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Model-Based Calibration for Battery Characterization in HEV Applications

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Abstract— **In Hybrid Electric Vehicle (HEV) applications, unlike electric vehicles, operation with the battery system requires control in a relatively limited range of state-of-charge (SoC), where best efficiency, gradual aging, and no self-damaging operations are expected. In this context, one of the main, critical technical challenges is the estimation of the SoC under vehicle operations, which typically do not involve full charging or discharging. This task is particularly arduous to accomplish in real-time, due to the complex and nonlinear behavior of the battery, as well as the inevitable presence of on-board measurement errors. In this work, we describe a model-based calibration process for capturing the important characteristics of modern batteries used in typical HEV applications. This process consists of reproducible procedural steps, including pre-specified data collection, while ultimately admitting a calibration. The resulting models are useful in HEV system control design for algorithms centered on maintaining the battery SoC, in algorithms for prognostics and diagnostics, and in prediction and estimation tasks.**

I. INTRODUCTION

While Li-ion batteries are quickly emerging as the technology of choice for future Hybrid Electric Vehicles (HEVs), current production HEVs utilize NiMH battery packs. In these HEV applications, unlike electric vehicles, the batteries have to be controlled to operate in a relatively limited range of State-of-Charge (SoC) where best efficiency, slow aging and no self-damaging operations are expected. In this context, one of the main technical challenges and of key relevance is the estimation of the State-of-Charge (SoC) under vehicle operations, which typically do not involve full charging or discharging ([2] - [5]). This task is particularly arduous to accomplish in real-time, due to the complex and nonlinear behavior of the battery, as well as the inevitable presence of on-board measurement errors.

Several physically-based and ad-hoc algorithms have been proposed in the literature (and some implemented in production) for determining the battery pack SoC during vehicle operation. Broadly speaking, these algorithms are based on different approaches, including current integration, SoC estimation based on Open Circuit Voltage (OCV), approximate model inversion (Kalman filters, model observers, etc.), or black-box methods (ANN, fuzzy logic, etc.) ([3], [5] - [10]). Practical algorithms for on-board SoC estimation in vehicles typically involve more than one of the mentioned approaches, and many are highly proprietary. However, regardless of the approach, these algorithms involve very significant calibration effort to provide robust SoC estimators for the life of the vehicle subject to a wide range of electrical and thermal conditions.

Furthermore, an effective SoC estimation algorithm for real time applications must be computationally fast, rely only on commonly available quantities (basically load voltage, current, temperature), be immune to noise and allow for off-line calibration.

With increasing complexity in modern HEVs comes an increasing number of control parameters, translating to a substantial increase in calibration time. Increased time, as well as complexity, due to required calibration adds to the overall development effort and, therefore, cost. The automotive engineering field has gradually come to realize the tremendous potential of model-based control as a solution to this fast-growing calibration problem. A model-based approach to calibration typically consists of building statistical models from real data to characterize important behaviors, upon which control theory design steps can be utilized to produce a "calibration". Thus, the use of time-series analysis, efficient and effective optimization algorithms, and proven system identification techniques become very important in this process, because the dependence on realistic plant data is critical.

In this work, we advocate the use of a model-based calibration process, consisting of reproducible procedural steps, for capturing the important characteristics of modern batteries used in typical HEV applications. Such a process involves a pre-specified rich data collection, ultimately allowing for a semi-automated calibration; the result can be characterized as "data in, calibration out". The resulting models are useful in HEV system control design for algorithms centered on maintaining the battery state-of-charge, in algorithms for prognostics and diagnostics, and in prediction and estimation tasks.

Specifically, we present in this paper a model structure and a suitable identification procedure to yield a globally valid equivalent electrical circuit model for a NiMH battery. This model, which is intended to account for the relevant

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dynamics experienced in HEV applications, is well suited for designing a model-based SoC estimator. Together with the model structure, a detailed procedure is provided to identify all parameters from a single experiment, specifically designed to excite the relevant dynamics and span the entire useful range of State-of-Charge. All the model parameters are allowed to vary in a piecewise linear manner with respect to the SoC, and then optimized using a genetic algorithm to yield a globally valid model in a form which is easy to integrate into a control, diagnostics or prognostics framework.

II. BATTERY MODELING

Much research has been done on battery modeling for the purpose of SoC estimation. First, there are physically-based models involving description of the internal reactions kinetics. Although errors of SoC estimators based on such models are reported to be less than 2%, the prominent nonlinearities of these models cause them to be impractical for real-time applications in HEVs ([11] - [13]).

Malkhandi [9] and Salkind [10] present a method for NiMH's SoC and State of Health (SoH) prediction using fuzzy logic modeling. Other studies propose Kalman Filters (KF) and extended Kalman filtering techniques as well as sliding mode observers as a self-correcting solution for determining the SoC ([7], [8]). Accuracy of these learning methods still leaves substantial uncertainties. Probably the most relevant discriminant is represented by the real time constraint on SoC calculation.

