

# Optimizing Electric Vehicle Battery Life through Battery Thermal Management

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## ABSTRACT

In order to define and to optimize a thermal management system for a high voltage vehicular battery, it is essential to understand the environmental factors acting on the battery and their influence on battery life. This paper defines a calendar life aging model for a battery, and applies real world environmental and operating conditions to that model. Charge and usage scenarios are combined with various cooling/heating approaches. This set of scenarios is then applied to the calendar life model, permitting optimization of battery thermal management strategies. Real-world battery life can therefore be maximized, and trade-offs for grid energy conversion efficiency and fuel economy/vehicle range can be determined.

## INTRODUCTION

Lithium-ion (li-ion) batteries are at the advent of deployment into large-scale full-speed light duty vehicles. A concern remaining over such products, and especially for those utilizing the batteries for energy storage, is regarding their field durability and life. The high voltage battery system is normally considered as a component of the vehicle powertrain. Additionally, the HV battery is a key component in the emissions system and must be On-board Diagnostic (OBD) compliant, for hybrid and plug-in hybrid electric vehicles. The expectation is all powertrain components should be able to reliably deliver a customer 10 years of service, or 150,000 miles equivalent operation [1]. The battery will be expected to comply with these requirements. Since batteries are only entering the market, no substantial real-world data is yet available, which could be used believe such expectations will be met. Automotive developers have had to rely upon accelerated testing and aging models, based upon known degradation mechanisms for the technology.

A similar concern lies over the correct methods for the thermal management of the battery. Most degradation mechanisms will be accelerated by exposure to elevated temperatures. Temperature differentials within the battery tend to increase cell-to-cell performance variability over life, and further degrade overall battery performance. This phenomenon is of particular concern for a battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV), since these both of these batteries have a substantial portion of their energy regularly charged and discharged, with heat generation during both operations.

Particular to BEVs and PHEVs is the concept of overall system efficiency. This is sometimes called the “wall-to-wheels” efficiency, and is a measure of all electrical energy losses introduced during the transition of electricity from the charger source (the wall) to the vehicle's traction drive (the wheels) [2]. A full electric powertrain is, in principle, significantly more efficient than liquid and gaseous-fueled vehicle powertrains [3]. Concern over the demands placed upon the electrical utility grid by large fleets of electrified vehicles has driven concerns over the levels of efficiency achievable by such vehicles, and has also found its way into several regulatory goals and constraints. How the end user utilizes their vehicle, both in terms of driving and charging, can also have a marked impact on the overall system efficiency.

Loss of cell energy (electrochemical capacity) and resistance increase are the two primary modes by which an electrochemical cell's performance will degrade. The underlying mechanisms for the degradation of both characteristics are usually kinetic in nature, although discrete chemical side-reactions can exist, which do not necessarily adhere to a strict classical kinetic model. Battery capacity loss is dominated by the removal of active Li-ion species from the

primary charge/discharge reactions [4]. Battery impedance growth is presumed to be primarily driven by a growth in the effective thickness of the anode Secondary Electrolyte Interphase (SEI) layer, thereby increasing the ionic diffusion path. Both degradation mechanisms would be expected to proceed with the square-root of time [5]. As indicated above, some side-reactions may also exist in specific electrochemistries, and for this reason the degradation rates observed in actual cells will often depart from a square-root relation, and approach a linear relation. This shift also can be thermally excited, appearing during elevated temperature storage and/or operation.

Kinetically driven reactions within batteries have been commonly modeled using an Arrhenius-based relationship [6]. Many such reactions, including those indicated above adhere to a doubling with each 10°C increase in local temperature. This often has been used as a practical rule of thumb in the prediction of the effects of temperature on a performance characteristic with a kinetically-driven degradation reaction. Care must be taken in applying the rule, since secondary reactions can induce a departure from this relationship. For these reasons, empirical verification of cell behavior over time, and at multiple temperatures is normally required, during the development of the battery system, in order to provide a prediction for battery operational and non-operational life.

