicated here: assuming that when in production, mature Li-S technologies will also provide a sufficient power output and lifetime in the future, its ability to operate in a wide temperature range of operation and its distinct safety advantages make it very attractive for automotive applications. Li-S technology has developed dramatically, though it has not yet been deployed in a full-scale EV to date. As part of efforts to bring it to market, Innovate UK has co-funded a research project called 'Revolutionary Electric Vehicle Battery' (REVB) to embedding model-based methods in the cell development process: the collaborators in this project – OXIS Energy, Imperial College London, Cranfield University and Ricardo, aim to demonstrate advanced Li-S vehicle battery technology with 400 Wh/kg cell-level energy density. Part of this project involves the development of battery management algorithms to get the most out of Li-S and manage its state effectively.

This study, as a part the REVB project, addresses battery model identification for state-of-charge (SOC) estimation in EV energy storage applications. Two case studies are investigated here: NiMH and Li-S. The NiMH battery chemistry is selected as it is a mature battery technology which has been the subject of many previous studies. It is also 'safe', and therefore suitable for an experimental laboratory environment. As might be expected from the REVB project context, the second chemistry is Li-S. For application in EVs, an 'equivalent circuit' modelling approach is chosen which is fast enough for real-time applications. Experimental tests are carried out in order to parametrise the battery models under different working conditions. The battery measurement consists of current (the controlled input) and terminal voltage (measured as an output), all in the time domain. The measurement data is used to identify battery parameters. Figure 1 demonstrates the whole structure of the proposed framework in this study, including the battery measurements, parameter identification and SOC estimation parts. 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 effects of temperature are taken into account in this part of the framework, where SOC estimation is performed by a set of estimators which have been trained at different temperatures. 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. The number of identified parameters used can change with regard to the battery chemistry, and an investigation of this is a particular contribution of this study.

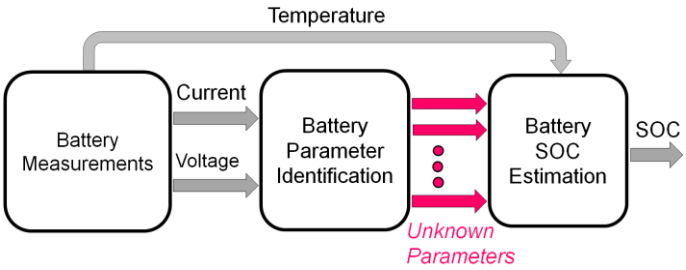


Figure 1: Battery parameter identification for SOC estimation

## 2 Battery model identification

### 2.1 Equivalent circuit battery model

Electrical circuit modelling or equivalent circuit network (ECN) modelling is a common method for simulating battery performance. Having less complexity than high-fidelity electrochemical models, ECN models have been used in a wide range of applications and for various battery types [4]-[7]. ECN battery models are constructed by putting resistors, capacitors and voltage sources in a circuit. Schematic of an equivalent circuit battery model, called a 'Thevenin' model [8][9] or one RC network model (1RC model), is illustrated in Figure 2. In this structure, $V_t$ is battery's terminal voltage, $V_{OC}$ is open circuit voltage (OCV), $R_O$ is internal resistance, $R_P$ and $C_P$ are equivalent polarization resistance and capacitance respectively. In this study, 1RC model is used as the battery model structure. The dynamic equations of such a model are as follows:

$$\begin{cases} V_t = V_{OC} - R_O I_L - V_P \\ \dfrac{dV_P}{dt} = -\dfrac{1}{R_P C_P} V_P + \dfrac{1}{C_P} I_L \end{cases} \tag{1}$$

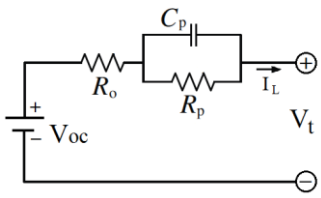


Figure 2: Thevenin battery model (1RC model)

