IFAC-PapersOnLine, Volume 49, Issue 11, 2016, Pages 48-53
Proceedings of the 8th IFAC International Symposium on Advances in Automotive Control (2016)
19 - 23 June 2016, Norrköping, Sweden

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

Abbas Fotouhi*, Daniel J. Auger*, Karsten Propp*, Stefano Longo*

** School of Aerospace, Transport and Manufacturing, Cranfield University, MK43 0AL, UK.*
(e-mails: a.fotouhi@cranfield.ac.uk; d.j.auger@cranfield.ac.uk; k.propp@cranfield.ac.uk; s.longo@cranfield.ac.uk)

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

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.

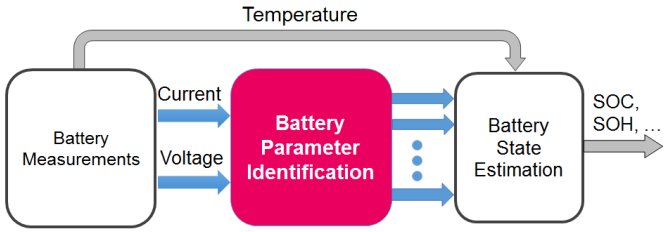

Fig. 1. Online battery state estimation based on parameter identification

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

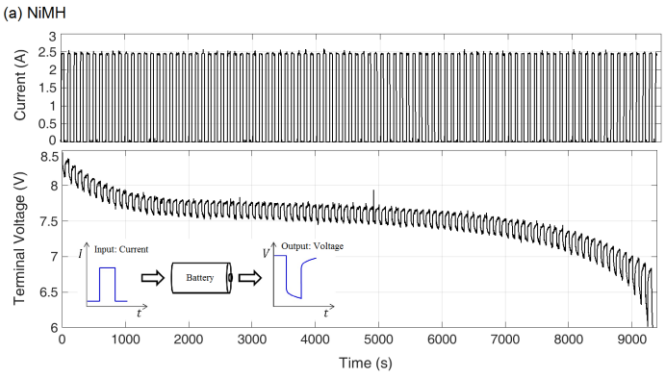

Fig. 2. Measurements during a discharge test by applying current (input) and measuring terminal voltage (output)

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-

tively. Adding more RC networks to the battery model (such as 2RC in Fig. 3(c)) may improve its accuracy but it increases the complexity too. Other elements can be added to the model as well to consider the hysteresis effect for example. As mentioned before, this study is not focused on modelling accuracy discussion as it has been addressed in a number of previous studies. However, this study aims at running the system identification algorithms at different levels of complexity which depends on the number of unknown parameters. This is done here by adding more RC networks to battery model.

2.3 Battery identification algorithms

Three identification algorithms are investigated here which are gradient descent (GD), Snyman (2005), genetic algorithm (GA), Goldberg (1989), and prediction error minimisation (PEM), Ljung (1987). Explaining these standard algorithms is out of the framework of this study and the readers can refer to the above mentioned references. It should be noted that there are other algorithms for battery parametrisation in the literature as well. GA and PEM algorithms are selected as two standard techniques in the literature which most of the readers are familiar with them. GD algorithm is selected based on the results of this study which demonstrate that simpler algorithms (like GD in comparison with GA and PEM) may also be applicable for battery parametrisation regarding its application. This topic will be discussed in more details in the following sections.

In order to investigate both the convergence speed and the accuracy of the battery parametrisation algorithms, different versions of one algorithm are also considered. For example, GD's speed increases by making step size bigger however this leads to less accuracy. On the other hand, GA accuracy can be improved by increasing the population size (PS) and/or number of generations (NoG); however this leads to less convergence speed. In this study, two versions of GD algorithm are used; one is more precise (GD1) whereas the other is faster (GD2). Similarly for GA, two versions are tested; in the more precise version (GA1), PS and NoG are 30 and 35 respectively for the R model whereas in the faster version (GA2), the parameters are 10 and 15 respectively. For the 1RC model, more PS is considered; 50 in GA1 and 20 in GA2. For PEM algorithm, just one version is used.

