Evaluating Real-Life Performance of Lithium-Ion Battery Packs in Electric Vehicles

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In regard to the increasing market launch of plug-in hybrid electric vehicles (PHEVs), understanding battery pack performance under electric vehicle (EV) operating conditions is essential. As lifetime still remains an issue for battery packs, it is a necessity to monitor the battery pack’s state-of-health (SOH) on-board. Standard laboratory performance tests for health evaluation do not apply since operation interruptions and additional testing equipment are out of the question during ordinary EV usage. We suggest a novel methodology of performance estimation from real-life battery data. On the basis of battery pack data collected during PHEV operation, a support vector machine model capturing battery behavior characteristics is constructed. By virtually testing this battery model, access to standard performance evaluation figures can be gained. The SOH indicator “10 s discharge resistance” as known from hybrid pulse power characterization (HPPC) tests is chosen to exemplify how performance can be followed over a year.

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Lithium-ion batteries have raised high expectations as energy storage in electric vehicles (EVs). In such challenging applications, it is essential to know how long the battery pack will last - both in the short term, until the next charge, and in the long run in terms of lifetime. In order to soundly estimate the battery’s instant performance capability as well as predict and improve lifetime, the performance and degradation of batteries as a function of their use in plug-in hybrid electric vehicles (PHEVs) has to be better understood.

On the way to understanding EV battery performance, batteries are conventionally tested in laboratory environments with standard driving cycles as load profiles mimicking vehicle operation.1,2 Recently, even thermal cycling has been added.3 In terms of modeling, both simple data-fitting models from laboratory data, for instance equivalent circuits from impedance measurements,4 and mathematical models on the basis of physical and chemical processes in the battery5–9 are common. Laboratory tests can provide fundamental insight into calendar life and cycle life of batteries revealing dependencies on temperature, cycling depth, and state-of-charge (SOC).7,8 However, those tests have limited validity for real-life applications since the conditions during vehicle operation are complex. Field testing of traction battery packs is thus an important complement. In this way, the behavior of the battery pack can be monitored in its actual application instead of testing it in a laboratory.

Real-life battery testing in electric vehicles is scarcely represented in literature. Liaw’s research group analyzed data from nickel-metal hydride (NiMH) electric vehicle battery packs with the help of driving and duty cycles in 20077,10 and Svens et al. recently presented a method for single battery cell field testing.11 The difficulties with on-board battery testing lie in the constant battery pack operation and the poorly defined operating conditions. As a result, reference test procedures, well-established in laboratory testing and commonly used for battery state-of-health (SOH) estimation, are not available in field tests.

The primary standard tests, constant current discharge and hybrid pulse power characterization (HPPC),12,13 are employed to derive aging-sensitive characteristic values as capacity and internal resistance respectively. Those battery performance indicators are then (amongst others such as self-discharge) applied to describe the battery’s SOH, i.e. the battery’s ability to meet the performance specified at beginning-of-life (BOL). Impedance increase and capacity loss are followed as a percentage of BOL performance over time and set into relation to end-of-life (EOL) criteria dependent on application-specific performance targets.

In this paper, we show how standardized reference tests can be virtually applied to real-life PHEV battery data with the help of a statistical learning approach. HPPC test results are presented as example of a figure of merit evaluating on-board performance.

Methods

On-board battery pack data.— The data that underlies this project is CAN-bus data from a Volvo V70 plug-in hybrid electric vehicle prototype tested by ETC Battery and FuelCells Sweden AB during one year within the scope of a joint Volvo Cars-Vattenfall project. The car has been equipped with a 32 Ah Li-ion battery pack whose specifications are summarized in Table I. Both the behavior of the battery pack and information on the operating conditions were collected from January to December 2010.14 The data was logged with a 2 Hz frequency whenever the ignition was started or the charging cable was connected to the grid.

The logged signals that are most important to this battery performance study are battery pack voltage, battery pack current, battery pack temperature (average of cell temperatures) and battery pack state-of-charge (SOC). The first three variables were measured whereas the SOC was estimated by the battery management system (BMS) provided by the manufacturer with a resolution of 0.4%. Note that discharge current is defined as positive and charge current thus is negative. Apart from information on the battery behavior, operating condition variables such as date, time, vehicle speed, ambient temperature, and PHEV mode (battery discharge, battery regenerative charge, battery grid charge, diesel drive) have been monitored.

