Maximizing Lithium Ion Vehicle Battery Life Through Optimized Partial Charging

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***Abstract*—The limited lifetime, high cost, and large size of current lithium ion batteries are some of the primary obstacles to wider adoption of electric vehicles and plug-in hybrid electric vehicles. Simulations presented in this paper predict that Li-ion battery life can be extended through intelligent charging, especially when predictions of next-day energy needs are used to charge the battery only as needed. As-needed charging minimizes battery degradation by minimizing time spent at high state-of-charge. Preliminary results presented here indicate that the battery of a vehicle used for daily commuting and short errands could see its useable life extended by up to 150% over unoptimized charging.**

***Index Terms*—Batteries, Electric vehicles, Machine learning algorithms, Optimization, Numerical simulation**

I. Introduction

Lithium-ion (Li-ion) batteries represent a major component of the cost and weight of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) [1]. Battery energy capacity and internal resistance degrade with time and use. Hence, designing batteries to last the life of a vehicle while still meeting minimum energy and power constraints presents a challenge [2]. Intelligent charge power control algorithms can extend battery life by minimizing the degradation that occurs during charging [3], [4]. A vehicle equipped with a supervisory charge controller that minimizes the effects of charging on battery life can potentially be equipped with a smaller, less expensive battery while still meeting battery capacity and power requirements over a specified vehicle lifetime.

There are three major drivers of Li-ion battery degradation: battery temperature as a function of time, charge-discharge cycling, and state of charge (SOC) as a function of time [2]. When other factors are held constant, minimizing the time a battery spends at high SOC (corresponding to high open-circuit voltage) minimizes degradation. Therefore if a prediction of the next day's battery energy requirement is available, the battery can be charged only as needed—rather than charging to a nominal maximum SOC as is typical—minimizing battery degradation.

This paper presents a new method of optimizing Li-ion battery life that combines the constrained nonlinear charge optimization technique presented in [4] with the use of a machine learning algorithm that predicts the amount of energy needed for the next day's driving. The result is that the battery is charged in an optimal manner, and only to the extent needed, leading to greatly improved battery life.

The negative effects on battery life of time spent at high voltages are well documented in literature [2], [5]. Vehicle manufacturers are aware of these effects. For example, the Nissan LEAF EV includes a "long battery life" user control setting that stops charging at 80% SOC, allowing users to trade driving range for extended battery life [6]. However, the study described here appears to be the first published work to propose and quantify an automated method of maximizing battery life through partial charging.

The National Renewable Energy Laboratory (NREL) has developed a Li-ion battery degradation model that has been validated against empirical data [7], [8].[1] The model takes into account periodic temperature and SOC profiles to estimate how battery energy capacity fades and internal resistance grows over time. We use this model to estimate the usable lifetime of a battery charged using the method presented here as compared to the lifetimes of batteries charged using other methods. Toyota Prius PHEV usage data was used to produce weekly charge profiles under three charge scenarios. The three scenarios were simulated in NREL's battery model to estimate battery life under each.

II. Optimized Partial Charging Method

Given a vehicle that is charged nightly, the problem of optimal charging can be divided into two sub-problems: determination of the energy needed for the next day's driving,

[1] NREL's model was developed for Li-ion batteries with graphite anode and nickel-cobalt-aluminum cathode.

and provision of that amount of energy in the optimal manner.

A. Determining energy needs

The energy needed for the next day can be determined using a machine learning algorithm that estimates the next day's driving behavior based on past driving patterns. The degree of certainty of an estimate of the next day's driving needs is used to add in a safety margin to avoid undercharging the vehicle. Alternatively, a user may input his required driving range to allow for expected driving needs.

B. Optimized charging

Once the next day's energy needs are known, the charge optimization method presented in [4] is used to determine an optimal charge power profile. The charge optimization method seeks to minimize the effects of three factors that lead to battery degradation: temperature profile, daily charge cycling (depth of discharge), and state of charge profile. A simplified battery degradation model is used to estimate those effects. The degradation due to each factor is taken to be independent of the other degradation factors, although in reality they are linked. Degradation is also assumed to be independent of battery state of life[2], again not a perfect reflection of reality. Despite these approximations, model results correlate fairly well with results produced by NREL's model. Effects on both battery energy capacity and maximum battery power are modeled, and simplified, nonlinear algorithms are used to estimate the incremental degradation resulting from a given charge cycle.