In [1], a model-based SoC estimation is presented, which blends a simple current integration with an estimate of the SoC based on a model inversion. The model used in the inversion is an interesting structure that combines a simple electrical circuit with a set of dynamic open circuit voltage maps. The high degrees of freedom in that model structure make it a candidate for applying our identification methodology. Henceforth, this is the only model structure that will be investigated in this paper. The following sections present the model structure and its dynamical equations. As a simplification for this paper, all battery data are taken in isothermal conditions, making temperature an irrelevant factor in the model. However, the results produced can be readily extended to include temperature.

A. Battery Load Voltage Relaxation

It has been observed by many that all batteries exhibit significant dynamical behaviors in their current voltage relationship and this is often characterized by Electrical Impedance Spectroscopy (EIS) or other suitable techniques. While the physical source of these observed dynamical effects is linked to electrochemistry, species diffusion, etc., their net behavior is often approximated by considering equivalent electrical circuits of reduced order which mimics relevant parts of the frequency response as determined by EIS. Equivalent circuits of batteries are often represented by 1st, 2nd or 3rd order linear differential equations with the possible addition of some non-linear element like the Warburg impedance (1/2 order). All such electrical models rely on the determination of an ideal voltage source, the Open Circuit Voltage (OCV). Typically the OCV is considered to a monotonic function of SoC (and temperature), and the parameter values of the equivalent electrical circuit are either fixed or varying as a function of SoC, current direction and temperature.

B. Open Circuit Voltage Hysteresis Effect

However, in addition to electrical effects described above, batteries also exhibit very pronounced hysteresis behavior in the OCV. These effects are particularly significant and slow in NiMH (see [4]). In the context of an electrical circuit representation, batteries typically exhibit different OCV curves in charge and discharge. This complex phenomenon severely limits the ability to identify a battery electrical equivalent circuit which is uniformly valid, and to use such a model to estimate the SoC.

To construct a uniformly valid electrical equivalent circuit, we want to model the battery's "true" OCV which is defined as the voltage measured at the battery terminals when no load is applied and all internal processes are completely relaxed. Because the internal relaxation in this battery chemistry lasts many hours, the direct measurement of this "true" OCV is very lengthy (practically impossible), as even experiments conducted at minute charge and discharge currents (such as 0.1C, as recommended in the literature and manufacturer data) will yield two different OCV curve separated by approximately 0.1V per cell depending on the direction of the current. This "hysteresis" behavior relaxes with time extremely slowly. Hence, the model developed must either properly account for the root causes of this behavior, or develop an *ad hoc* method for two different OCV curves with an appropriate slow relaxation behavior. The first choice is not practical for automotive applications such as SoC estimation. It is clear that with the second approach, the model, by construction, depends on the protocol by which the OCV curves are determined; this is because they are not absolute, but an artifact of the experiment (current level, resting time, etc.).

The study in [1] suggests that the hysteresis behavior of the OCV can be successfully captured combining an equivalent electrical circuit with different OCV maps while providing a physically meaningful smooth transition from one map to the other, as well as suitable relaxation. Because optimization is used, we do not need to construct accurate OCV maps. Rather, as long as a preliminary set of curves is available, an optimization tool can be used to find the curves in an automated fashion.

C. Battery Model Structure

Taking into consideration all of the above considerations, a first order equivalent electrical circuit model, adapted from [1], is chosen as shown in Figure 1. The diodes shown are ideal diodes and are only used to reflect the fact that the resistances in the RC circuits are different during charging and discharging. The capacitance on the other hand does not

