Health-Aware and User-Involved Battery Charging Management for Electric Vehicles Using Linear Quadratic Control

Fang, H.; Wang, Y.

TR2015-022 October 28, 2015

Abstract

This paper studies control-theory-enabled charging management for battery systems in electric vehicles (EVs). Charging is a crucial factor for the battery performance and life as well as EV users' anxiety. Existing methods run with two shortcomings: insufficiency of battery health awareness during charging,and failure to include the user into the charging loop. To address such issues, we propose to perform charging that deals with both health protection and user-specified charging needs or objectives. Capitalizing on the linear quadratic control theory, a set of charging strategies are developed. A simulation-based study demonstrates their effectiveness and potential. We expect that charging with health awareness and user involvement will improve not only the battery longevity but also user satisfaction.

American Society of Mechanical Engineers (ASME)

HEALTH-AWARE AND USER-INVOLVED BATTERY CHARGING MANAGEMENT FOR ELECTRIC VEHICLES USING LINEAR QUADRATIC CONTROL

Huazhen Fang*
Department of Mechanical Engineering
University of Kansas
Lawrence, Kansas 66045
Email: fang@ku.edu

Yebin Wang
Mechatronics Group
Mitsubishi Electric Research Laboratories
Cambridge, Massachusetts 02139
Email: yebinwang@ieee.org

ABSTRACT

This paper studies control-theory-enabled charging management for battery systems in electric vehicles (EVs). Charging is a crucial factor for the battery performance and life as well as EV users' anxiety. Existing methods run with two shortcomings: insufficiency of battery health awareness during charging, and failure to include the user into the charging loop. To address such issues, we propose to perform charging that deals with both health protection and user-specified charging needs or objectives. Capitalizing on the linear quadratic control theory, a set of charging strategies are developed. A simulation-based study demonstrates their effectiveness and potential. We expect that charging with health awareness and user involvement will improve not only the battery longevity but also user satisfaction.

1 Introduction

Holding the promise for reduced fossil fuel use and air pollutant emissions, electrified transportation has been experiencing a surge of interest in recent years. Battery systems are crucial for the performance of electric vehicles (EVs) and the consumer acceptance. To improve the operating performance, safety and longevity of batteries, a considerable amount of research and development effort has been made to advanced battery management, especially state-of-charge (SoC) estimation, state-of-health (SoH) estimation and thermal monitoring, see [1–7] and the references therein. Recently, there has been a growing attention to optimal charging strategies to reduce the charging-induced harm. Improper charging (e.g., charging with a high voltage or current density) can cause rapid buildup of internal stress and resistance, crystallization and other negative effects. The consequence is fast capacity fade and shortened life cycle, and finally, impaired consumer confidence [8–10].

Popular charging ways in industrial practice, especially for inexpensive lead-acid batteries used for cars and backup power systems, are to apply a constant voltage or force a constant current flow through the battery [2]. Such methods, though easy to implement, can lead to serious detrimental effects for the battery. One improvement is the constant-current/constant-voltage charging [1,2]. As illustrated in Figure 1, it applies a constant current, and when the voltage increases to a desired level, switches to the constant voltage mode with the current diminishing accordingly. A main issue with such methods is the lack of an effective feedback-based regulation mechanism. With an open-loop architecture, they simply take energy from power supply and put it into the battery. As a result, both the charging dynamics and the battery's status feedback information are not well exploited to control the charging process for improvements of efficiency and health protection. This calls for the deployment of closed-loop model-based control. Constrained optimal control has thus been used in [8, 11, 12], in conjunction with electrochemical or equivalent circuit models, to address fast charging subject to input, state and temperature constraints for health. To mitigate the computational cost, a rule-based, easier-to-implement method is proposed in [13,14] to handle charging under constraints using an on/off strategy. An adaptive control scheme for energy-efficient fast charging is crafted in [15]. In [16–18], optimal EV charging pattern is designed with considerations of both the electricty cost and battery degradation. In spite of such works, the existing work still remains limited to date, leaving much capacity of feedback-controlled charging unexplored yet.

