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Modelling of HEV Lithium-Ion High Voltage Battery Pack using Dynamic Data

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Abstract: A new approach is proposed for developing a model for High Voltage (HV) Lithium-ion (Li-Ion) battery pack using Hybrid Electrical Vehicle (HEV) drive cycles data. A variety of drive cycle's data have been collected from the test vehicle at various operating conditions. The equivalent electrical circuit for the HV battery is formulated using mathematical equations and discrete state space equations. The Open Circuit Voltage (OCV), Offset Voltage at Zero Load conditions (VZL), battery pack internal resistance (R_{batt}) are considered as various components of the mathematical equations and battery pack RC filter states are represented using discrete state space equations at various battery temperature (Batt Temp) conditions (-7^{0}C to 45^{0}C). The parameter estimation problem is then considered as the problem of simultaneously estimating the parameters of all the coefficients formulated in the battery pack mathematical and state space equations. This is mathematically posed as a constrained optimization problem and a variant of genetic algorithm (GA) is used to solve it. Modelling is done using MATLAB®/ Simulink® tools. The developed model is validated on actual vehicle drive cycle data. The results obtained by the proposed approach are closely matching with the actual battery response under different drive cycles. The distinction of the approach is that it does not call for any lab tests, additional instrumentation and cell level measurements yet serves the purpose of fair fidelity model for the design, analysis and control of the HEV powernet.

Keywords: Parameter Estimation, Hybrid Electrical Vehicle, Lithium-Ion Battery, HV Battery Pack, Dynamic Data, Genetic Algorithm

1. INTRODUCTION

Hybrid electric vehicles (HEV) and Electric vehicles (EV) use a large electrochemical battery as onboard electrical energy storage (ES). Due to the advantage of high power rating, high energy density, and high cycle life, the Lithium-ion (Li-ion) batteries are used as energy storage devices in HEVs and EVs. To achieve the required electrical traction power and the range, the practice is to connect low-voltage lithium-ion cells in series and parallel combinations to construct a dedicated High Voltage (HV) battery pack. A Battery Management System (BMS), along with protective circuitry and a communication bus is provided for management, monitoring, and diagnosis. Measurement of state-of-charge (SOC) is one of the basic functions of BMS, which indicates the remaining charge of the battery. SOC is an indication for the user, which provides information on when the battery needs recharging.

In future, the number of hybrid vehicles on road are expected to increase tremendously, hence the need for dynamic models of various subsystems inclusive of the battery would grow for the development of the on-board subsystems, their control and monitoring. It is important to calculate the state-of-charge (SOC), open-circuit voltage (OCV), and the terminal voltage with acceptable accuracy under arbitrary current profiles at various operating conditions of the vehicle. An accurate and computationally less intensive model with good runtime prediction and voltage response characteristics are crucial requirement specifications of HV battery model for the development and validation of various HEV/EV systems.

Several approaches are available in the literature (Jackey *et al*., 2007, Jonathan J *et al*., 2008, Plett, G. *et al*., 2004, 2006, RA Jackey *et al*., 2009) to model various types of batteries. In most of the approaches that are reported and used to develop the battery pack model, it is important to have the cell level data and measurements. Using this data equivalent battery cell model has been developed and further integrated to create the entire battery pack model. This requires additional instrumentation for the battery pack and laboratory set up to conduct specialised tests to extract the dynamics of battery cell behaviour. In this paper, the proposed battery model structure uses the measured parameter values by the available sensors on the battery pack rather than using the cell level data, which in-turn saves the cost of additional instrumentation. The specifications of HV battery pack installed in the considered vehicle under test (HEV) are provided in Table 1.

Table 1: Specifications of HV Li-Ion Battery Pack

Operating Voltage	360 V
Number of Cells	96
Cell Network Configuration	Series
Rated Capacity	4.2Ah

HV battery dynamic data has been created using Standard drive cycles Urban Dynamometer Driving Schedules (UDDS) and customized drive cycles at various operating conditions. The battery model parameter estimation problem is then considered as the problem of simultaneously estimating the parameters of all the coefficients formulated in the battery pack state space equations. The defined model structure parameters are optimized using Genetic Algorithm (GA) solver.