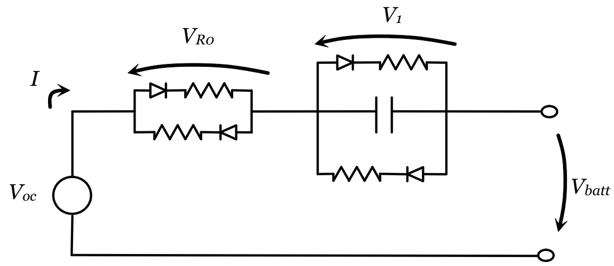

Fig. 1. Electrical circuit model of battery

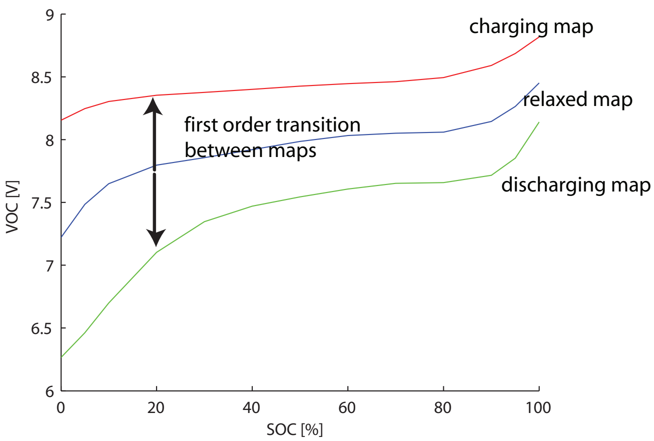

Fig. 2. Transition between different maps modeled by 1st order system

change between charging and discharging. This is to maintain an energy-conservative model representation. However, unlike other such 1st order models in the literature, the open circuit voltage is prescribed by three maps: a "charging" map, a "discharging" map and a "relaxed" map, together with a 1st order system that models the transition between the maps (see Figure 2). The charge OCV curve and discharge OCV curves are readily obtained empirically, as they do not require any significant relaxation period. Obtaining the relaxed map, on the other hand, can take many hours of experimentation due to the long relaxation time explained in Section II-B. Therefore the relaxed curve used here is approximately the average between the charge and discharge curves. This assumption does not result is a sufficiently accurate curve, but it does provide a starting point from which we can proceed.

D. Battery Model Analysis

Analysis of the electrical circuit shown in Figure 1 is straightforward. The system output V_{batt} is found using Kirchoff's voltage law:

$$V_{batt} = V_{oc} - V_{R_0} - V_1. \tag{1}$$

The RC circuit is described by two ordinary differential equations obtained using Kirchoff's current law and the definition of an ideal capacitor:

$$\frac{dV_1}{dt} = -\frac{V_1}{C_1 R_{1j}} + \frac{1}{R_{1j}} I, \quad j = charge/discharge \tag{2}$$

In such a model, the parameters V_{oc}, R_i, and C_i are unknown functions of SoC and temperature. For the purpose of this paper, the temperature was kept constant within a few degrees Centigrade to simplify the model identification problem. In an actual application, the dependency on temperature must be explicitly captured, thus increasing the complexity of the identification problem by an order of magnitude.

The open circuit voltage (V_{oc}) is determined by the output of a first order system. Define a state x as the difference between the current OCV and the relaxed OCV value at the current SoC (which we call $E_m(SoC)$). Then the dynamical equation for x is given by

$$\dot{x} = -\frac{1}{t}x + \frac{1}{t}(E(I,SoC) - E_m(SoC)), \tag{3}$$

where t is the time constant and $E(I,SoC)$ is defined as

$$E(I,SoC) = \begin{cases} E_c(SoC) & I < -1\text{A} \\ E_m(SoC) & |I| \leq 1\text{A} \\ E_d(SoC) & I > 1\text{A} \end{cases} \tag{4}$$

where E_c represents the charging OCV, and E_d represents the discharging OCV. The OCV to be used by the model is then given by $V_{oc} = x + E_m(SoC)$. The SoC used for modeling is obtained by beginning a test at a known SoC and then integrating the current. To prevent rapid switching between the charge and discharge equations in the case of unavoidable noise in the current measurement, a hysteresis element is included to add a dead band of ± 1 A around 0 A. With this, the model switches state only if the measured current exceeds 1 amp in magnitude.

The above assumptions result in a relatively simple model that, at the same time, provides a description for the relevant behavior of the battery.

III. PARAMETER IDENTIFICATION AND OPTIMIZATION USING LINEAR SPLINE TECHNIQUES

To construct the battery equivalent circuit model, all the components of the RC circuit in Figure 1 (resistances and capacitances in particular) must be identified. Because available experimental techniques for extracting these quantities can be inaccurate, the OCV curves and the relaxation time constants can be optimized to result in better models. In this section we address the methodology for identification.

A. Optimization

There is no simple analytical method for identifying a parameter varying linear continuous model as in (1), (2), and (3). We propose to use an optimization routine to pick the unknown coefficients in the model so that the output of the model best matches the measurement. Several popular optimization techniques can be used for this purpose, each with its own advantages and disadvantages. We choose to use a genetic algorithm (GA) to do this optimization (see [17] for a detailed introduction).

A genetic algorithm uses the principles of evolution to find the best parameters to a problem. The algorithm starts with a set of candidate solutions, usually referred to as the initial population. A fitness function is used to assign a merit value to each candidate solution in the population. Then the algorithm randomly selects two solutions and combines them to generate two new solutions. The selection process is random but the solution with higher fitness value is more likely to be selected. This emulates the natural selection idea, in which the traits of the fitter individual are more likely to be preserved than those of the weaker. To prevent the algorithm from sticking at a local optimum, the next generation solutions are mutated so that they contain traits foreign to their parents. Mutation occurs randomly and with very low probability. This reproduction cycle repeats for many generations until the fitness of the best solution in the latest generation is high enough.