### 2.2 Battery experiments

The batteries studied here are a six-cell NiMH battery pack, and a single Li-S cell developed by Oxis Energy Ltd [10]. Technical specifications of both batteries are presented in Table 1. The test bench which is used for NiMH battery experiments is explained in [11] with details. For Li-S cell experiments, the Maccor Series-4000 battery tester is used. The battery tester is a voltage/current device that applies a current and measures the voltage or Vis versa. The current and voltage limits are +/- 5A and +/- 5V for each channel. The cell is contained inside an aluminium test box which is connected to the equipment using crocodile clips. The test box is contained inside a Binder thermal chamber to set the desired temperature during each test. Li-S cell test equipment is depicted in Figure 3.

In both case studies (NiMH and Li-S), experiments are conducted by applying consecutive discharge current pulses to the battery and measuring terminal voltage as the output. Each test starts from fully charged state and continues until the terminal voltage drops below the cut-off voltage that means depleted charge state. In Figure 4, battery measurements including current (input) and terminal voltage (output), which are recorded at 25°C, are shown for two tests on NiMH and Li-S.

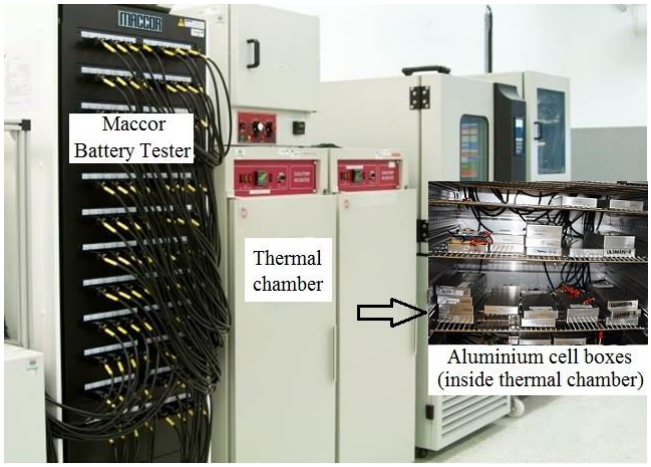


Figure 3: Li-S cell test equipment

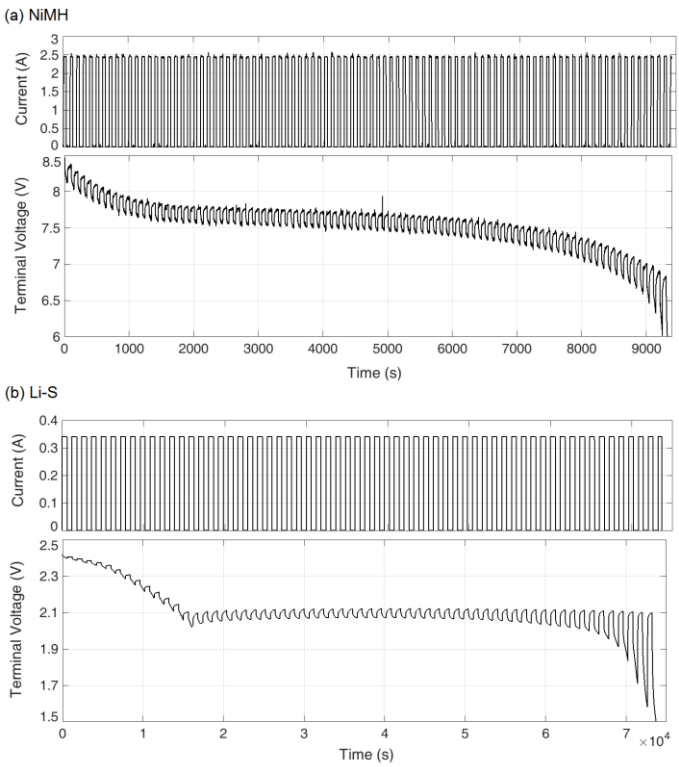


Figure 4: Battery measurements; (a) NiMH, (b) Li-S

Table 1: NiMH battery pack and Li-S cell specifications

| Battery chemistry | NiMH | Li-S |
|---|---|---|
| Rated capacity | 2400 mAh | 3400 mAh |
| No. of cells | 6 | 1 |
| Rated voltage | 7.2 V | 2.1 V |
| Full-Charged voltage | 8.5 V | 2.4 V |
| Cut-off voltage | 6 V | 1.5 V |
| Schematic |  |  |