Battery calendar life requirements have been defined by the United States Advanced Battery Consortium (USABC) [7,8]. The calendar life expectation for a PHEV is 15 years at 35°C, resulting in an irreversible energy loss of 20% of the battery's rated energy, at beginning of life (BOL). The calendar life for EV applications has historically been extrapolated to a 15 year requirement at 25°C. The calendar life for power-assist applications is 15 years at 30°C, and it is expected that all applications will be harmonized to this value.

Calendar life determination begins with the selection of a relevant battery state of charge (SOC), and a set of test temperatures. Recommended methods are provided by the USABC in each applicable test manual [1, 7, 8]. It is preferred that four (4) test temperatures be used, in order to resolve linear relationships within the conventional Arrhenius acceleration model. These temperatures should ideally be selected over a temperature range that is both relevant to the end use application, and provide unambiguous test results, within a reasonable time period. The preferred test temperature range is normally 25°C to 65°C, and measurements would be in 10°C increments (e.g.: 25, 35, 45, 55°C, or 30, 40, 50, 60°C). Care must be taken in the selection of the maximum temperature, since secondary reactions may be initiated, which would result in a departure from the classical aging model. Conversely, low temperatures result in impractical, long tests, where resolution of aging effects becomes a challenge. Nonetheless, the application of this test

data to an Arrhenius model can provide a good first-order prediction for calendar life.

Climate-based modeling requires an understanding of the results from accelerated aging, and applying temperature-specific acceleration rates. Real-world temperature data can be processed into cumulative time within a given narrow temperature increment, and the aging contribution for that time-temperature section determined. Integration over all temperature-time blocks provides a life prediction for the battery at a specific geographic location [9]. This method allows for the comparison of relative climates and geographic locations, and their expected effect on the battery's life.

Electric vehicle use is normally characterized with a drive profile. A drive profile will reflect a particular type of usage. For example, the profile may be weighted by city (stop-start, low speed), highway (high speed and long accelerations), or a combination. Individual profiles also may be combined, in order to generate more comprehensive representations of vehicle use. Profiles will vary in average power, and will therefore have the battery generate various levels of heat. For li-ion batteries the majority of heat is derived from Joule heating of the cells and from some of the associated electronics [10]. It is therefore common practice to utilize battery DC resistance measurements as the primary method for determining heat generation potential.

Thermal management system design focuses on the equalization of temperature differentials within the battery pack, as well as minimizing the pack temperature increase with respect to the ambient temperature. Through analysis, it is possible to determine the relative aging effects on individual cells, and the battery in general.

Electric vehicle charging carries with it similar considerations of heat and efficiency, as those seen during optimization of drive strategies. Charging powers have been categorized into three classes, based upon the voltage and power delivered. It is expected that the majority of charging episodes will involve Class 1 (e.g.: 120VAC, 15A service, 1.3kW typical), or Class 2 (e.g.: 240VAC, 30A service, 6.6kW typical) charge powers [11]. Fast charging concepts, delivering powers of up to 66kW also are being considered, with a goal of reducing battery charge times to 20 minutes or less. Concerns of rapid charging include the stress it will place on the electrochemistry, and the thermal stresses that will be introduced through the exceptionally high currents.

## ANALYSIS

The analysis incorporated the creation of a standardized calendar life model and an operational (cycling) model, and applying both to real-world operational results, in order to predict the impact of various usage methods on battery life.

From this analysis, thermal management strategies for the optimization of battery life were developed.

A standardized calendar life model was used, to predict the effect of battery temperature on battery life. The temperature acceleration factors were applied to temperature profiles for specific geographical locations, to determine the expected battery calendar life for each of those locations. Temperature excursions, due to specific charge and drive duty cycles, were applied to the results, to determine expected battery life, under real-world conditions. The net effect of energy use for thermal management on vehicle energy efficiency vs. battery life were then contrasted.