<table>
<thead>
<tr>
<th>Table I. Specifications of Li-ion battery pack as used in the joint Volvo Cars-Vattenfall project.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
</tr>
<tr>
<td>Number of cells</td>
</tr>
<tr>
<td>Thermal management</td>
</tr>
<tr>
<td>Weight</td>
</tr>
<tr>
<td>Volume</td>
</tr>
<tr>
<td>Cathode</td>
</tr>
<tr>
<td>Anode</td>
</tr>
<tr>
<td>Nominal voltage</td>
</tr>
<tr>
<td>Nominal capacity</td>
</tr>
<tr>
<td>Maximum voltage</td>
</tr>
<tr>
<td>Minimum voltage</td>
</tr>
<tr>
<td>Maximum charge/discharge current</td>
</tr>
</tbody>
</table>
Support vector-based battery data analysis.— The complexity of battery systems impedes a description by mathematical equations. Empirical inference is a way to nevertheless find patterns in a large amount of battery data by essentially building a model from examples. In this article, the applicability of support vector machines (SVM), a supervised method based on statistical learning theory that is able to deal with nonlinear systems, is explored. SVM, which has been developed by Vapnik,15 has traditionally been used for classification, but it is also applicable for regression problems such as in the present case. The SVM concept is indicated in the following; a detailed derivation can be found elsewhere.16 A SVM training data set may consist of \( L \) points with input \( x \) of dimensionality \( D \) and output \( y \),

\[
\{x_i, y_i\} \quad \text{where} \quad i = 1, \ldots, L, \quad y_i \in \mathbb{R}, \quad x \in \mathbb{R}^D.
\]  

[1]

In the case of nonlinear regression, a kernel trick is used to increase the dimensionality of the input space to a feature space where the system is linear. Here, we apply a radial basis function (RBF),

\[
K(x_i, x_j) = e^{-\gamma ||x_i-x_j||^2},
\]  

where \( \gamma \) is the kernel option. The idea of SVM is then to find a hyperplane that best describes the training data by identifying the optimal offset from the origin \( b \) and the normal vector to the hyperplane \( w \),

\[
y_i = w \cdot \Phi(x_i) + b,
\]  

where \( \Phi(x_i) \) is the kernel mapping of the input. A SVM implementation in C, SVMlight,17 has been used to predict battery voltage from two input variables that are known to influence voltage, namely current and SOC. For the purpose of voltage prediction, SVM is applied according to the following procedure:

1) Data selection: selection and preparation of two data samples,
2) Training run: creation of a SVM model with the SVMlight function ‘svm_learn’ from one data sample,
3) Test run: voltage prediction with the SVMlight function ‘svm_classify’ from current and SOC of another data sample by interpolation from the SVM model derived in 1),
4) SVM performance estimation: evaluation of the difference predicted/true voltage values by computing the maximum relative error and the root mean square percentage error (RMSPE) as well as SVMlight’s output on runtime and number of support vectors.

The performance of a SVM depends on the choice of parameters. Apart from the chosen kernel function and its parameters, there is the soft-margin parameter \( C \) and the size of the \( \varepsilon \)-insensitive loss function \( \varepsilon \). The best choice of parameters is still an open research issue.18 We use an empirical method where the aforementioned procedure is applied on different sets of parameters in order to find the optimum set with minimized error (grid search).