Generally, a system identification problem can be considered as an optimisation problem where we are trying to find the optimum values of a model's parameters to minimise an error function. It should be noted that here we are talking about predefined model structures with unknown parameters. So, the parameter vector (θ) is determined so that the prediction error (ε) is minimised, defined as follows:

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

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. In this case, the battery model's parameters are optimised so that the least difference between the measured terminal voltage and the model's output is achieved. For this purpose, a fitness function, i.e. the root mean square error (RMSE) function, is used as follows:

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

The battery parameters are not fixed and the optimisation solution depends on SOC, temperature, etc. Because the battery identification problem has a time-varying solution, the identification process should be repeated many times using a short history of measurements. The current and voltage measurements are used as the inputs of the optimisation problem. The identification horizon can be a "time window" or "SOC window" where the latter is used in this study.

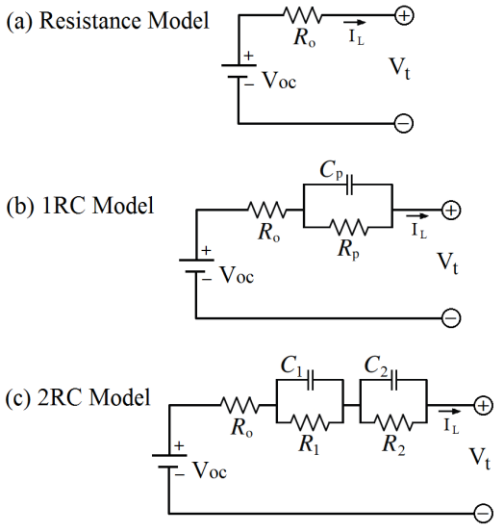

Fig. 3. Equivalent circuit battery models

3. IDENTIFICATION RESULTS

At first, a visual analysis is proposed in this section in order to get a better understanding about the battery model identification problem. RMSE values are obtained as a function of the unknown battery parameters. Such surfaces are plotted for *R model* as depicted in Fig. 4. The model has two unknown parameters, V_{OC} and R_O, which should be obtained during the optimisation process. The surfaces, shown in Fig. 4, are obtained by using the measurement history in the past 2% SOC. For example, for the plot which is obtained at 50% SOC, the measurements from 48% to 50% SOC are used. There is a point on each surface at which RMSE has the least value which is the optimal solution. It should be noted that the optimum point of the identification surface moves with regard to SOC however, it keeps its general shape as a smooth V-shape surface. Looking simple, the battery identification surfaces contain significant information about this particular optimisation problem which has not been discussed in the literature. These results demonstrate that even a simple optimisation algorithm like GD might be applicable for battery parametrisation. Another outcome of these surface plots is the idea of developing an analytical solution for the battery parametrisation problem when *R model* is enough for a specified application.

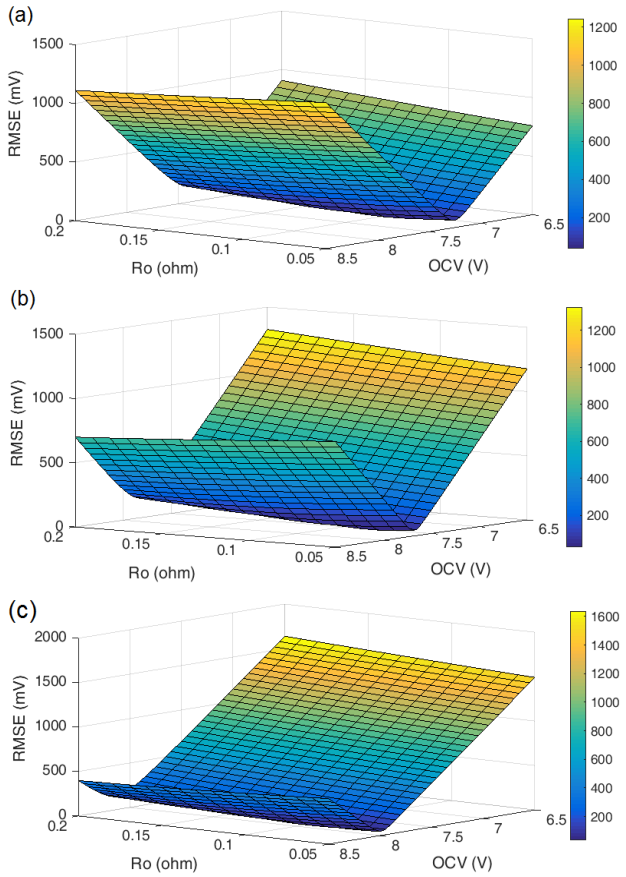

Fig. 4. Battery model identification surface (R model) at (a) 10%, (b) 50% and (c) 90% SOC