The main advantages of the proposed approach are,

i) The HV battery pack model can be developed with no additional instrumentation on the HV battery (which is expensive), except hall effect current sensor,

ii) Proposed methodology uses the sensor readings at battery pack level rather than accessing the individual cell data,

iii) Standard and specially designed drive cycles are used to generate the required measurement data rather than specially design lab tests on the battery pack,

iv) The use of constrained optimization formulation enables to use a-priori knowledge and experience during the parameter estimation, and

v) The use of genetic algorithm almost ensures that the estimated parameters are global optima within the specified constraints.

The model has been implemented using MATLAB®/ Simulink®. The developed model is validated against various drive cycles data collected at various operating conditions of the vehicle and battery temperatures.

2. PROPOSED MODELLING APPROACH

The proposed modelling approach was developed, in the view of the limitations and availability of the drive cycle data. Few of the limitations are given below:

i) Fastest Sampling Time of the data available is 0.1 Seconds against expected sample time of 0.01 seconds,

ii) Unavailability of the test setup and access to the HV battery to obtain the SOC v/s Open Circuit Voltage (OCV) Curves,

iii) HV battery SOC is limited to around 30% to 80% of Maximum SOC by the Battery Control Module (BCM) of the HEV under test,

iv) High discharge current during the engine start condition.

The methodology adopted for data collection, description of the proposed algorithm and parameter estimation algorithm are explained in the following sections.

2.1 Data Collection

To capture the dynamics of the HV Li-ion battery, a variety of drive cycles has been created and the test data has been collected from the available HEV vehicle at various operating conditions. Typical operating conditions considered during the test data collection are

i) Various vehicle Start-up conditions (Hot Start/Cold Start)

ii) Various Vehicle Air-Conditioning (AC) operating conditions (AC ON/ AC OFF)

iii) Various ambient temperature conditions (-7^{0}C, 25^{0}C, 35^{0}C, etc…) to cover the possible range of battery operating conditions.

2.2. Proposed Algorithm

HV battery equivalent electrical circuit (Hongwen *et al.*, 2011, Jonathan *et al.*, 2008, Min Chen. *et al.*, 2006) considered in the proposed approach is shown in Figure 1. The equivalent electrical circuit is composed of open circuit voltage (OCV), series battery resistance (R_{batt}) and two RC filters (RC1, RC2) as shown in Figure 1.

From the equivalent circuit of HV battery pack, the terminal voltage is calculated using (1) given below:

$$\hat{y}(k) = OCV(k) - R_{batt} * i(k) - \Phi(k) \tag{1}$$

$$\begin{aligned}
&where, OCV(k) - open\ circuit\ voltage\ at\ k\text{-}th\ time\ instant \\
&R_{batt} - series\ battery\ resistance \\
&i(k) - battery\ current\ at\ k\text{-}th\ instant \\
&\Phi(k) - effective\ Voltage\ due\ to\ RC\ filters\ at\ k\text{-}th\ time\ instant \\
&\hat{y}(k) - predicted/simulated\ battery\ voltage\ at\ k\text{-}th\ time\ instant
\end{aligned}$$

In the proposed approach, linear dynamics of the RC Filters are mathematically represented using discrete state space equations. Based on the simulations experience, it is observed that, at zero load conditions the *OCV(k)* alone is not able to provide desired terminal voltage. So in the proposed work an offset voltage function has been added to meet the desired terminal voltage at zero load conditions and Equation (1) is further modified as shown in (2).

$$\hat{y}(k) = OCV(k) + VZL(k) - R_{batt} * i(k) - \Phi(k) \tag{2}$$

$$\begin{aligned}
&where, VZL(k) - \text{Offset Voltage at zero load conditions} \\
&\qquad\qquad \text{at k - th time instant}
\end{aligned}$$

OCV(k) and *VZL(k)* are calculated as a function of SOC and battery temperature at k-th instant. *OCV(k)* and *VZL(k)* are represented using (3).