Virtual test for battery state-of-health estimation.— Apart from testing a SVM model with another set of current and SOC input data in order to estimate its voltage prediction error, we use SVM models as voltage look-up tables for hypothetical inputs. By choosing the current and SOC vectors of a standard battery performance test as input (Figure 1), the resulting voltage prediction can serve as source for computing performance figures. We call this novel concept a virtual test. Similar to an ordinary laboratory test, a virtual test can be performed on the basis of real-life data SVM models and figures of merit estimating the battery’s SOH can subsequently be computed. Capacity and internal resistance are important performance figures with respect to battery pack health7 that can be derived from a constant current discharge test and a HPPC test respectively. We focus here exemplarily on a HPPC test adapted from a battery test manual13 to estimate the 10 s discharge resistance, \( R_{\text{10disch}} \),

\[
R_{\text{10disch}} = \frac{U_{0b} - U_{0f}}{I_{\text{max}}},
\]  

[4]

where \( U_{0b} \) and \( U_{0f} \) are the voltages at the start of the test and after 10 s on the voltage response curve and \( I_{\text{max}} \) is the current during the discharge current pulse (Figure 1a). The theoretical SOC input vector

\[
SOC(t) = SOC_{\text{start}} - 100 \cdot \frac{\int Idt}{Q_{\text{nom}}}. \tag{5}
\]

Results and Discussion

Support vector machine model.— Following the above four-step procedure, two battery data samples for SVM training and test run were selected in order to optimize the SVM parameters for this kind of input data. Those data samples included only the PHEV modes as all other modes have been omitted. It was important to roughly match the range of the variables (current, SOC and voltage) of training and test run as a SVM model is only able to soundly predict within the range of the variables (current, SOC and voltage) of training and test run. Those data samples included only the PHEV modes battery discharge and regenerative charge; data from diesel drive and grid charge have been omitted. It was important to roughly match the range of the variables (current, SOC and voltage) of training and test run. The selected vectors were prepared for SVMlight by scaling to a [0,1] interval according to,

\[
X_{\text{scale}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}. \tag{6}
\]
Figure 2. Measured (a) battery pack current and (b) SOC from a 14 min driving event in March 2010. The data has been used in the presented SVM test run in order to tune SVM parameters.

Figure 3. (a) Predicted and measured battery pack voltage for test data from March 2010 (Figure 2). The prediction is based on a SVM model with training data from April 2010. (b) Relative error for voltage prediction from Figure 3a. The maximum relative error is 1.39%, the RMSPE is 0.28%.

where $X$ represents the respective variable and its minimum and maximum values.

SVM$^{\text{light}}$ was trained with scaled voltage, current, and SOC vectors from a 15 min (1775 data points) driving event in April 2010 with an average battery pack temperature of 23 $^\circ$C. The obtained SVM model was subsequently tested with current and SOC vectors (Figure 2) from a 14 min (1621 data points) driving event in March where the average battery pack temperature was similar (19 $^\circ$C). On the basis of those two data sets, the SVM parameters were tuned with a grid search approach where SVM$^{\text{light}}$ runtime, number of support vectors, maximum relative error as well as RMSPE served as assessment criteria. The best SVM performance was obtained for a RBF kernel with $\gamma = 14$, $C = 1.0134$, and $\epsilon = 0.01$.

With this parameter set, the training took a runtime of 1.6 CPU seconds (AMD Athlon II X2 dual-core processor) and resulted in 339 support vectors. The comparison between predicted and actual battery pack voltage is illustrated in Figure 3a. The relative error for the voltage prediction (Figure 3b) showed a maximum of 1.39% right in the beginning of the driving event. SOC inaccuracies are common directly after the logging start when the battery has been at rest and the SOC value from the prior logging does not coincide with reality (Figure 2b). The RMSPE thus was lower, 0.28% (the corresponding root-mean square error was 0.97 V). The error of the predicted voltage does additionally not seem to increase with time or follow any other trend. 2-fold cross-validation (switching of training and test data) of the SVM model with the SVM parameters mentioned above yielded averaged error values of 1.45% maximum relative error and 0.40% RMSPE. The decreased prediction performance in the validation round can be related to the fact that the variable ranges of the new test data, i.e. the original training data, exceed the ranges of the new training data, i.e. the original test data as displayed in Table II.

Setting the derived model error results in context by comparing to other SVM battery voltage prediction studies, does not allow straightforward conclusions. There are several studies on SVM-based SOC estimation, but to our knowledge just one other study on SVM-based voltage prediction where the relationship between voltage, current, temperature and SOC has been predicted for a NiMH battery pack during an automotive driving cycle in the laboratory. The authors used a least squares SVM method with a RBF kernel for a training set of 3000 points and a test set of 6500 points. No information on the used software or the SVM parameters is given, but a maximum relative error of 3.61% is mentioned. A direct comparison of the maximum relative errors is however difficult as the battery pack voltage differs and the data has been collected in the laboratory using a larger sample, a different battery type (Li-ion vs. NiMH) and an additional input (temperature).
Table II. Representative data selections for each month from January to December 2010 as well as for SVM training and test run.