In this paper, we propose to perform control-based EV charging management in a *health-aware* and *user-involved* way. Since the battery system is the heart as well as the most expen-

*Address all correspondence to this author.

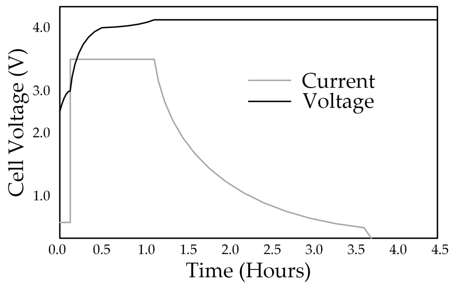

FIGURE 1: Constant-current/constant-voltage charging.

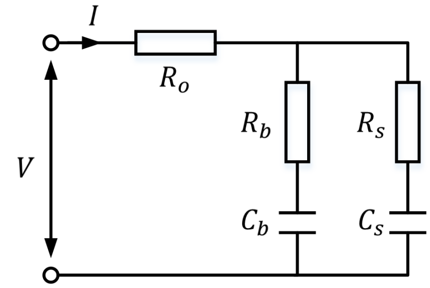

FIGURE 2: The battery RC model.

sive component of an EV, health protection during charging is of remarkable importance to prevent performance and longevity degradation. Incorporated in the form of various constraints, it has been a major design consideration in the controlled charging literature mentioned above. Furthermore, we put forward that user involvement will bring significant improvements to the charging strategies. The current practice excludes the EV user from the charging management indeed. However, it will create two-fold advantages if the user can give the controller commands or advisement about the charging objectives based on his/her immediate situation. First, the battery health will be protected better. The user's advisement can translate into information useful for the EV charger. For instance, given the user's prediction of parking time, a healthier way than simply fast charging can be adopted, as it may happen for charging while working or at home. In another scenario, the user can specify the charging objective as 50% full in 1 hour if he/she has a drive to the airport in 1 hour but only needs half capacity. The charger can make wiser, more health-oriented charging decisions while meeting the user specifications with such information. Second, a direct, positive impact on user satisfaction may result arguably, because offering a user options to meet his/her different charging needs is indicative of a better service quality and enhance his/her perception of level of involvement.

We will build health-aware and user-involved charging strategies via investigating two problems. The first one is *charging with fixed terminal charging state*. In this case, the user will give target state-of-charge (SoC) and charging duration, which will be incorporated as terminal state constraint. The second problem is *tracking-based charging*, where the charging is implemented via tracking a charge trajectory. The trajectory is generated on the basis of user-specified objectives and battery conditions. The design will include health considerations. The solutions, developed on the basis of *linear quadratic optimal control*, will be presented as controlled charging laws expressed in explicit equations. The proposed methods differ from existing ones in [8, 11, 12] in two aspects. From the viewpoint of application, they keep into account both user specifications and battery health. Technically, they, though based on optimization of quadratic cost functions, do not require real-time optimization and thus are computationally more attractive. We notice that the linear quadratic control is a fruitful area, with many established results and new progresses, e.g., [19–22], potentially deployable for the charging control problem.

The rest of the paper is organized as follows. Section 2 presents an RC model oriented towards charging dynamics. Section 3 offers the development of charging strategies, with Section 3.1 on charging with fixed terminal charging state decided by the user and Section 3.2 on tracking-based charging. Section 4 shows numerical results to illustrate the effectiveness of the design. Finally, concluding remarks are gathered in Section 5.

2 RC Model for Charging

While the energy storage within a battery results from complex electrochemical and physical processes, it has been useful to draw an analogy between the battery electrical properties and an equivalent circuit which consists of multiple linear passive elements such as resistors, capacitors, inductors and virtual voltage sources. Throughout the paper, we consider a second-order RC model shown in Figure 2.