$$\begin{aligned}
OCV(k) &= f(SOC(k), BatteryTemperature(k)) \\
VZL(k) &= g(SOC(k), BatteryTemperature(k))
\end{aligned} \tag{3}$$

Sequential steps to calculate each of the components given in (2) & (3) of the proposed model are provided in the approach below:

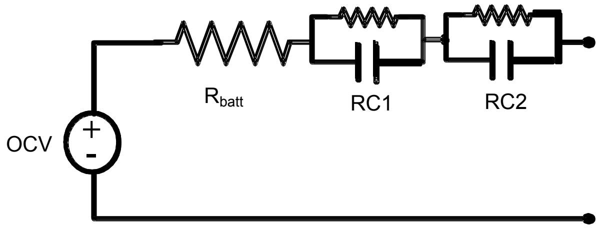

Figure 1: Battery Equivalent Electrical Circuit

Begin

1. Inherit the SOC v/s Open Circuit Voltage (OCV) characteristic for the various battery temperatures from open literature.
2. Create the offset voltage at Zero Load conditions (VZL) v/s SOC 2D Look-Up-Table (LUT) for various battery temperatures using the drive cycle data.
3. Formulate the equivalent discrete state space equations for both the RC Filters.
4. Estimate the model parameters (R_{batt}, State Space coefficients) using GA Optimization Techniques.
5. Validate the converged model using the data from the drive cycles other than that used for building the model.

End

As a matter of simplification and time saving measure the SOC v/s OCV characteristic curves for Li-Ion cell are inherited from the literature (R.C., Krein *et al.*, 2008) and is assumed to be from real life battery under consideration. The OCV characteristic curves are available for constant ambient temperatures of 3^0C, 27^0C and 62.5^0C. As the data is available for constant ambient temperature conditions, we have taken an assumption that, while creating the OCV data the battery cell temperature and ambient temperature are maintained around the same value. The inherited SOC v/s OCV characteristic curves for HV battery pack are shown in Figure 2.

2.2.1 Creation of the Offset Voltage LUT

The offset voltage at Zero Load Conditions is calculated at zero battery current for selected battery temperatures and SOC. The sequential steps of the approach for calculating VZL Look-Up-Table are given below:

Begin

1. From the test drive cycle data, create cluster of data sets, where battery current is zero. Data cluster contains the variable, batter temperature, battery SOC and battery voltage corresponding to zero battery current.
2. From the created data clusters, create sub-clusters with the data samples of nearest battery temperature. Take the weighted average of the battery temperatures to create a LUT point. Sub-cluster contains respective battery SOC and battery voltage variables.
3. For the selected sub-cluster temperature data, calculate the offset voltage values, which is the difference between actual battery voltage and the respective open circuit voltage across the available SOC data points.
4. The distributed SOC and the Offset Voltage are further smoothened and generalized using 2^{nd} order polynomial curve fitting for the offset voltage values with respect to the battery SOC and battery temperature.
5. Repeat Step-3 and Step-4 for all the sub-clusters created in Step-2.
6. Create the SOC v/s VZL LUT points for the selected battery temperatures.

End.

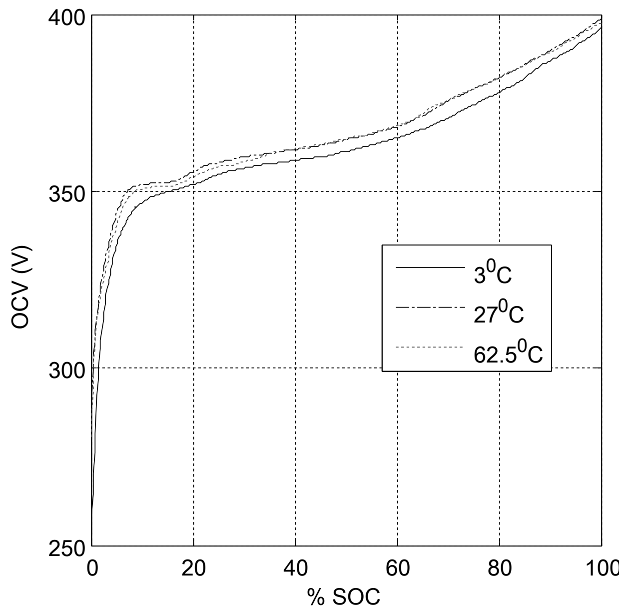

Figure 2: SOC v/s OCV at various ambient temperatures- 3 ^{0}C, 27^0C and 62.5^0C