### 2.3 Identification algorithm

In the proposed approach, a system identification technique is utilized to find the battery parameters based on input-output battery measurements which are current and terminal voltage. Prediction-Error Minimization (PEM) algorithm is utilized for battery model identification.

In the identification procedure, the model's parameter vector θ is determined so that the prediction error $\varepsilon(t_k,\theta)$ is minimized. The error is defined as follows:

$$\varepsilon(t_k,\theta) = y(t_k) - \hat{y}(t_k|t_{k-1};\theta) \tag{2}$$

where $y(t_k)$ is the measured output at time k and $\hat{y}(t_k|t_{k-1};\theta)$ is predicted value of the output at time k using the parameters θ. The prediction error depends on the parameter vector, so an iterative minimization procedure has to be applied. Consequently a scalar fitness function is minimized as follows:

$$E_N(\theta) = \det\left(\frac{1}{N}\sum_{k=1}^{N}\varepsilon(t_k,\theta)\,\varepsilon^T(t_k,\theta)\right) \tag{3}$$

For the model shown in figure 2, the parameters vector has four elements as follows. The parameters are optimized so that the least difference between measured terminal voltage and model's output is achieved.

$$\theta = [R_O\,, V_{OC},\, R_1,\, C_1] \tag{4}$$

$$\varepsilon(t_k,\theta) = V_t(t_k) - \hat{V}_t(t_k|t_{k-1};\theta) \tag{5}$$

Both NiMH and Li-S models are identified using PEM algorithm based on the experimental data presented in the previous section.

### 2.4 Identification results

The four parameters of 1RC model are obtained for both NiMH and Li-S cases using PEM algorithm as presented in Figure 5 and Figure 6 respectively. The identification process is repeated over the whole range of SOC at regular intervals called "identification window" or "identification horizon". The battery identification window can be a time window or SOC window. However, a combination of both is designed and used in this study because of the electric vehicle (EV) application. Since the power demand from an EV's battery pack can change in a wide range, identifying the battery model at regular time intervals is not effective. On the other hand, EV battery's SOC can change in few seconds when the power demand is very high. This may cause numerical problems for the identification process when the number of data points is not enough to identify the parameters. Here, the identification process is repeated every 1% change in SOC. So, the battery model is identified using the measurement's history in the past 1% SOC. However, the identification window's length is extended to the past 2 minutes when it is less than that.

Figure 5 demonstrates that the OCV-SOC curve of NiMH battery is a very smooth curve with always positive gradient which makes it suitable for SOC estimation. The ohmic resistance is sensitive to SOC variation just at low and very high SOC levels however this sensitivity is less in the middle. The NiMH battery polarisation resistance is almost flat in a wide range of SOC between 20% and 80% which means it is not suitable for SOC estimation at all. Finally, the polarisation capacitance is not identified reliably and the fluctuation makes it unsuitable to be used for SOC estimation. On the other hand, Figure 6 demonstrates completely different results for the Li-S cell. The main difference is the OCV-SOC curve which is flat for Li-S battery in a wide range. So, against the NiMH battery, we really need to investigate other parameters in this case. In the next part, an observability analysis is performed to show the difference between the two battery types using a mathematical representation.

## 3 Battery SOC estimation

In this section, battery state-of-charge (SOC) estimation is studied for the two case studies, NiMH and Li-S. For this purpose, an observability analysis is performed firstly in both cases. Then the connection between the identification and estimation parts is discussed using the proposed framework depicted in Figure 1.