Developed by Saft Batteries, Inc., this model was intended for the simulation of battery packs in hybrid EVs [23, 24]. It has been used in [25] to study battery model identification. The bulk capacitor C_b represents the battery's capability to store energy, and the capacitor C_s accounts for the surface effects, where $C_b \gg C_s$. The associated resistances are R_b and R_s, respectively, with $R_b \gg R_s$. Let Q_b and Q_s be the charge stored by C_b and C_s, respectively, and define them as the system states. The state-space representation of the model is given by (1). It can be verified that this system is controllable and observable, indicating the feasibility of controlled charging and status monitoring.

When a positive current is applied for charging, both Q_b and Q_s will grow. However, the voltage of C_s, denoted as V_s, increases at a rate much faster than the voltage of C_b, denoted as V_b. For a high current I, the terminal voltage V, which is largely dependent on the fast increasing V_s, will grow quickly. Then Q_s will reach the maximum in a short time and end the charging process, though Q_b still remains at a low level. This is in accordance

$$\begin{cases} \begin{bmatrix} \dot{Q}_b(t) \\ \dot{Q}_s(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{C_b(R_b+R_s)} & \frac{1}{C_s(R_b+R_s)} \\ \frac{1}{C_b(R_b+R_s)} & -\frac{1}{C_s(R_b+R_s)} \end{bmatrix} \begin{bmatrix} Q_b(t) \\ Q_s(t) \end{bmatrix} + \begin{bmatrix} \frac{R_s}{R_b+R_s} \\ \frac{R_b}{R_b+R_s} \end{bmatrix} I(t), \\ V(t) = \begin{bmatrix} \frac{R_s}{C_b(R_b+R_s)} & \frac{R_b}{C_s(R_b+R_s)} \end{bmatrix} \begin{bmatrix} Q_b(t) \\ Q_s(t) \end{bmatrix} + \left(R_o + \frac{R_b R_s}{R_b+R_s} \right) I(t). \end{cases} \tag{1}$$

of the "rate capacity effect", which means that the total charge absorbed by the battery goes down with the increase in charging current as stated by the Peukert's law. In addition, the RC model can also describe another concerning effect, the "recovery effect". That is, when the charging stops, the terminal voltage V will decrease by (1), due to the charge transfer from C_s to C_b.

The overall SoC is given by

$$\mathrm{SoC} = \frac{Q_b - \underline{Q}_b + Q_s - \underline{Q}_s}{\bar{Q}_b - \underline{Q}_b + \bar{Q}_s - \underline{Q}_s}, \tag{2}$$

where $\underline{Q}_j$ and $\bar{Q}_j$ with $j = b, s$ denote the unusable and the maximum allowed charge.

To develop and apply digital control, the model in (1) can be discretized with a sampling period of T_s. The discrete-time model takes the following standard form:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k, \\ y_k = Cx_k + Du_k. \end{cases} \tag{3}$$

where $x = \begin{bmatrix} Q_b & Q_s \end{bmatrix}^\top$, $u = I$, $y = V$, and A, B, C and D can be decided via applying a discretization method to (1).

For health consideration, we need to constrain the difference between V_b and V_s throughout the charging process. Here, $\tilde{V} = V_b - V_s$ drives the migration of the charge from C_s to C_b. It, intuitively, delineates the gradient of the concentration of ions within the electrode. Created during charging, the concentration gradient induces the diffusion of ions. However, too large a gradient value will cause internal stress increase, heating, solid-electrolyte interphase (SEI) formation and other negative side effects [26–28]. Mechanical degradation of the electrode and capacity fade will consequently happen. Thus uniformity of the ion concentration should be pursued at the maximum possible level during charging. It is noteworthy that such a restriction should be implemented more strictly as the SoC increases, because the adverse effects of a large concentration difference would be stronger in this case.

Next, we will build the charging strategies on the basis of the RC model. The development will be laid out in the framework of linear quadratic control, taking into account both health awareness and user needs.

3 Health-Aware and User-Involved Charging Strategies

In this section, we develop charging strategies for two cases. The first one is concerned with the user defining the final charging state. It will be treated via linear quadratic control subject to fixed terminal state resulting from the user objective. In the second case, charging is managed via tracking a charging trajectory which is produced according to the user objective.