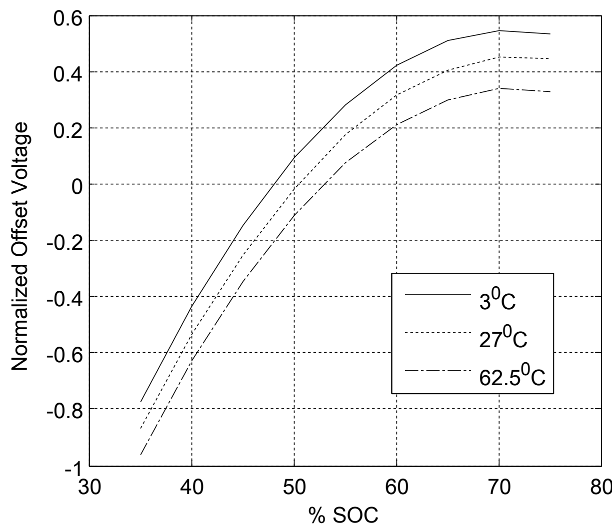

Figure 3: SOC v/s Normalized Offset Voltage at Zero Load conditions (VZL) at selected constant battery temperatures -3 ^{0}C, 27^0C, and 62.5^0C

The VZL 2D Look-up-Table (*g(SOC, Battery Temperature)*) profile curves for some of the selected battery temperatures (3^0C, 27^0C, 62.5^0C) are shown in Figure 3. The profile curves shown in Figure 3 are normalized profile data curves rather than the actual VZL data. The above curves are calculated using linear interpolation and extrapolation from the available battery temperature data which were little different from the values in Figure 2.

2.2.2 State Space representation of the Filters

In the proposed approach, linear dynamics of the RC filter states is represented using discrete state space equations (Jackey *et al.*, 2007, Plett, G *et al.,* 2004, RA Jackey. *et al.*, 2009, R.C., Krein. *et al.*, 2008) as given below in (4):

$$[h(k+1)] = diag[\alpha] * [h(k)] + [B] * i(k) \\ \Phi(k) = [C] * [h(k)] \tag{4}$$

The vector $[\alpha]$ has N number of filter "poles", with $|\alpha| < 1$ for ensuring the stability (RA Jackey, *et al.*, 2009), corresponding to time constants of the filter states. In this work, we have chosen two poles, i.e, N = 2. The vector $[B]$ is the input weight matrix, $[C]$ is output coefficients matrix and $i(k)$ is the battery pack current at the k-th time instant and $\Phi(k)$ is the effective voltage due to RC filters.

2.3. Parameter Estimation

The battery pack model parameters estimation problem is posed mathematically as a constrained optimization (minimization) problem (Christopher, *et al*., 1995, S.S.Rao., 1996). The objective function to be minimized is a function of the simulation error i.e. some function of error between model simulated output $\hat{y}$ and the actual measured output y. The objective function selected in this work for minimization is Mean Square Error (MSE) between the actual and simulated output. Equation for MSE is mentioned below in (5).

$$M.S.E = \sqrt{\frac{\sum Error^2}{Number\ of\ Samples}} \\ Error = (y - \hat{y}) \\ Where,\ y - Measured\ Battery\ Voltage \\ \hat{y} - Simulated\ Battery\ Voltage \tag{5}$$

This constrained optimization problem can be represented as given in (6).

$$\underset{\theta}{Min}\{\varepsilon(y-\hat{y})\} \\ s.t.\theta_{lower} \le \theta \le \theta_{upper} \\ where, \theta = \{R_{batt}, [\alpha][B][C]\} \tag{6}$$

In (6), a set of the decision variables is actually a set of parameters to be estimated i.e. θ = {series battery resistance, filter coefficients, weight factors, output matrix coefficients}, whereas θ_{lower} and θ_{upper} are lower and upper constraints (bounds) on the parameters to be estimated. The constrained optimization formulation allows the user to exploit a-priori knowledge about the possible range of the model parameters.