In our case, the candidate battery model is implemented on a computer and simulated using data collected during the physical experiment. Then the GA is used to pick the unknowns (resistance, capacitance, time constants and so on) in the model such that the average absolute difference between the model battery voltage output and the measured battery voltage at pre-specified sample points is minimized. In other words, the fitness function to be used by the GA is the negative of this sum. Because the laboratory data set is designed in such way that all the relevant dynamics of the battery are excited, the optimized model with the highest fitness value should have desirable behavior in all aspects of the battery behavior.

There are many public domain software implementation of GAs freely available for use (examples: GALib ([15]) and PIKAIA ([14])). In this work, the software package PIKAIA is used because of its flexibility, simplicity, and adaptability. To find the fitness of a candidate solution, we must evaluate the solutions of the ordinary differential equations (ODE) shown in (1), (2), and (3). The long experimental data set and the complexity of ODE solvers make each evaluation very time consuming. If only one computer is used, the optimization process can be very tedious. Consequently, we chose to use a version of PIKAIA called MPIKAIA ([16]), which has the capability of allowing multiple computers to work on a single task. We worked to optimize MPIKAIA significantly to reduce peer to peer communication, thereby reducing unnecessary computational overhead. In a typical GA, approximately 95% of the computational time is spent evaluating the fitness of the sample solutions. Calculation of the fitness of one candidate solution does not interfere with the calculation of another candidate solution. Therefore the task of fitness evaluation can be distributed to multiple computers such that the speed increases linearly with the number of computers (up to some limits). The final software solution in this work is implemented on the parallel computing cluster at The Center for Automotive Research. This cluster is comprised of 20 separate computers with Core-2 Duo processors, which essentially amounts to 40 independent workers that can participate on a job.

B. Linear Splines for SoC Dependent Parameters

Previous research on battery modeling has shown that the parameters of an RC circuit battery model are dependent on the state of the charge and temperature. The usual approach in modeling and identification is to exercise a battery within a narrow band of a particular SoC and temperature and find a constant linear model for that region. Doing this for many ranges of SoC and temperature results in a family of models that when used together can describe the behavior of the battery over the entire spectrum of SoC and temperature. In other words, the composite model is a linear parameter varying (LPV) model where the model coefficients are piecewise constant functions of the SoC and temperature.

While simple and relatively effective, this type of model suffers from its inherent transitional discontinuity. If the SoC vacillates between two SoC regions where the model coefficients are different (for example, because of noise in measurement), there may exist undesirable chattering behavior. We propose to use an LPV model where the coefficients are linear spline functions of the SoC (for information on spline functions and its applications in automotive systems modeling, see [19], and [18]). By definition, linear spline functions are piecewise linear continuous functions. They are especially effective when the domain of the function is fixed to a compact set, such as in this case where the SoC is always bounded to the interval [0% to 100%]. To specify a linear spline function, one needs a partition and a set of coefficients which specify the slopes of the piecewise linear function on each subinterval of the partition. In the case of SoC, an effective sample partition is [0, 5, 10, 20, . . . , 80, 90, 95, 100] (all in percentage), because battery behavior across a 10% change in SoC is relatively constant. Linear splines techniques are easily generalized to multi-dimensional (for instance SoC and T) with or without cross-terms, making this technique particularly attractive to deal with the practical battery identification problem which includes temperature.

A battery model with coefficients which are linear spline functions of the SoC does not suffer from transitional discontinuity. With a rather dense partition such as the one described above, the model will be quite flexible, resulting in a reasonable approximation of the battery behavior. Furthermore, many linear parameter varying control design techniques that have surfaced recently can be applied to this model which enables them to be used effectively in HEV applications. For example, a linear parameter varying observer can be used in state of charge estimation, which is the ultimate goal for battery modeling in HEV applications.

C. Model Identification

With an algorithm such as a GA, it is tempting to simply let the GA run to find all the SoC-dependent coefficients, the OCV curves, and the relaxation time constant, simultaneously. However, there can be over 90 parameters for a full first order LPV model with three separate OCV curves, even under the isothermal assumption. The size of the problem is easily double that if temperature effects are included. With so many parameters, the GA would have to search in a very large space, in which the probability of finding a good solution is small. To make the problem more tractable, bounds are specified for each unknown coefficient as tightly as possible (bounds result from physical insight and intuition). But even then the curse of dimensionality is still prevalent. A prudent approach is to reduce the problem size and gradually increase the complexity. This will ensure that meaningful solutions can be found at each stage. As an added benefit, such a layered approach can also indicate whether a simpler model is sufficient to capture the dynamics of the battery.