The minimum points of the above mentioned surfaces are obtained at different SOC levels using GD, GA and PEM algorithms. Each optimisation solution point contains two values corresponding to OCV and ohmic resistance. The two parameters are obtained every 2% SOC using the three identification algorithms as illustrated in Fig. 5. The parameters are obtained by applying the algorithms to fit the *R model* to experimental data. The fitting quality is measured by RMSE criterion, introduced in equation (2). The RMSE values and identification time are compared for different algorithms in Fig. 6 and Table 2. Based on the results, all the algorithms are able to get the minimum RMSE for *R model* however, the identification time changes using different algorithms.

The results that are presented in Fig. 6 are not valid for other model structures. This is a part of the main discussion of this study called “application-oriented” trade-offs between accuracy and simplicity. Regarding the application, the simplest model structure should be selected first and then a suitable algorithm should be selected after doing the trade-offs. In order to investigate the effect of the battery model structure, different structures are assessed in this study too. Fig. 7 depicts RMSE and identification time for 1RC model. It is clear that the trade-offs are different in this case comparing to the case of *R model*. The fitting error has decreased by adding one RC network to the *R model*. On the other hand, the identification time has increased by adding more complexity to the model. So, it is important to see if it is beneficial to use the more accurate model or keeping the faster one. To investigate the effect of model structure separately, the identification results are obtained using a fixed algorithm (i.e. PEM) and different model structures (i.e. R, 1RC and 2RC models) as stated in Table 3. RMSE values are quite similar for 1RC and 2RC and this result is also demonstrated for a short part of the test in Fig. 8 where the predicted terminal voltage values are compared vs. experimental data. In other words, there is no remarkable improvement in voltage prediction by adding the second RC network in this case. Further discussions about the results are presented in the next section.

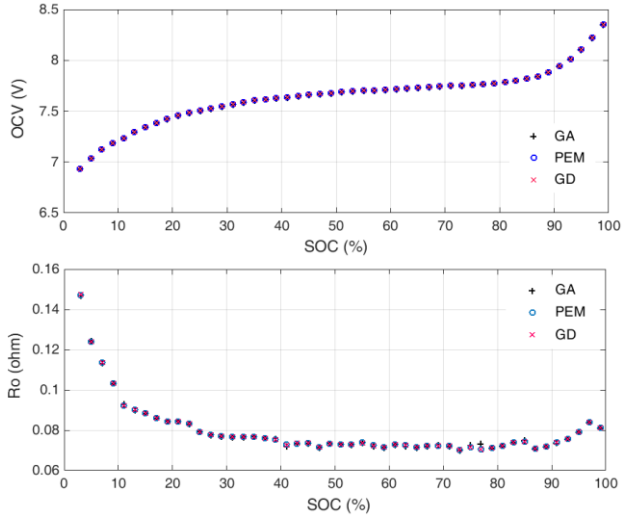

Fig. 5. Identified values of battery OCV and resistance vs. SOC using GA, PEM and GD algorithms

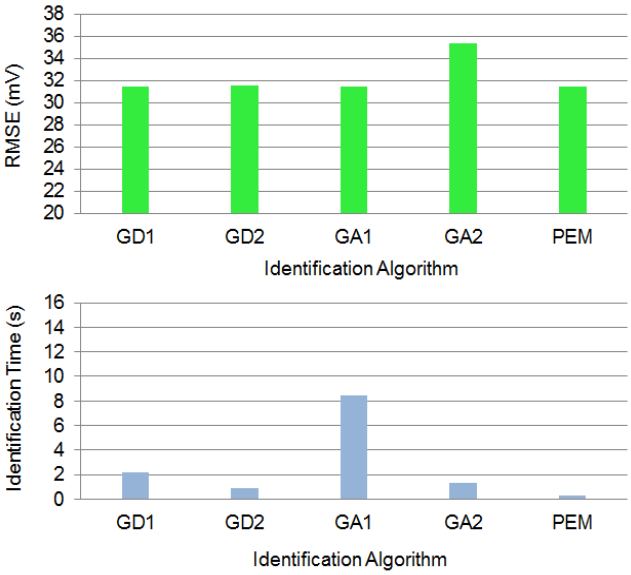

Fig. 6. RMSE and identification time using different algorithms to parametrise R model