An algorithm for the parameter estimation is given below:

Inputs
1. Set of measured input-output data.
2. Constraints on the parameters: θ_{lower}, θ_{upper}

Outputs:
A set of estimated parameters θ.

Algorithm:

Begin

1. Select initial set of values for the parameters θ within the prescribed constraints.
2. Simulate the model output response using the input data set and the selected parameter set.
3. Compute the objective function using the error between the actual output response and the simulated model output.
4. If the minimum of the error function is not reached, go back to Step-1, otherwise, go to next step, i.e. Step-5.
5. Terminate the algorithm with the resulted parameter set where the minimum of the error function is obtained, along with the minimum value of the error function achieved.

End

In the present work this constrained optimization problem is solved using GA (Christoper, *et al*., 2007, N.Chaiyaratna, *et al*., 1997, S.S.Rao 1996, Z.Zibo, *et al*., 1995), which is a most adopted and established optimization technique that is observed to reliably find the optimum solution.

The optimized series battery resistance (R_{batt}) values show that they have smooth relationships with temperature. The optimized R_{batt} values are further smoothened using 2nd order polynomial curve fitting. Variation of normalized R_{batt} parameter values with respect to battery temperature is given in Figure 4.

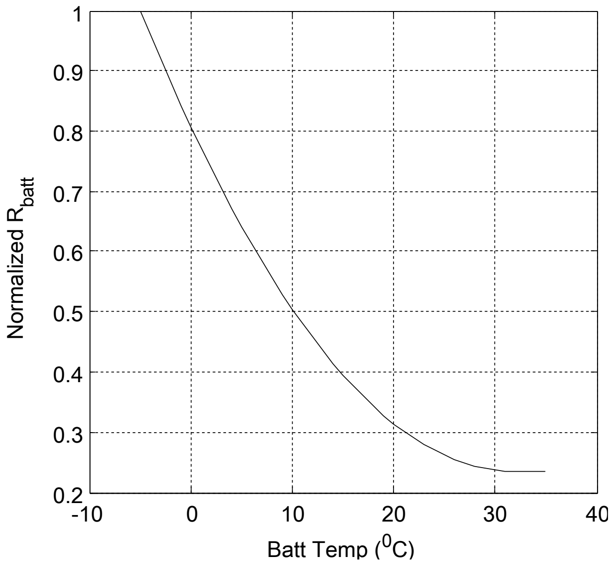

Figure 4: Series battery resistance variation with battery temperature (Batt Temp)

3. RESULTS AND DISCUSSIONS

As described in the previous sections, the developed model has been validated against various HEV test drive cycles data sets at various vehicle and battery temperature operating conditions. The performance of the HV battery pack model is assessed using Mean Square Error (MSE) and visual inspection. The validated data sets comprised of the standard drive cycles (UDDS, UDC, NEDC, etc...) and generic vehicle road trial data sets which are at difference operating conditions other than used for identification of the battery pack parameters. The battery current and the corresponding battery temperature and SOC profiles of selected validation test drive cycle data sets (Testdataset-1 and UDC repeated 4 times (UDC4)) considered in this paper are shown in Figure 5 and Figure 6 .

Figure 7 shows the comparison of actual battery voltage logged from the test vehicle and simulated battery pack model voltage for validation Testdataset-1. The Figure 8 shows the exploded view of a section of Figure 7 for 500 seconds data. The model output is closely matching with the actual battery voltage responses in both the charging and discharge cycle patterns and the dynamics shown are well captured by the model. The Figure 9 shows the comparison of actual battery voltage logged on the test HEV and simulated battery model voltage for the validation data set UDC4. The model responses shown are reasonably matching with the actual battery voltage responses. The MSE performance measures of Testdataset-1, UDC4 and standard drive cycles, UDDS and NEDC are shown in Table 2.