### 3.1 Observability analysis

Referring to the battery differential equations in Eq.(1), an observability analysis would be possible if a state-space representation of the model is available in the standard form in below:

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases} \tag{6}$$

where *x* is the state vector, *u* is the input (i.e. current), *y* is the output (i.e. terminal voltage) and A, B, C and D are matrices that include battery model's parameters. Since the above state-space representation is obtained for linear systems, we need to linearize the nonlinear battery model. For this purpose, a method which is presented in [12] is used here. In this method, $V_P$ and SOC are model states, current is the input and terminal voltage is the output. For $V_P$, it is easy to write it in the standard state-space format however, there is more to do for SOC. Using Coulomb-Counting (CC), SOC is calculated by integrating the load current to know how much capacity is used and remained. Assuming $SOC_0$ as the initial

SOC at time $t_0$, the battery's SOC at time $t$ is defined as follows:

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

where $i(t)$ is the current in ampere (A) and is assumed positive for discharging and negative for charging. Parameter $\eta$ is the battery Coulombic efficiency and $C_t$ is cell's total capacity in ampere-second (A.s) when the time is in second. Therefore, SOC is a number between 0 and 1 representing depleted and fully-charged states respectively.

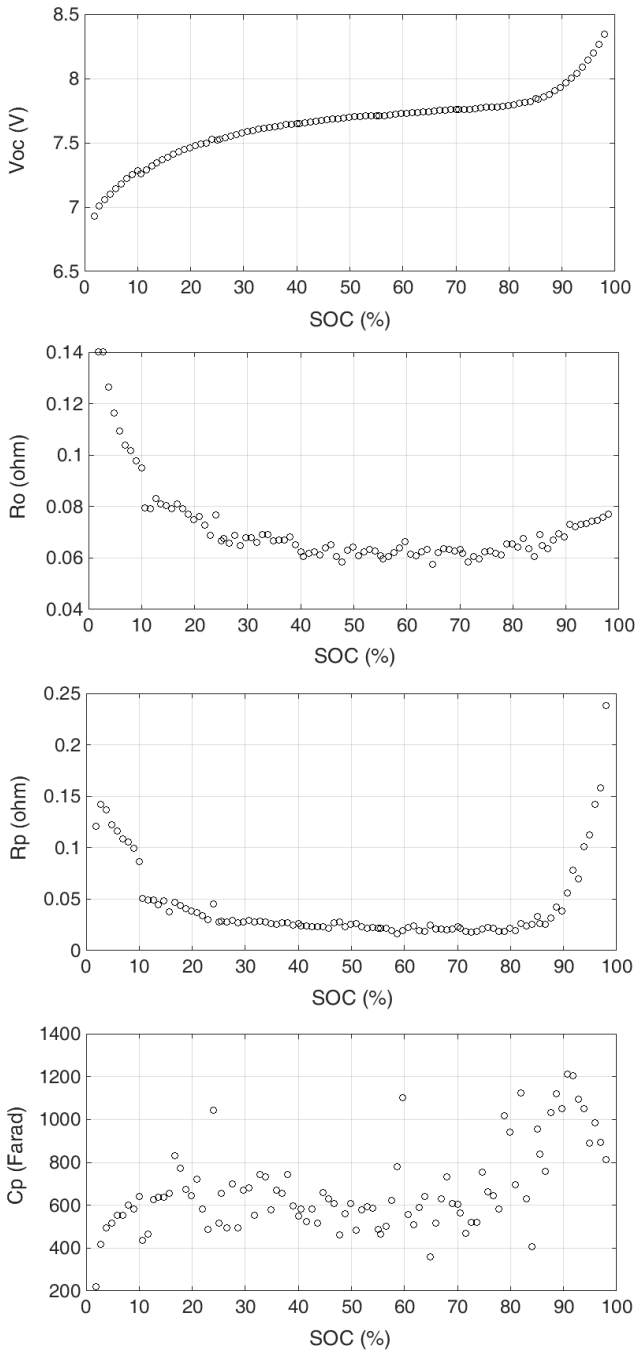


Figure 5: Identified parameters of the NiMH model

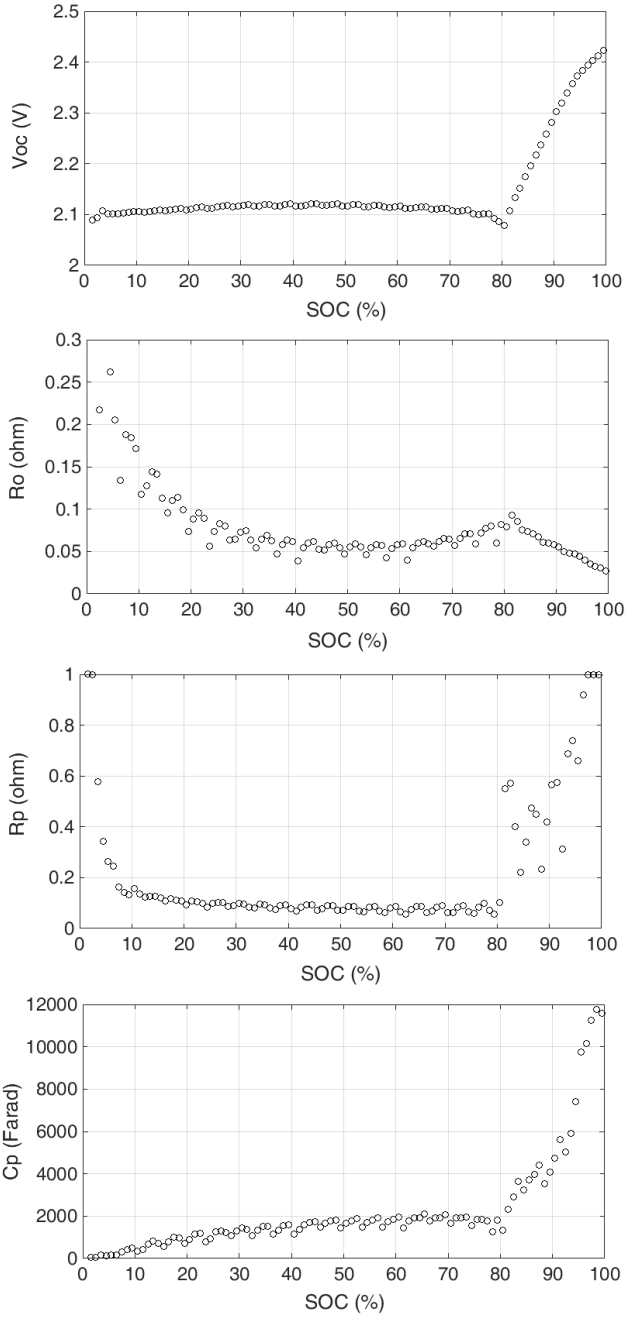


Figure 6: Identified parameters of the Li-S model

There is still one term in the output equation that is not match with the standard form of state-space. OCV ($V_{OC}$) can be obtained as a nonlinear function of SOC based on the identification results. Such a nonlinear function can be divided into small linear parts using the gain scheduling method developed in [13]. Considering $\Delta_{SOC}$ as the SOC interval length, battery OCV can be written for the *i*th SOC interval as follows:

$$\begin{aligned} &V_{OC} = a_i \,.\, SOC_i + b_i \\ &where \;\; (i-1).\Delta_{SOC} \le SOC_i \le i.\Delta_{SOC} \end{aligned} \qquad (8)$$

The coefficients *a* and *b* are obtained from OCV-SOC curve and are constant at each small segment as illustrated in Figure

7. So, OCV can be replaced by its linearized approximation in the output equation as follows:

$$V_t = a_i.SOC + b_i - R_O I_L - V_P \tag{9}$$

Consequently, the state-space representation of the battery model is obtained as follows:

$$\begin{cases} \begin{bmatrix} \dfrac{dV_P}{dt} \\ \dfrac{dSOC}{dt} \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{R_P C_P} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_P \\ SOC \end{bmatrix} + \begin{bmatrix} \dfrac{1}{C_P} \\ \dfrac{\eta}{C_t} \end{bmatrix} I_L \\ V_t - b_i = \begin{bmatrix} -1 & a_i \end{bmatrix} \begin{bmatrix} V_P \\ SOC \end{bmatrix} - R_O I_L \end{cases} \tag{10}$$