Because energy capacity fade and power fade are largely independent processes, *incremental degradation* is defined as

$$\max\left(\frac{\Delta L_Q}{L_Q}, \frac{\Delta L_P}{L_P}\right).$$

Here L_Q is the battery's *energy capacity lifetime* (the time it takes a new battery's energy capacity to fade enough to fall below the minimum design capacity), and ΔL_Q is the *incremental change in energy capacity lifetime* resulting from a charge profile. Likewise, L_P is the *power lifetime* (the time it takes a new battery's maximum power to fade enough to fall below the design power), and ΔL_P is the *incremental change in power lifetime* resulting from a charge profile.

The problem of providing a given charge energy in a given time window while minimizing battery degradation is a constrained nonlinear optimization problem, solved in [4] using Matlab's `fmincon()` function with an interior-point algorithm. In order to avoid local minima, `fmincon()` is seeded with six charge profiles known to approximate typical optimal charge profiles. The optimized charge power profiles that result tend to follow a compromise between two trends: spreading of charge over time to minimize very high temperatures associated with fast charging, and delay of charging until late in the available time window to minimize time at high SOC [4].

III. Sample Results

The above method was tested using driving data from Toyota Prius PHEVs sampled at 1 Hz. A typical driving week was selected involving five days of commuting 26-40 km (16-25 miles) round-trip, one longer trip of 65 km (40 miles), and one day on which the vehicle was not used. Because of the relatively small size of Prius PHEV batteries,[3] a hypothetical simulated SOC profile was generated for a larger battery with 18 kWh of available energy between a minimum SOC of 20% and a maximum SOC of 90%, assuming an average distance of 5 km per kWh of battery energy. Fig. 1 shows weekly SOC profiles for four charge scenarios:

1. Full nightly charging at 6.6 kW (SAE level 2) to 90% SOC upon plug-in, without regard for battery degradation.
2. Full nightly charging to 90% SOC, with charge power profile optimized to reduce battery degradation.
3. Partial nightly charging as needed to provide for the next day's driving, optimized to reduce battery degradation. An ideal ability to perfectly predict the next day's energy requirement is assumed.
4. Partial nightly charging as needed to provide for the next day's driving with 16 km (10 mi) spare range, optimized to reduce battery degradation.
5. Partial nightly charging as needed to provide for the next day's driving one hour before departure and with 16 km spare range, optimized to reduce battery degradation.

In scenario 1, the battery spends the majority of its time fully charged at 90% SOC. In scenario 2, the battery spends the majority of its time between 70% and 90% SOC – still fairly high. In scenario 3 the battery spends the majority of its time between 20% and 40% SOC, and in scenarios 4 and 5 the battery spends the majority of its time between 30% and 50% SOC.

Because internal battery temperature data were not available, battery temperature rise was estimated from the mean absolute charge or discharge power over the preceding 10 minutes multiplied by a nominal thermal resistance of 2 °C/kW. Weekly temperature profiles for the four charge scenarios are shown in Fig. 2.

Because differences in temperature profile and the magnitude of daily charge-discharge cycles among the five scenarios are minor, SOC-related effects are expected to dominate any differences in battery degradation. There is one exception: in scenario 5, the charging completes one hour

[2] A battery's *state-of-life* is the current state of its internal resistance and energy capacity.

[3] The advantages of the partial charging method presented here are applicable for batteries large enough to power a complete typical daily drive with some energy to spare.