3.1 Charging with Fixed Terminal Charging State

A charging scenario that frequently arises is: according to the next drive need, a user will inform the charging management system of his/her objective in terms of target SoC and charging duration. This can occur for overnight parking at home, several-hour parking at the workplace, or when a drive to some place is needed in just half an hour. As discussed before, the objective offered by the user, if incorporated into the dynamic charging decision making process, would create support for health protection more effective than charging with maximum speed.

From the perspective of control design, the considered charging task can be formulated as an optimal control problem, which minimizes a cost function commensurate with the harm to health and subject to the user's goal. With the model in (3), the following linear quadratic control problem is of interest:

$$\begin{aligned} \min_{u_0,u_1,\cdots,u_{N-1}} \quad & \frac{1}{2} x_N^\top S_N x_N + \frac{1}{2} \sum_{k=0}^{N-1} \left(x_k^\top G^\top Q_k G x_k + u_k^\top R u_k \right), \\ \text{subject to } \quad & x_{k+1} = Ax_k + Bu_k, \ x_0, \\ & x_N = \bar{x}. \end{aligned} \tag{4}$$

where $P \geq 0$, $Q_k \geq 0$, $R > 0$ and $G = \begin{bmatrix} 1/C_b & -1/C_s \end{bmatrix}$. In above, Gx_k is the voltage difference between C_b and C_s indeed. The quadratic cost function, defined over the user-specified time range $[0, NT_s]$, intends to constrain the voltage difference and magnitude of the charging current. The minimization is subject to the state equation and the fixed terminal state $\bar{x}$ as a result of user's target SoC. In the final state, the battery should be at the equilibrium point with $V_b = V_s$. Together with (2), $\bar{x}$, can be determined from the specified SoC value. The weight coefficient Q_k should be chose in a way such that it increases over time, in order to reflect the truth that the stronger health protection is needed as the SoC builds up.

A closed-form solution for (4) can be developed, which will lead to the state-feedback-based charging strategy as follows [19]:

$$K_k = (B^\top S_N B + R)^{-1} B^\top S_{k+1} A, \tag{5}$$
$$S_k = A^\top S_{k+1}(A - BK_k) + Q_k, \tag{6}$$
$$T_k = (A - BK_k)^\top T_{k+1},\ T_N = I, \tag{7}$$
$$P_k = P_{k+1} - T_{k+1}^\top B(B^\top S_{k+1} B + R)^{-1} B^\top T_{k+1},\ P_N = 0, \tag{8}$$
$$K_k^u = \left(B^\top S_{k+1} B + R\right)^{-1} B^\top, \tag{9}$$
$$u_k = -\left(K_k - K_k^u T_{k+1} P_k^{-1} T_k^\top\right) x_k - K_k^u T_{k+1} P_k^{-1} \bar{x}. \tag{10}$$

Since the state x_k is not measurable directly, it is necessary to convert the above strategy to be based on the output feedback. One straightforward avenue to achieve this would be to replace x_k by its prediction $\hat{x}_k$ that minimizes another quadratic cost function. This is justifiable by the certainty equivalence principle, which allows the optimal output-feedback control design to be divided into the separate designs of an optimal state-feedback control an optimal estimator [29]. Here, we use the one-step-forward Kalman predictor given by

$$L_k = A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1}, \tag{11}$$
$$\hat{x}_{k+1} = A\hat{x}_k + Bu_k + L_k(y_k - C\hat{x}_k - Du_k), \tag{12}$$
$$\Sigma_{k+1} = A\Sigma_k A^\top + W - A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1} C\Sigma_k A^\top, \tag{13}$$

where W and V symmetric positive defnite matrices accounting for the covriances of the process and measurement noises. Note that the Kalman filter has been in wide use for battery SoC estimation, e.g., in our previous work [30–33]. Then the optimal control law in (10) changes to be:

$$u_k = -\left(K_k - K_k^u T_{k+1} P_k^{-1} T_k^\top\right) \hat{x}_k - K_k^u T_{k+1} P_k^{-1} \bar{x}. \tag{14}$$