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of data points</th>
<th>Current / A</th>
<th>SOC / %</th>
<th>Temperature / °C</th>
<th>Voltage / V</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM training</td>
<td>1775</td>
<td>−51.3−223.4</td>
<td>46.4−88.0</td>
<td>22−25</td>
<td>320.2−366.8</td>
</tr>
<tr>
<td>SVM test</td>
<td>1621</td>
<td>−43.4−145.1</td>
<td>51.2−87.2</td>
<td>18−21</td>
<td>323.9−364.4</td>
</tr>
<tr>
<td>January</td>
<td>2762</td>
<td>−79.8−238.0</td>
<td>32.4−97.2</td>
<td>20−29</td>
<td>294.3−385.7</td>
</tr>
<tr>
<td>February</td>
<td>3791</td>
<td>−75.1−246.3</td>
<td>30.4−98.4</td>
<td>12−24</td>
<td>283.4−386.9</td>
</tr>
<tr>
<td>March</td>
<td>5351</td>
<td>−56.4−255.1</td>
<td>37.2−98.4</td>
<td>16−26</td>
<td>299.2−386.7</td>
</tr>
<tr>
<td>April</td>
<td>2957</td>
<td>−55.6−223.4</td>
<td>47.6−94.4</td>
<td>19−25</td>
<td>320.2−381.8</td>
</tr>
<tr>
<td>May</td>
<td>2049</td>
<td>−76.8−242.9</td>
<td>37.2−98.4</td>
<td>19−29</td>
<td>296.2−386.4</td>
</tr>
<tr>
<td>June</td>
<td>5197</td>
<td>−55.8−242.7</td>
<td>42.4−98.4</td>
<td>27−32</td>
<td>324.1−388.5</td>
</tr>
<tr>
<td>July</td>
<td>3683</td>
<td>−67.2−192.0</td>
<td>32.4−98.4</td>
<td>25−32</td>
<td>312.6−385.4</td>
</tr>
<tr>
<td>August</td>
<td>3494</td>
<td>−65.4−192.0</td>
<td>29.6−98.4</td>
<td>28−37</td>
<td>294.2−387.5</td>
</tr>
<tr>
<td>September</td>
<td>5630</td>
<td>−63.4−179.3</td>
<td>30.4−98.4</td>
<td>24−30</td>
<td>290.7−386.1</td>
</tr>
<tr>
<td>October</td>
<td>3648</td>
<td>−57.5−179.5</td>
<td>18.0−98.0</td>
<td>26−33</td>
<td>285.4−385.8</td>
</tr>
<tr>
<td>November</td>
<td>3777</td>
<td>−60.8−246.6</td>
<td>30.0−98.0</td>
<td>21−28</td>
<td>297.8−385.4</td>
</tr>
<tr>
<td>December</td>
<td>3950</td>
<td>−57.0−186.4</td>
<td>32.4−98.4</td>
<td>12−22</td>
<td>304.6−388.4</td>
</tr>
</tbody>
</table>

Battery state-of-health estimation.— After having proven the applicability of SVM for voltage prediction of real-life battery pack data in the previous section, SVM models from data selections from different points in time have been constructed in order to follow if and how battery behavior changes with time. Typical battery discharge mode driving cycles among the available data span 2000 to 6000 data points corresponding to 1000 to 3000 s. Table II presents representatively selected driving events for each month from January to December 2010. SVM models have been prepared from each data sample with the SVM parameter set as displayed above.

A virtual HPPC test that matches the ranges of all SVM models was prepared. Therefore, the HPPC test as suggested by a PHEV battery test manual has been modified. Instead of the maximum discharge current that is hardly reached in real-life operation, a more representative current of 65 A was chosen for the HPPC discharge pulse (Figure 1a). The SOC start value was set to 90% (Figure 1b).