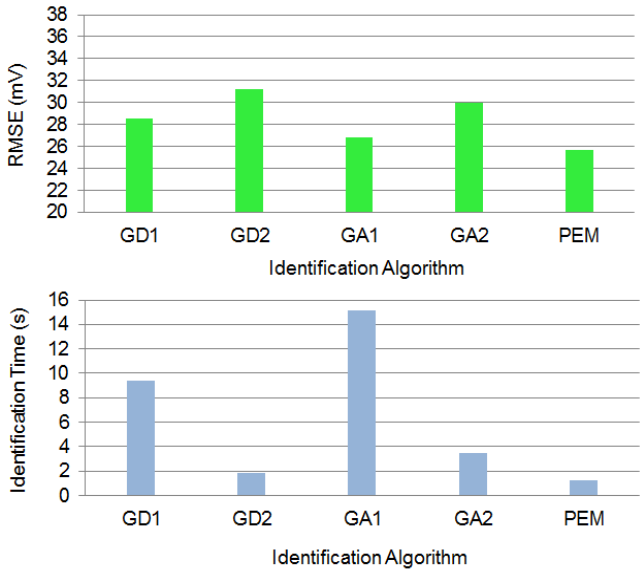

Fig. 7. RMSE and identification time using different algorithms to parametrise 1RC model

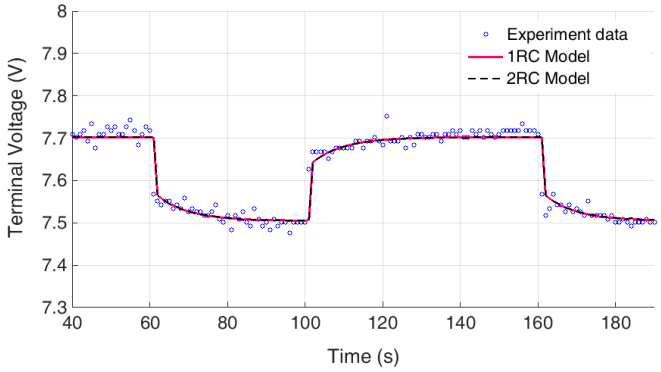

Fig. 8. Battery terminal voltage prediction vs. experimental data for 1RC and 2RC models using PEM algorithm

Table 2. Identification error and time using different algorithms and model structures

Method	Average RMSE (mV)		Average identification time (s)	
	R Model	1RC Model	R Model	1RC Model
GD1	31.49	28.55	2.19	9.38
GD2	31.52	31.20	0.86	1.81
GA1	31.49	26.85	8.48	15.17
GA2	35.35	29.94	1.30	3.50
PEM	31.49	25.70	0.34	1.27

Table 3. Effect of adding RC networks on battery model identification error and time

Model	Method	Mean RMSE (mV)	average Id time (s)	Max. RMSE (mV)	Max. Id time (s)
R	PEM	31.49	0.34	63.11	0.45
1RC	PEM	25.70	1.27	44.63	2.22
2RC	PEM	25.23	3.01	40.80	3.93

4. RESULTS ANALYSIS AND DISCUSSION

The results of this study can be classified into three main parts which are discussed in the followings.

4.1 Study of the battery model parametrisation problem using a new visual approach

At the first stage of this study, the battery model parametrisation problem was handled using a new visual approach to get a better understanding of the problem. Battery model identification surfaces (Fig. 4) are obtained which contain useful insight to the problem. The simplest model structure (*R model*) was used to visualize the optimisation problem in two dimensions. This new presentation of the battery model parametrisation problem, which is done here for the first time, led us to select simpler algorithms like GD due to the smoothness of the surfaces. GD algorithm is not applicable for problems that have lots of local minima however; our results demonstrate that it can be used for the battery parametrisation problem. In addition to the use of GD algorithm, the idea of developing an analytical solution is also originated from this visual analysis which can be established in future studies. As discussed before, the outcomes of such an analytical solution would be battery OCV and ohmic resistance. It depends on the application that these two parameters are sufficient or more complexity is needed. This is part of the contribution of this study called application-oriented trade-off between accuracy and simplicity.

The identification surfaces are obtained at different SOC levels (Fig. 4(a) to (c)). It is demonstrated how the optimum point of the surface moves with regard to the battery SOC. It is also demonstrated that the V-shape and smoothness of the surface remains consistent. Although, other factors like temperature and state-of-health (SOH) are not investigated in this study but does not affect our general results and conclusions. The reason is that here we just need to show that the model is time-varying regardless of the cause of the change.