## ACCELERATED CALENDAR LIFE

For the purposes of this study, the battery electrochemistry used was one which exhibited capacity fade and resistance increase proportionate to the square-root of time, and a temperature sensitivity of doubling of reaction rate approximately every 10°C increase, over a sufficiently wide temperature range (e.g.: 25-60°C). While experimentally verified, the models derived from this data include:

For a given temperature (T):

Capacity Fade:

$$C_t = C_0 - A_T t^{1/2} \quad (1)$$

Resistance Growth:

$$R_t = R_0 + B_T t^{1/2} \quad (2)$$

Where:

$C_t$  = Battery Capacity (in Amp-hours) at time t (in hours).

t = time at temperature (in hours)

$C_0$  = Beginning of life Capacity (in Amp-hours).

$A_T$  = Temperature-specific Capacity Fade rate ( $A \cdot h / (h^{1/2})$ )

$R_t$  = Battery DC resistance (in ohms) at time t (in hours).

$R_0$  = Beginning of life Battery DC resistance (in ohms).

$B_T$  = Temperature-specific Resistance growth rate ( $ohm / (h^{1/2})$ )

Temperature effects on the degradation of these properties will normally follow a specific Arrhenius relationship, associated with the kinetic theory of chemical reactions (shown in its natural logarithmic form):

$$\ln(k) = \ln(A) - \frac{E_a}{R} \left( \frac{1}{T} \right) \quad (3)$$

Where:

k = Rate Constant

A = Pre-exponential factor

$E_a$  = Activation energy

R = Gas Constant

T = Absolute Temperature, K

For the purpose of describing capacity fade and internal resistance increase, the equation can be further simplified, as follows:

$$\ln(F) = \ln(A) - B \left( \frac{1}{T} \right) \quad (4)$$

Where:

F = % capacity fade, or % resistance increase.

A and B are specific proportion factors.

A simple acceleration model was defined for a battery which achieves the nominal USABC calendar life target of 15 years to 20% capacity loss, at 30°C, and with a temperature acceleration factor of approximately doubling of fade rate with each 10°C ambient temperature increase. The capacity fade rate as a function of square-root time is shown in [Figure 1](#). The effects of temperature for acceleration for the same data set are shown in [Figure 2](#). A similar model also was constructed for resistance increase, based upon an end of life criteria of 15 years to 30% resistance increase, at 30°C.

## CLIMATE EFFECTS ON CALENDAR LIFE MODEL

“Real world” temperatures vary naturally with respect to season and geographic location. Data is publically available, through the National Oceanographic and Atmospheric Administration (NOAA), for a wide range of U.S. locations [9]. The United States contains several distinct climate zones, and data was collected and analyzed for several cities within these various climate zones. The data represented 20-year averages for daily norms, high and low temperatures. [Figure 3](#) represents the yearly average temperature variations for each of the selected cities. [Figure 4](#) represents the average, high and low temperatures for three cities from different climate zones. For example, Minneapolis, MN has the widest