Figure 4 demonstrates the voltage response of this HPPC test for the SVM model from January. A look at the voltage behavior during the discharge pulse reveals a voltage drop as expected. The constant voltage during the rest subsequent to the discharge pulse does not coincide with normal battery characteristics on the other hand. The absence of a time-dependent voltage relaxation can be explained by the lack of time dependence in the model.

The discharge resistance derived according to equation from the January plot in Figure 4 is depicted in Figure 5 together with the discharge resistances of the other months of 2010. Following the 10 s discharge resistance values from January to December, we observe that, starting from 137 mΩ in January, the resistance is lower in the middle of the year and rises again in the end of 2010. In order to verify the significance of the obtained discharge resistance values, data from five comparable driving events in February with average battery pack temperatures ranging from 13 to 18 °C was selected. The 10 s discharge resistance values from these samples yielded an average value of 151 mΩ with a 4 mΩ standard deviation. This low deviation gives reason to consider the resistance values from Figure 5 to be significant. Furthermore, a comparison of the derived 10 s discharge resistances with a laboratory test (0.11 mΩ at 65 A, 28 °C, 86.4% SOC, June 2011) shows that the results lie within the correct order of magnitude. Still, more laboratory tests are needed to soundly validate our method.

![Figure 4](image1.png)

**Figure 4.** Voltage output from a virtual HPPC test with SOC and current input from Figure 1 for a SVM model based on data from January 2010.

![Figure 5](image2.png)

**Figure 5.** 10 s discharge resistance as derived from virtual HPPC tests (Figure 1) for driving events from January to December 2010 (Table II).
development in the considered time interval. If aging influenced the resistance, the trend line in Figure 6 should be shifted downwards (toward higher resistance) for later months in 2010. When inspecting the positions of points from different months, we cannot observe such an explicit trend. Another study on Li-ion batteries with NMC-based cathode,1 found similar results, where no distinct resistance increase could be observed for PHEV cycling at moderate temperatures during one year.

It can also be mentioned that the battery pack has been used conservatively during the study year; the Ampere-hour throughput was equivalent to about 150 full cycles. Aging seems thus also from this perspective unlikely to influence resistance to a large extent.

When looking at longer time intervals, where aging is expected to affect resistance development, the addition of battery pack temperature as input variable would help in order to distinguish between the impacts of aging and temperature on the resistance value. Apart from instantaneous values, such as battery pack temperature and ambient operating conditions, battery pack voltage also depends on the battery’s operation history. Especially mass transport (mainly diffusion in electrolyte and electrodes) is a time-dependent process that is responsible for a large part of the polarization in lithium-ion batteries.2 The time dependence that could be caught by, for instance, a moving average of the battery current should add the so far missing time-dependent voltage relaxation in the HPPC test voltage response (Figure 4).

Conclusions

We have presented a proof of concept for the evaluation of battery performance from on-board data without additional testing equipment or interruptions of the ordinary operation. Support vector machines are identified as a powerful method to handle large amounts of real-life battery data. From on-board battery pack data, SVM models with battery behavior information can be conveniently constructed. Additionally to SVM battery modeling, the concept of a virtual test is introduced. Virtual tests allow to access meaningful battery performance evaluation figures familiar from laboratory tests. This kind of virtual test can be generally applied to any type of battery model.

Combining these two methods of support vector-based battery models and virtual tests, SOH figures of merit can be estimated from real-life battery operation. This procedure offers the potential to further explore battery performance in real applications and facilitates the comparability between laboratory and field tests.

The model as presented in this article does not take into account all variables with high impact on battery voltage. In addition to current and SOC, time dependence and temperature are important. Those variables should be included in future models in order to further improve the voltage prediction.

Putting the suggested method into practice, a SVM model like the one described may be implemented in the BMS of an electric vehicle. The support vectors can be continuously updated from operation history, e.g. in combination with an extended or unscented Kalman filter, providing access to up-to-date SOH information via virtual tests. On-board knowledge of the battery pack SOH is first of all beneficial for estimating which battery performance can be expected for the ongoing operation. It may in the second place serve as basis for lifetime predictions and improvements of future battery pack designs and BMS.

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References