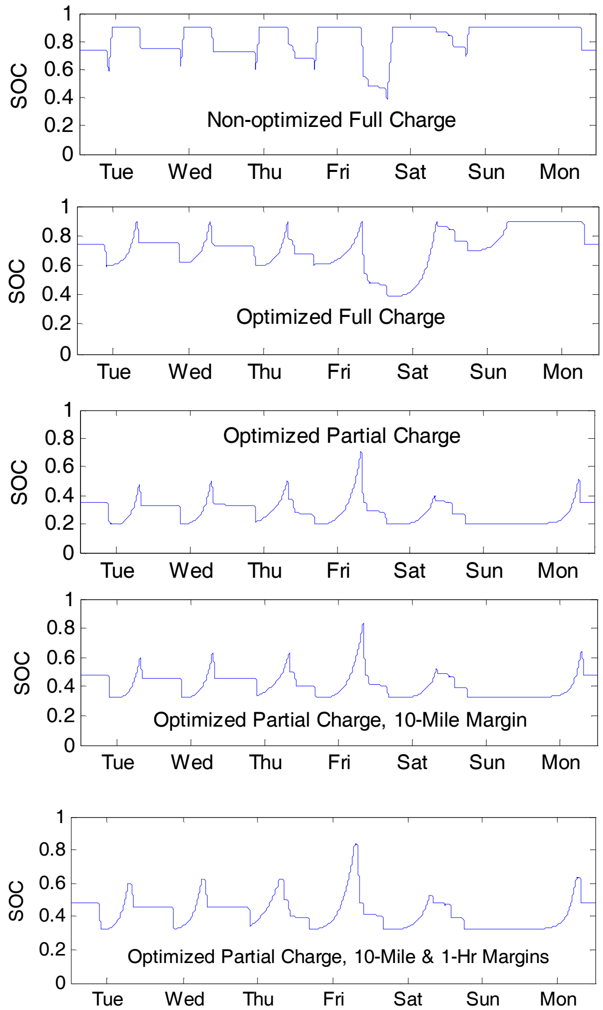

Fig. 1. Weekly SOC profiles for the four charging methods. Horizontal axis labels indicate the beginning (midnight) of each day.

before driving begins (instead of immediately before as in scenarios 2, 3, and 4). This means that the battery has time to cool down to room temperature before driving begins.

The week-long, one-second interval SOC and temperature profiles for these five scenarios were simulated in NREL's battery life model. The model simulates the effect of repeating the weekly drive profiles over a period of several years, tracking the fall in battery capacity, Q, and the rise in internal resistance, R. Internal resistance $R(t)$ is related to maximum output power $P_{max}(t)$ at time t by the equation $R(t) = R_0P_0/P_{max}(t)$, where R_0 is the initial internal resistance and P_0 is the initial maximum power [4]. P_{max} and P_0 are defined as in [9].

The end of a battery's life is defined as the time when either capacity Q or maximum power P_{max} falls below a specified minimum. Batteries are often designed so that the minimum value of Q is 80% of its initial value [10]; that is the end-of-life criteria used in this study. A battery's

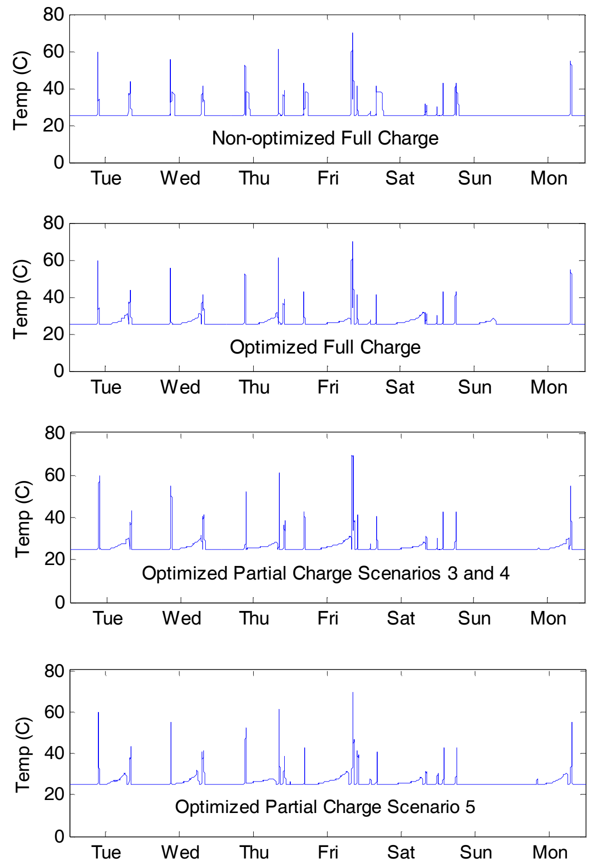

Fig. 2. Battery temperature profiles under the four charging scenarios. (Third plot represents both scenarios 3 and 4.)