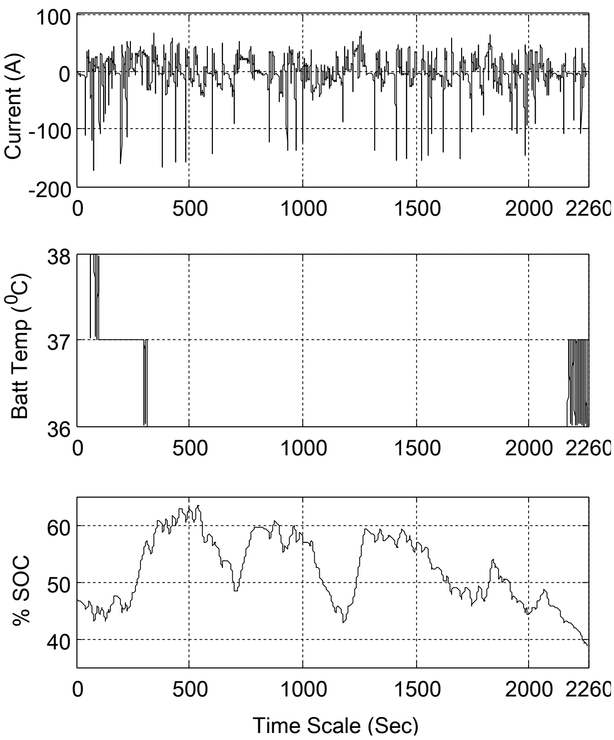

Figure 5: Battery current profile of selected Validation Testdataset-1 with respect to corresponding battery temperature (Batt Temp) & % SOC

Table 2: MSE performance measure values of the selected test drive cycle data sets using proposed approach

Test Drive Cycle	MSE
Testdataset-1	1.69
UDC4 Drive Cycle	1.05
UDDS Drive Cycle	1.60
NEDC Drive Cycle	1.65

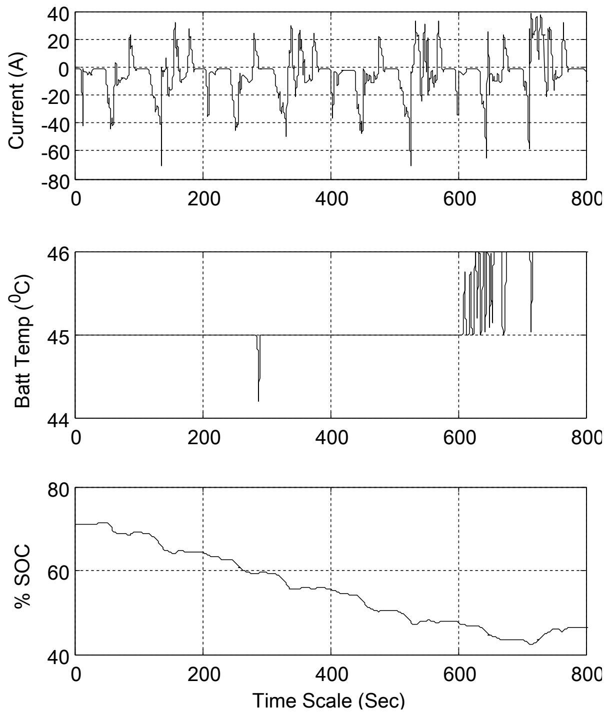

Figure 6: Battery current profile of selected UDC4 with respect to corresponding battery temperature (Batt Temp) & % SOC