We choose to simplify the problem into three separate identification exercises. In the first identification, the RC parameters in the model are considered non-SoC-dependent. The OCV curves used are those found experimentally (see Figure 2 for the OCV curves). With these reductions, the total number of unknowns is only nine, which is small enough that good results can be obtained using the GA without good initial estimates. This overly simple model is unlikely to produce acceptable results. However, using the outcome as an initial estimate for future identifications is a good strategy to obtain meaningful results. Furthermore, this is an effective way to narrow down the bounds on the parameters for the LPV model, in case the physics based intuition is not sufficient.

In the second identification exercise, the open circuit voltage curves and the relaxation time constant also become part of the unknowns in addition to the constant RC circuit parameters. We could search for all three curves, but since the charging and discharging curves are easily measured, they are reasonably accurate. The middle curve on the other hand is obtained by averaging the two other curves, which is completely heuristic and most likely inaccurate. Therefore we choose to only modify the middle curve. This logical second step allows us to improve the OCV curves shown in Figure 2, and therefore improve the model performance.

We parameterize the unknown OCV curve as linear spline functions of the SoC. It is also constructed to satisfy characteristics of the OCV curve. In particular, it must be strictly monotonically increasing with the SoC and is nonintersecting with the other two curves. The number of unknowns in this problem is more than twice the previous problem. However, using the RC parameters found in the previous step as well as the initial heuristic relaxed curve as the initial guess, identifying so many parameters is a tractable task. Since the relaxed OCV curve is directly related to the SoC, obtaining a good curve is very useful to the overall problem of SoC estimation.

The final identification step improves upon the previous by allowing the RC circuit parameters to be linear spline functions of the SoC as well. This large model contains about 70 unknown parameters, which results in a very large searching space for the GA. Therefore it is important that we start the search using results from the previous step. The end result of this step is the full LPV battery model.

IV. MODELING RESULTS

To validate the approach outlined above, we applied the aforementioned technique to a Panasonic NiMH module (six cells) with nominal capacity of 6.5 A.h. This battery is taken from a Toyota Prius battery pack. First we designed a comprehensive current profile (approximately 16,000 seconds, or 4.5 hours) that can excite the various parameters of this battery. Then the GA is applied to the first half (first 8,000 seconds) of the data set according to the layered approach outlined above to find the full LPV model that best fits the data. Finally, the model is executed over the entire data set as a validation.

A. Experimental Setup

The initial SoC, initial OCV, and the initial state of relaxation of the battery are all critical components that will impact the integrity of the data set, which in turn will affect the accuracy of the model. Therefore, prior to any data taking, we first charge the battery to 100% SoC according to manufacturer specified procedures. Then the battery is discharged to 85% SoC (6.5 A for 10 minutes). After that the battery is allowed to rest for over 8 hours (note that 8 hours is short enough that the internal discharge of the battery will be negligible). This set of procedures gives us an accurate initial SoC and an accurate initial OCV, which can be used to initialize the battery model during parameter identification. By integrating the current using the initial SoC as initial condition, we also obtain an accurate SoC measurement for the battery over the entire span of testing. In this study, we restrict the battery SoC during this profile to be between 30% and 100%. The lower SoC region is avoided because unexpected and unrealistic voltage drop can occur in this region that would cause data problems. Since this region is typically avoided in HEV applications, omitting it does not limit the usability of the resulting model.

The current profile engineered for the battery is a series of asymmetrical charging and discharging staircases, with resting inserted in between. Figure 3 shows examples of these asymmetrical staircases. Using these staircases allows us to accomplish several goals for a good input design. First, step inputs allow the time constant and input coefficients of the first order RC circuit to be identified. Second, by grouping staircases in various ways, we can allow the SoC to traverse the entire desired region. In this way the dependence on SoC for various parameters can be identified. Figure 4 shows the SoC profile that resulted from this current profile. Third, the various switches between charging staircase and discharging staircase allows us to find the dependence of the parameters on the current direction. Fourth, the resting period inserted in between charging and discharging allows identification of the OCV dynamical equation. Last but not least, steps are consistent with actual current demand in an HEV. All of these merits make asymmetrical staircases a good option to use for an excitation current profile.

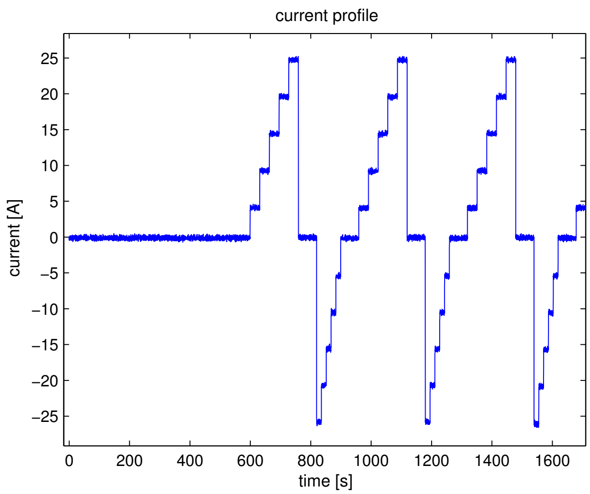

Fig. 3. Current profile designed to excite the battery.