minimum power is often a smaller percentage of its initial value for reasons described in [4]; this study defines the end-of-life maximum power as 60% of the initial maximum power. The actual battery lifetime is the lesser of the capacity lifetime and the power lifetime.

Fig. 3 shows battery capacity Q and maximum power P_{max} produced by NREL's model for scenario 3 (idealized partial charging). Red lines are drawn in both plots indicating end-of-life criteria. The end of the battery's capacity lifetime occurs around 11.5 years, and the end of its power lifetime occurs around 13 years, as seen in Fig. 3. As expected, energy end-of-life occurs before power end-of-life; the actual end-of-life is the lesser of the two lifespans – 11.5 years in this example.

Similar simulations were performed for all five charging scenarios. Energy capacity lifetime and power lifetime results predicted by NREL's model for each scenario are shown in Fig. 4. Optimized full charging (scenario 2) leads to a moderate increase in battery life (1.8 years in the example shown) over unoptimized charging (scenario 1). Optimized partial charging (scenario 3) leads to a significant increase in battery life over unoptimized charging (about 6 years in this example).

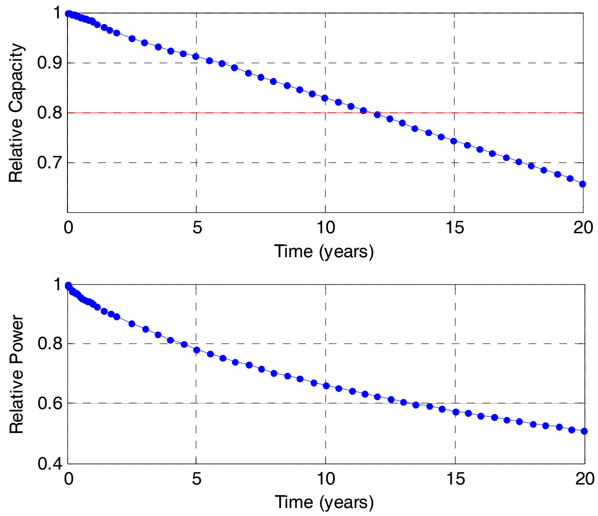

Fig. 3. Sample plots of simulated energy capacity and power capacity over a battery's lifetime, showing end-of-life criteria.

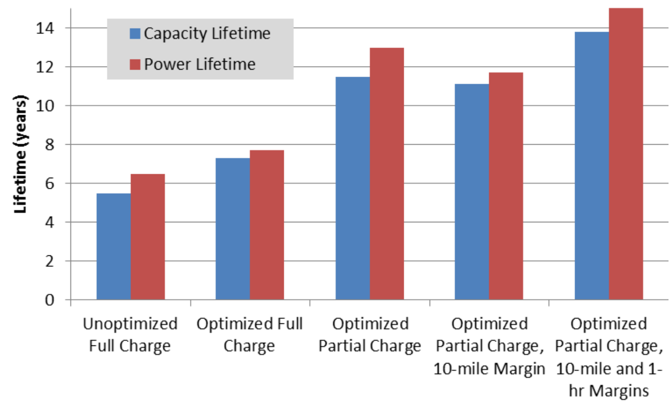

Fig. 4. Comparison of battery energy and power lifetimes under the five charging scenarios. One power lifetime result over 15 years is truncated.

Any realistic charging method would need to leave some margin for error and for driver peace of mind. Scenario 4 gives an error margin of 12.4 SOC percentage points, representing 3.2 kWh of battery energy or 16 km (10 mi) of driving range. This safety margin represents about 40% of the driver's typical daily distance of 39 km (24 mi). Even with this significant safety margin, lifetime gains are significant (5 years in this example). These large increases in lifetime result from the very minimal time spent at high SOC.