4.2 Study of different algorithms for battery parametrisation

The second part of the results was obtained by comparing the identification algorithms. Five identification codes are prepared based on three standard algorithms to assess the trade-off between accuracy and convergence speed. It is obtained from Fig. 5 and Table 2 that the R model's parameters can be identified using all the three algorithms (GD1, GA1 and PEM) and there is no difference between their accuracy because of the simplicity of the model's structure. On the other hand, the identification time varies where PEM is the fastest and then GD and GA. It was also concluded that GA and GD algorithms are easily adjustable (by changing their internal parameters like step size or population size) which makes the compromise easier by trying different versions of them (e.g. GD1 and GD2).

Based on the results, PEM method is proofed as a suitable algorithm for battery model identification which has both speed and accuracy at the same time. However, another important criterion that should be considered for battery identi-

fication algorithm selection is the simplicity of programming and being easily embeddable. Regarding this aspect, GD algorithm is the simplest one that can be easily programmed and embedded comparing to PEM and GA. This advantage is more important for real-time application of the algorithm on less powerful electronic boards. This also confirms importance of the contribution of this study, which is application-oriented trade-off between accuracy and simplicity.

4.3 Study of the trade-off between accuracy and simplicity of the battery model structures

In addition to the identification algorithm selection, the battery model structure can also be selected using an application-oriented approach. In order to address this, we have focused on this question that how the identification algorithms can handle an additional complexity to the model? Here, the battery model's complexity is added gradually by putting more RC networks in the model which increases the number of unknown parameters from the identification point of view. Considering the results presented in Fig. 6 and Fig. 7, it is concluded that GD algorithm's speed decreases significantly by adding model's complexity while keeping the accuracy in a comparative level. In GD algorithm, the identification time that is needed for a battery model with k unknown parameters is proportional to 2^k. For example, the time needed to identify *1RC model* (which has 4 parameters) is 4 times more than *R model* (which has 2 parameters), and the time needed to identify *2RC model* (which has 6 parameters) is 16 times more than *R model* and so on. Therefore, GD method is not suggested for very complex models however it is a good choice when a simple and easily embeddable identification algorithm is needed for online applications.

On the other hand, GA algorithm may not be successful in a short period of time however the complexity can be handled if there is no time limitation such as in offline applications. In this case, GA algorithm outperforms GD because of its additional capabilities like jumping out of local minima. So, GA method is suggested to be used for very complex models when time is not an important factor. In addition, GA algorithm is difficult to be embedded because of its programming complexity. Referring to PEM method's results in Table 3 and Fig. 8, there is an improvement in RMSE by adding the first RC network. However, this achievement is obtained by increasing the identification time to four times more. Adding the second RC network causes a small improvement of error while the identification time approximately doubles. So, it is concluded that 2RC battery model structure is not suggested in this case. All in all, PEM method is suggested when battery model's complexity is needed in online applications however; its embeddable program is not as simple as GDs.

5. CONCLUSION

In this study, a new approach to the battery parametrisation problem was presented which is called application-oriented trade-off between accuracy and simplicity. The main advantage of this approach is avoiding unnecessary complexities by using the most efficient model structure and parametrisation algorithm in each case. The results of this study are mainly usable in predictive models rather than descriptive models. A good example of the predictive modelling application is real-time estimation of battery SOC and/or SOH. The choice of the parametrisation algorithm and the model structure depends on the required accuracy, required speed, computational effort and hardware limitations, etc. For the presented case, a NiMH battery, SOC estimation is possible just by using OCV which is available using the simplest model structure that is *R model*. Both PEM and GD algorithms are suggested in this case depending on the computational effort and hardware limitations. Considering another battery type, Lithium-Sulfur for example, OCV is not enough for SOC estimation and other parameters are required as well. Same discussions can be presented for battery SOH estimation which is another application for battery model parametrisation.

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2016-06-20

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Fotouhi A, Auger DJ, Propp K, Longo S. (2016) A study on battery model parametrisation problem: application-oriented trade-offs between accuracy and simplicity, IFAC-PapersOnLine, Volume 49, Issue 11, 2016, pp. 48-53. 8th IFAC International Symposium on Advances in Automotive Control, 19-23 June 2016, Norrköping, Sweden

http://dx.doi.org/10.1016/j.ifacol.2016.08.008