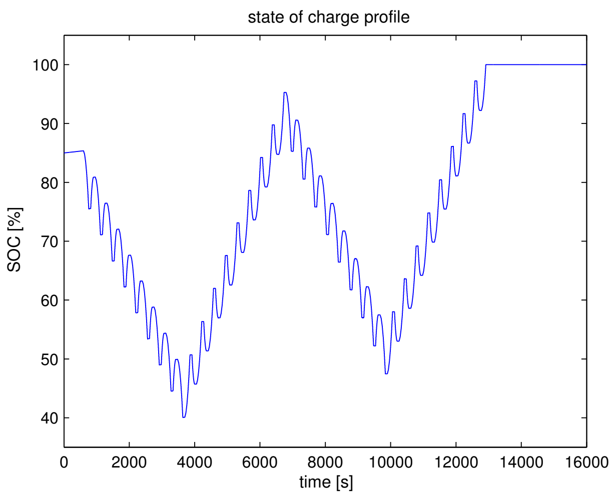

Fig. 4. State of charge profile resulting from the current profile.

TABLE I
MODEL FIT RESULTS

Test	Parameter Type	Modify OCV Curves	Mean Abs Error
1	Constant	No	0.055 V
2	Constant	Yes	0.028 V
3	SoC	Yes	0.020 V

B. Identification Results

The identification procedure presented in section III-C is performed using the dataset collected from the experiment. Table I summarizes the average absolute error between the model battery output voltage and the measured battery voltage.

First to be modeled is the constant parameter system, which uses the OCV curves obtained experimentally. Rather than directly identifying the RC circuit components (which produces a larger than desired search region), we decided to visualize the battery model as a ordinary first order system. Then the problem is to identify the time constant and input coefficient of the system. Figure 5 shows the battery voltage produced by the model and the measured voltage. As we can see there is very good agreement over the entire data set despite the fact that the model has only nine parameters. The average absolute error between the measured response and the model response is only 0.055 V, which is less than 1% of the nominal operating voltage of 7.2 V. From this identification, we were able to obtain tight bounds for the parameters, which will be used in all subsequent identifications. The numbers that the GA selected are as expected from physical intuition. For example, the relaxation time is identified to be on the order of 1 to 2 hours, which matches with our physical observations.

There is also a clear deficiency in this model. As seen in Figure 5, the initial model voltage does not fit the data very well. This is because the middle OCV curve does not accurately describe the OCV for each SoC (in particular the initial SoC). Figure 6 shows the OCV values produced by the model during the simulation, plotted on top of the OCV curves used. We can see that the OCV values are not tending to the middle OCV curve during the resting periods, especially in the beginning of the data set when the battery is truly at rest. This is a hint that the heuristically derived middle OCV curve needs to be optimized.

Therefore, in this next step, we allow the middle OCV curve to be adjusted as well. The bounds for the constant coefficients are tightened according to the results from the previous exercise. The model response is improved significantly over the previous exercise. The average error is reduced by almost half to 0.028 V. Figure 7 shows the model output vs. measurement while Figure 8 shows the OCV values on top of the optimized OCV curves. The GA did what we expected by adjusting the middle curves so that the behavior of the simulated OCV values adhere better to the data. In particular, the error in the beginning of the data is completely removed.

Lastly, we identify a model where the coefficients are allowed to be linear spline functions of the SoC. Once again, the fit improved as expected. The average error is now reduced to 0.020 V. Figure 9 displays the agreement of the voltage plots for the parameters found by the GA as a function of SoC. The change in OCV curve is not significant compared to the previous case (see Figure 10). This is expected since if the previous optimization did the job correctly, there would be no need for significant changes here. This shows that the construct of linear spline based LPV model structure is a sound choice.

To validate the final full LPV model, we allowed the model to execute over the entire 16,000 seconds represented in the data set. Figure 11 shows the resulting fit. The overall average absolute error is a mere 0.022 V, only slightly larger than the error over the modeling portion of the data. This shows that the model formed is not biased towards the modeling data. In an upcoming paper, we will illustrate the model behavior as validated for other profiles, including actual driving cycle data.