Scenario 5 results in the longest battery life of 13.8 years. This is unexpected when considering only SOC since the battery actually spends more time at moderate to high SOC in scenario 5 than in scenarios 3 and 4. However, the fact that the battery his time to cool after charging before the vehicle is driven means that the battery spends less time at simultaneously high SOC and temperature. As noted by other authors [11], time spent at simultaneously high SOC and temperature has a more powerful degrading effect on Li-ion batteries than would be predicted from considering each factor separately. Because the method of estimating battery temperature used here is fairly crude, this result should be interpreted qualitatively, and with caution. However, it does agree qualitatively with other work such as [11].

There are certainly drawbacks to charging using the method presented here, especially in the idealized case of scenario 3. EVs already cause "range anxiety" for some drivers, so further reducing a vehicle's range would be difficult to accept. Scenarios 4 and 5 present charge profiles that are more likely to be acceptable because the vehicles have spare energy. Scenario 5 has the additional advantage of allowing the driver to choose to leave earlier than planned if an unexpected need arises. Of the partial-charge scenarios presented here, scenario 5 is likely to be the most acceptable to users, and it also presents the greatest gain in battery life.

While the partial charging method presented here may exacerbate range anxiety for drivers of pure EVs, PHEV drivers would not have this problem. Therefore partial charging may be more appropriate for PHEV drivers, or for EV drivers who own another vehicle that could be used in case of an unexpected need. However, PHEV drivers would only benefit from partial charging if their battery were significantly larger than needed for typical drives. For this reason, PHEV40 drivers would be more likely to benefit than PHEV10 drivers, who likely use their full battery capacity each time they drive.[4] In general, the larger the battery in comparison to the driver's typical daily energy usage, the greater the lifetime gains available from partial charging.

It is important to consider the effects of the charging method presented here on the electric grid. These effects can be separated into two groups: the effects of partial charging, and the effects of charging optimized to minimize battery degradation (regardless of final SOC). The net effect on the grid of partial charging will be minimal because partial charging does not change the amount of energy consumed as compared to full charging, and considered alone it does not necessarily change the timing of energy consumption. Hence partial charging is expected to be viewed neutrally by grid operators.

Charging optimized to minimize battery degradation will have two benefits for the electric grid. The first is a reduction in time spent charging at maximum power due to the tendency to spread charging over time (which minimizes the time the battery spends at high temperatures). The second is a reduction in charging during evening peak load hours due to the tendency to charge late in the available window (which minimizes time spent at high SOC). Optimized charging may

[4] A PHEV40 is a PHEV with 40 miles of range in charge depleting mode when its battery is fully charged (i.e. 40 miles of all-electric range), while a PHEV10 has a 10-mile range in charge depleting mode.

lead to significant grid stress in the early morning hours just before people leave for work. Charging using scenario 5 will mitigate this stress by shifting the charging peak earlier in the morning, when other loads are low. As noted in [4], the optimized charging algorithm used here converts battery degradation into an estimated dollar value. Therefore it can easily take into account electricity price signals, allowing utilities to shift charging to any desired time (e.g. midnight to 5 a.m.). The net effect of the combination of optimized charging and partial charging presented here is therefore expected to be beneficial for the grid as well as the battery.

IV. Conclusions

This paper has presented a new method of charging Li-on vehicle batteries that uses a prediction of the next day's vehicle usage to charge the battery only as needed. This as-needed, partial charging method is combined with an optimized charging method presented previously by the authors. Simulation results presented here using NREL's Li-ion battery life model predict that battery lifetimes can be extended by many years. In the idealized-prediction case shown, optimized partial charging roughly doubles both battery energy capacity lifetime and battery power lifetime. Lifetime gains are significant even when allowances are made for range anxiety and imperfect knowledge of the next day's drive cycle. Most of this lifetime increase is due to SOC minimization through partial charging.

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