Having the model in state-space form, observability of the model can be analysed by calculating the observability matrix as follows [14]:

$$O = \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} -1 & a_i \\ \dfrac{1}{R_P C_P} & 0 \end{bmatrix} \tag{11}$$

Since $R_P$ and $C_P$ are positive non-zero numbers in the battery models, the only case in which the observability matrix is not full rank is when $a_i$ be zero. This will never happen for the NiMH model because of the OCV-SOC characteristics for this battery type. However, the results demonstrate that the system is not fully observable for the case of Li-S because of the particular features of Li-S battery OCV curve. Indeed, the coefficient $a_i$ can be zero for a Li-S battery. The whole range of SOC of a Li-S battery can be divided into two parts called high plateau (HP) and low plateau (LP). SOC cannot be estimated using OCV curve in LP because of its flat shape as depicted in Figure 7.

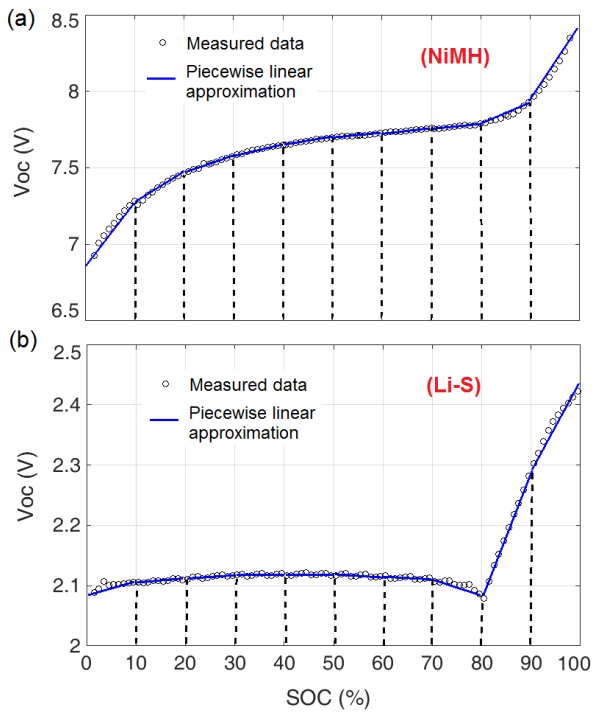


Figure 7: Piecewise linear approximation of OCV-SOC curves (a) NiMH, (b) Li-S

### 3.2 Battery SOC estimation using system identification

There are various battery SOC estimation methods in the literature which are applied for Lead-acid, NiMH and Li-ion batteries. As an example, Lithium-ion battery SOC is estimated using a proportional-integral observer in [12]. Our results in the previous section demonstrate that these common methods are not applicable for Li-S battery because of its unique features. In this study, a generic framework is proposed to be able to handle different battery types. In the proposed approach, a system identification tool is connected to an estimation tool to build an integrated system as demonstrated in Figure 1. As mentioned in the introduction section, an important question about the proposed framework is: which parameters are really needed to be identified for SOC estimation?

To find the answer of this question, battery OCV is investigated firstly as the most widely used battery parameter for SOC estimation. After investigating the two case studies (i.e. NiMH and Li-S) the results demonstrate that NiMH battery SOC is predictable by only using OCV [15]. In this case there is no need to use more battery parameters which just increase the computational effort with no gain. However, the situation is different for Li-S battery where OCV is not enough for SOC estimation. Consequently, other battery parameters should be used by the estimator in this case. The estimator can be in different forms. For example in [15], an adaptive neuro-fuzzy inference system (ANFIS) is designed and used for SOC estimation using the identification results for the NiMH battery pack. Other types of estimators can be used instead of ANFIS as well. The idea is to find the relationship between the identification results and SOC by using a mapping function like $f$ in bellow:

$$SOC = f(P_1, P_2, P_3, \ldots) \tag{12}$$

where $P_i$ is the *ith* identified battery parameter. As a designer, we are interested to use the minimum number of parameters in order to decrease computational effort especially for online applications.