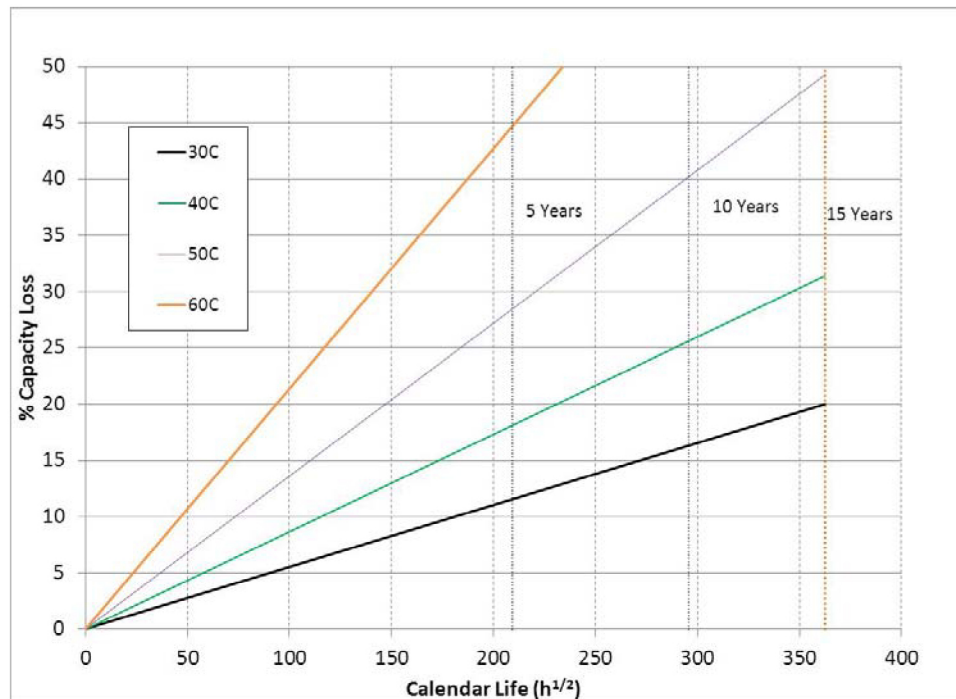


**Figure 1. Battery Calendar Life Capacity Fade Rate as a function of time and temperature (extreme temperatures omitted).**

annual variations (excluding Fairbanks); Phoenix, AZ has the widest variation in daily ranges, while Miami has the lowest daily and annual variations. Cumulative annual time at or below a particular temperature can then be determined, using this data (Figure 5).

From the battery acceleration model, above, it is possible to determine the contributions that time at each temperature will have on battery calendar life. For simplicity, acceleration rates were determined for each 5°C increment of temperature. The model results are provided in Table 1. These degradation rates can be combined with the cumulative time exposures, in order to determine the real-world calendar life estimates for each select city. A time-averaged model was applied:

$$F_{avg} = \frac{\sqrt[2]{\sum_{-40^{\circ}C}^{60^{\circ}C} (t_1 * F_c^2 * n)}}{t_{life}} \quad (5)$$

Where:

$F_c$  = Model Capacity Degradation (Fade) Rate (%/h<sup>1/2</sup>)

$t_1$  = time within one 5°C range, over one year  
(100% of time = 8760h)

$t_{life}$  = time for one life at target conditions  
(15 years = 131,400h)

$n$  = total number of discrete data points in range of study

**Table 1. Model-based degradation rates vs. temperature, for capacity and resistance.**

| Model-based<br>T°C | Cap<br>T(K) | Cap<br>%/vh | Z<br>%/vh |
|--------------------|-------------|-------------|-----------|
| -40                | 233         | 0.0005      | 0.0008    |
| -35                | 238         | 0.0008      | 0.0012    |
| -30                | 243         | 0.0012      | 0.0018    |
| -25                | 248         | 0.0017      | 0.0026    |
| -20                | 253         | 0.0025      | 0.0038    |
| -15                | 258         | 0.0036      | 0.0054    |
| -10                | 263         | 0.0051      | 0.0077    |
| -5                 | 268         | 0.0071      | 0.0107    |
| 0                  | 273         | 0.0098      | 0.0147    |
| 5                  | 278         | 0.0134      | 0.0200    |
| 10                 | 283         | 0.0180      | 0.0270    |
| 15                 | 288         | 0.0240      | 0.0360    |
| 20                 | 293         | 0.0317      | 0.0475    |
| 25                 | 298         | 0.0414      | 0.0621    |
| 30                 | 303         | 0.0537      | 0.0805    |
| 35                 | 308         | 0.0691      | 0.1035    |
| 40                 | 313         | 0.0881      | 0.1320    |
| 45                 | 318         | 0.1114      | 0.1671    |

The results of applying the analysis model to both capacity fade and to resistance growth are shown in Table 2, and illustrated graphically in Figure 6. The general model will therefore predict that an energy battery (for PHEV/BEV) will reach end of life due to capacity loss, rather than power fade.