As a final note, we comment on the computational burden

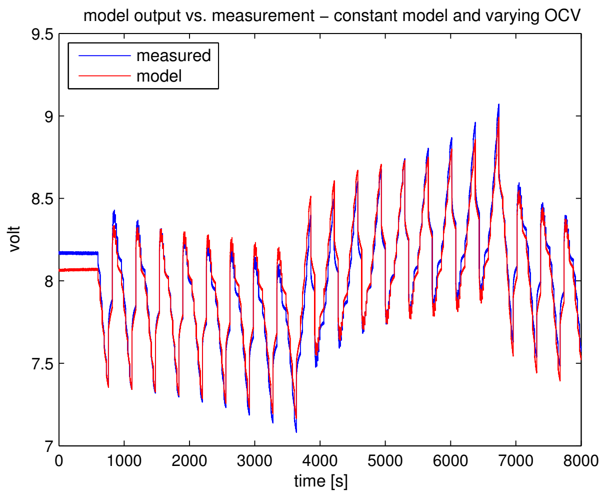

Fig. 5. Battery voltage from constant model with experimental OCV curves vs. measured voltage; average error = 0.055 V

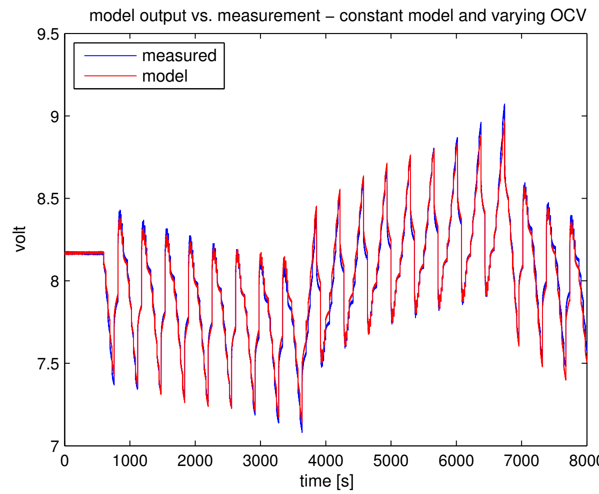

Fig. 7. Battery voltage from constant model with GA optimized OCV curves vs. measured voltage; average error = 0.028 V

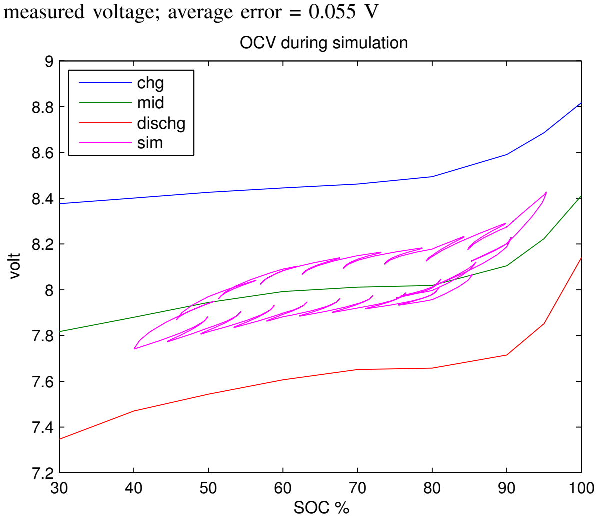

Fig. 6. OCV curves used for this identification

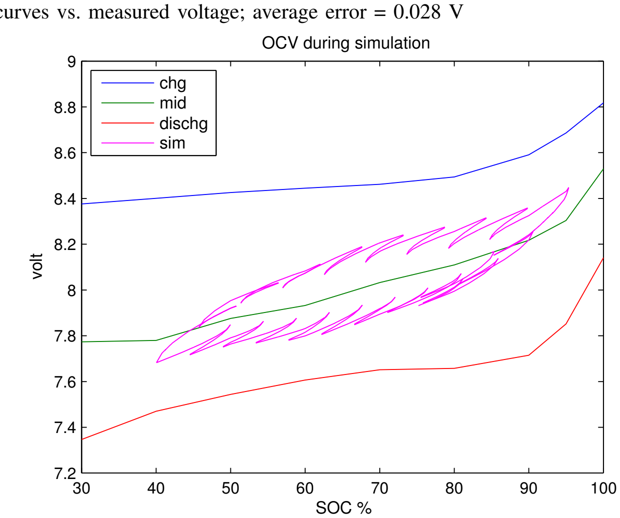

Fig. 8. Modified OCV curves in the second identification, where model parameters are constants

of this identification process. As an illustration, Table II offers time performance results for identifications carried out on a cluster of five computers. The longest time spent was for the full LPV model. But even at four hours, this automated procedure is very easy to perform. As a comparison, earlier results (not on the cluster) were carried out using the Matlab optimization toolbox, requiring several days to identify the constant model with only nine parameters. Given this comparison point, the process we described here offers a platform to perform quick model calibration as well as model structure studies. Moreover, although this identification work was performed under an isothermal assumption, we envision a straightforward generalization to include temperature dependence; we will report on this concept in an upcoming paper.