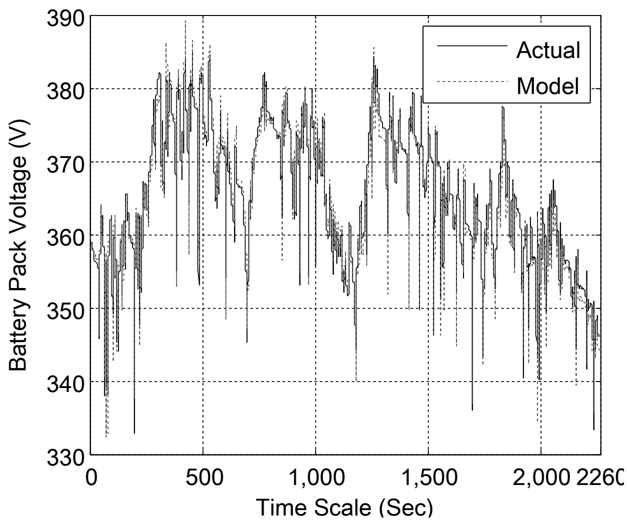

Figure 7: Comparison results of battery pack voltage of selected Testdataset-1 and simulated model output

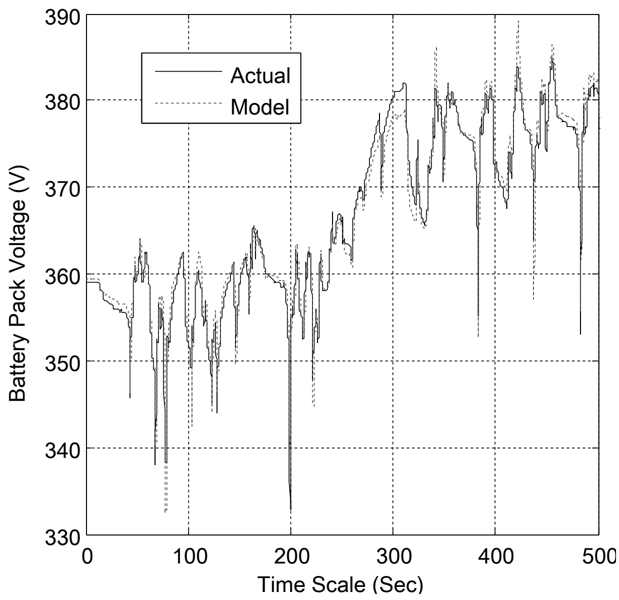

Figure 8: Exploded view of a section of Figure 7

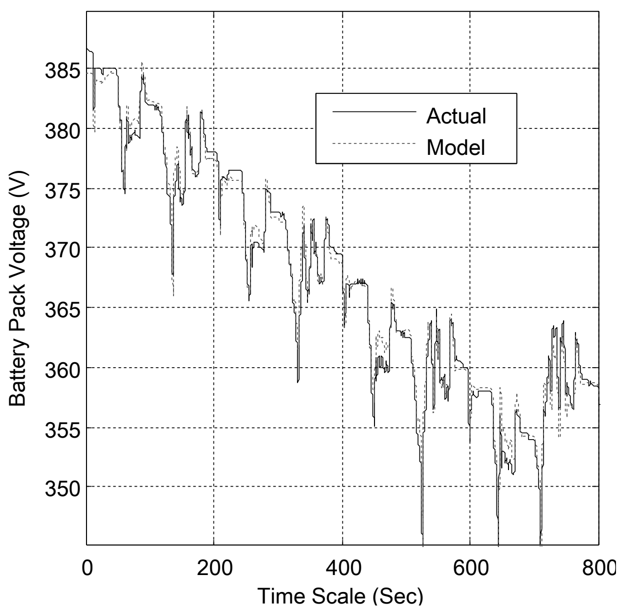

Figure 9: Comparison Results of battery pack voltage of selected UDC4 and simulated model output

4. CONCLUSION

The Li-ion battery pack of HEV can be modelled with reasonable accuracy using the proposed new approach. The developed model simulates the electrical dynamic characteristics across the operating conditions within the constraints of the limitations and assumptions mentioned in this paper. As described, HV battery pack model with accurate and satisfactory performance can be developed using dynamic drive cycle data, without any additional instrumentation on the HV battery. The HV battery model is validated using various vehicle drive cycle data (UDDS, UDC, NEDC) at various operating conditions (Hot, Cold drive cycles).The results obtained by the proposed approach are reasonably matching with actual HV battery responses measured from the HEV.

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