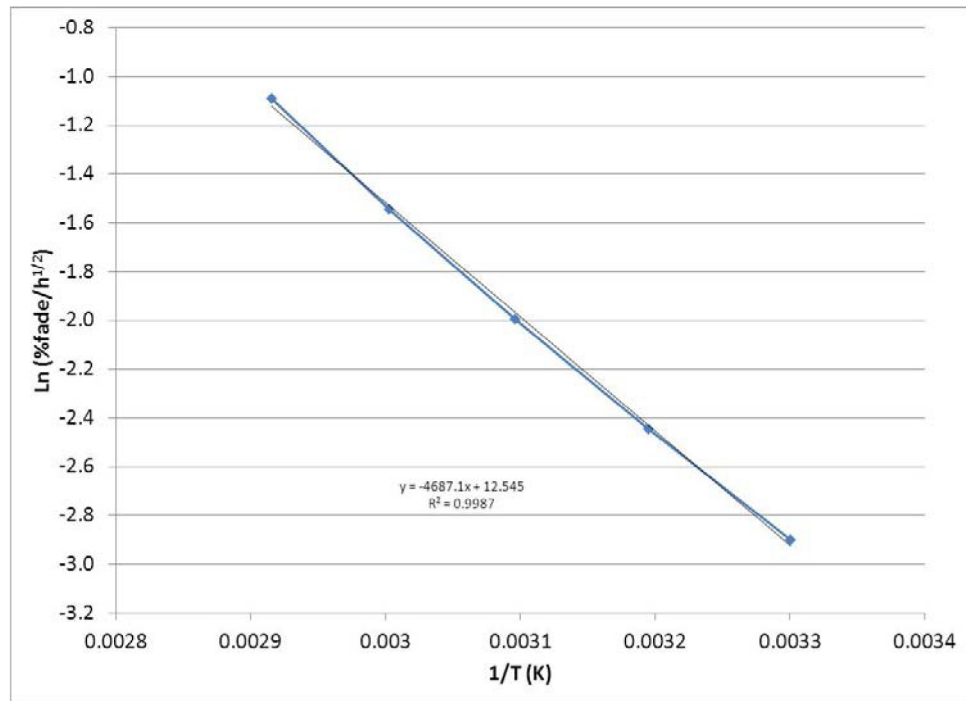


Figure 2. Arrhenius Relationship for Capacity Fade in Battery Model, depicted in Figure 1.

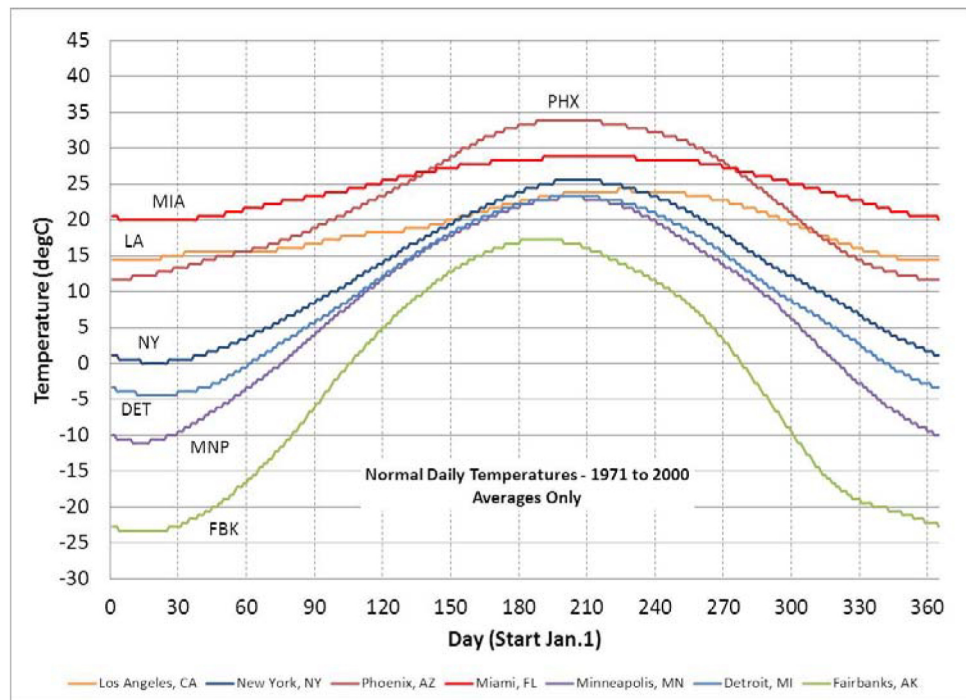


Figure 3. 20-Year Annual Daily Averages for Select U.S. Cities