The results demonstrate that design of a SOC estimator for Li-S battery can be challenging. The first conclusion is that OCV is not enough in this case however; it can be one of the choices beside other parameters. Figure 8 demonstrates that OCV can be used for SOC estimation in a specific range of SOC between 80% and 100% (i.e. HP). In other words, we are sure about the SOC value when OCV is more than 2.12V. Out of this range, the other parameters shall be used instead. For example, Li-S SOC can be determined if the ohmic resistance is more than 0.1 ohm. This can happen only when SOC is less than 15% as illustrated in Figure 8. Referring to Figure 6, the polarisation resistance and capacitance can be utilised for SOC as well. So, a combination of Li-S battery parameters should be used by an estimator to get the best results. Designing such an estimator and test it under different conditions, like the procedure presented in [15], needs to be done in a separate study. However, the results of this study can be used as a base for that target. The temperature effect should be also added by training different estimators to be used at different temperature levels.

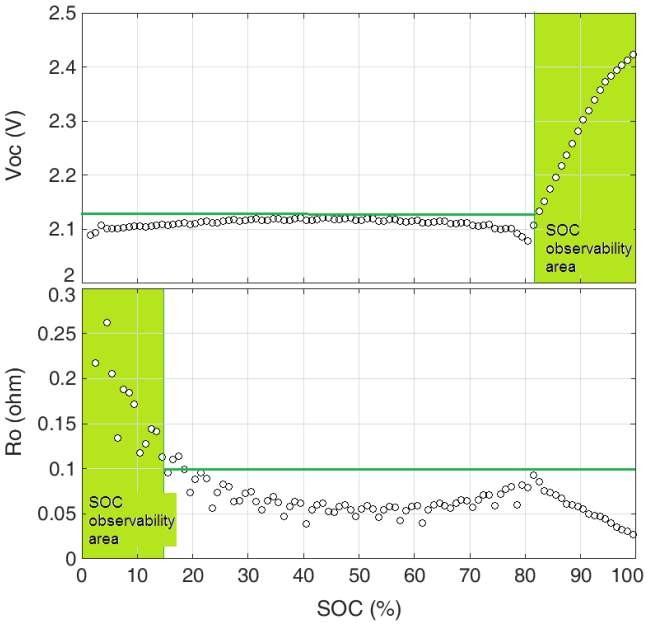


Figure 8: Li-S SOC observability using different parameters

## 4 Conclusions

In this study, Li-S real-time cell parametrisation is performed for a Thevenin equivalent circuit model using the PEM algorithm applied to experimental data, which is a new contribution in this area. A framework is also proposed in which a system identification tool is connected to an estimation tool as a unique integrated system. The connection between the two parts is a parameter set consisting of those parameters found to give the most effective SOC estimation. The results demonstrate that not all battery parameters are required to get effective SOC estimation, and some are best discarded. The results also demonstrate that the set of effective parameters can change with respect to the battery chemistry. This was shown by the investigation of two different battery chemistries, NiMH and Li-S. It is concluded that the OCV is adequate for NiMH battery SOC estimation. However, the problem is more challenging for Li-S battery because of its unique characteristics, particularly its flat OCV-SOC curve. An observability analysis demonstrates that unlike other battery types in the literature, the Li-S battery model's SOC is not observable from measurements of current and voltage alone. Consequently, existing SOC estimation techniques will not be applicable for Li-S or at least will need major modifications for this goal. This is an open research area, if it can be addressed; it increases the likelihood of realising the promise of Li-S as a next-generation battery technology.

## Acknowledgements

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