V. CONCLUSION

The goal of this work is twofold. First, we have presented a framework for model identification that is suitable for modeling a variety of battery types. Second, we have obtained a simple, yet accurate battery model for a NiMH battery that can be used in HEV applications to correctly assess the SoC of the battery pack, leading to useful control-oriented models. We demonstrated that genetic algorithm optimization can be used to quickly and easily identify the parameters in an LPV battery model for all SoC, when a sufficiently rich data set is available.

The approach to battery modeling described here represents a contribution in several ways. First, since all parameters of the battery can be identified together using a rich data set, the identification procedure is very simple. Compared to existing schemes for identifying constant models for various ranges of the SoC, this method is quicker and more efficient. Secondly, the use of linear splines for the model coefficient parametrization allows the final model to be continuous in nature, eliminating potential undesirable dynamic effects due to discontinuities. Lastly, the parallel computing GA

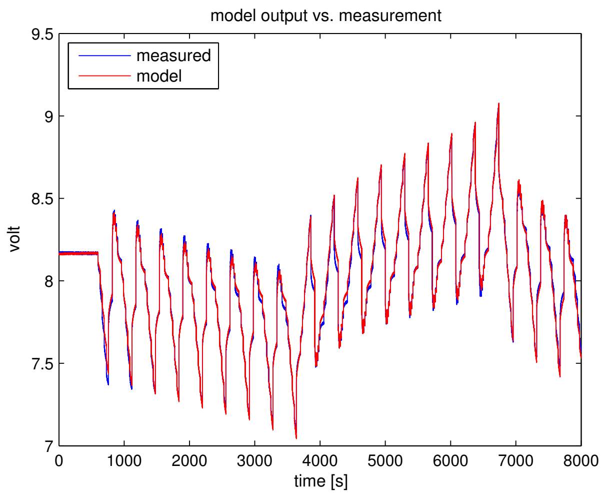

Fig. 9. Battery voltage from the LPV model with OCV curves modified by GA vs. measured battery voltage; average error = 0.020 V

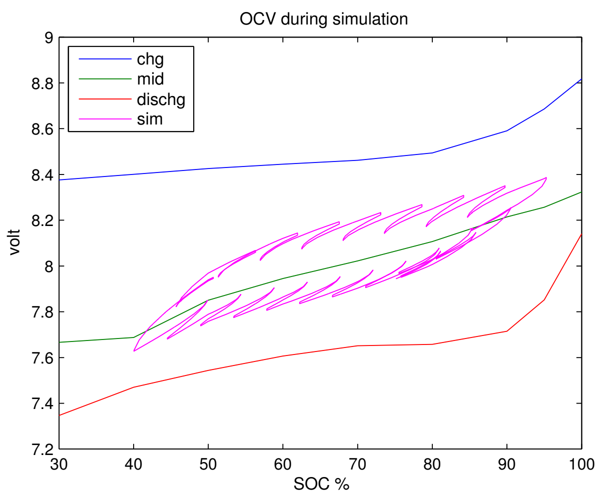

Fig. 10. OCV curves modified by GA in this identification

software structure with the computing cluster provides a viable platform for solving similar large scale problems.

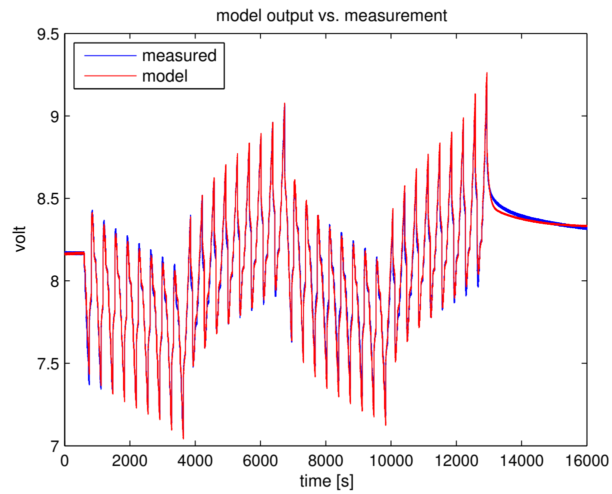

Fig. 11. Validation of the constant parameter model with OCV curves optimized by GA; average error = 0.022 V

TABLE II

SPEED OF COMPUTATION FOR EACH MODELING EXERCISE

Model Type	# of unknown	# of hours spent
Constant model / Experimental OCV	9	0.5
Constant model / GA find OCV	22	1.5
LPV model / GA find OCV	64	4

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