Putting together (5)-(9), (11)-(13) and (14), we achieve a complete description of the charging method via linear quadratic control with fixed terminal state, which is named `LQCwFTS` and illustrated in Table 1. The `LQCwFTS` method performs state prediction at each time instant, and then feeds the predicted value, which is a timely update about the battery's internal state, to generate the control input, i.e., the charging current to the battery. Much of the computation for `LQCwFTS` can be performed prior to the implementation of the control law. The sequences, K_k, S_k, T_k, P_k and K_k^u can be computed offline, and then K_k, $K_k^u T_{k+1} P_k^{-1} T_k^\top$ and $K_k^u T_{k+1} P_k^{-1}$ are stored for use when the control is applied. On the side of the Kalman prediction, offline computation and storage of L_k can be done. Then the only work to do during charging is to compute the optimal state prediction and control by (12) and (14), thus reducing the computational burden.

Offline backward computation (from time N to 0)
$K_k = (B^\top S_N B + R)^{-1} B^\top S_{k+1} A$
$S_k = A^\top S_{k+1}(A - BK_k) + Q_k$
$T_k = (A - BK_k)^\top T_{k+1},\ T_N = I$
$P_k = P_{k+1} - T_{k+1}^\top B(B^\top S_{k+1} B + R)^{-1} B^\top T_{k+1},\ P_N = 0$
$K_k^u = \left(B^\top S_{k+1} B + R\right)^{-1} B^\top$
Online forward computation (from time 0 to N)
Battery state prediction
$L_k = A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1}$
$\hat{x}_{k+1} = A\hat{x}_k + Bu_k + L_k(y_k - C\hat{x}_k - Du_k)$
$\Sigma_{k+1} = A\Sigma_k A^\top + W - A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1} C\Sigma_k A^\top$
Charging decision
$u_k = -\left(K_k - K_k^u T_{k+1} P_k^{-1} T_k^\top\right) \hat{x}_k - K_k^u T_{k+1} P_k^{-1} \bar{x}$

TABLE 1: The `LQCwFTS` charging strategy (Linear Quadratic Control with Fixed Terminal State).

3.2 Charging Based on Tracking

For user-involved charging, it will be beneficial if a desired path is generated in advance on the basis of user-specified objectives for the charging process to follow. In this case, the path can serve as the references for the controller to track. The path generation can be conducted with prior experience or knowledge of the battery electrochemistries and present conditions, which, in turn, will enhance the health awareness through charging. An EV manufacturer can design path generation algorithms and embed them into BMSs, from which the user can select the one that best fits the needs when he/she intends to charge the EV. While how to compute an optimal charging path will make a topic of future research, we focus on developing the charging method to track the path here.

Suppose that the user describes the target SoC and duration for charging, which is translated into the final state $\bar{x}$. Then a reference trajectory r_k for $k = 0, 1, \cdots, N$ is calculated with $r_N = \bar{x}$. Note that the trajectory constrains the difference between V_b and V_s to guarantee health. The linear quadratic state-feedback

Offline backward computation (from time N to 0) $K_k = (B^\top S_{k+1} B + R)^{-1} B^\top S_{k+1} A$ $K_k^s = (B^\top S_{k+1} B + R)^{-1} B^\top$ $S_k = A^\top S_{k+1}(A - BK_k) + Q$ $s_k = (A - BK_k)^\top s_{k+1} + Qr_k,\ s_N = S_N r_N$
Online forward computation (from time 0 to N) *Battery state prediction* $L_k = A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1}$ $\hat{x}_{k+1} = A\hat{x}_k + Bu_k + L_k(y_k - C\hat{x}_k - Du_k)$ $\Sigma_{k+1} = A\Sigma_k A^\top + W - A\Sigma_k C^\top (C\Sigma_k C^\top + V)^{-1} C\Sigma_k A^\top$ *Charging decision* $u_k = -K_k\hat{x}_k + K_k^s s_{k+1}$

TABLE 2: The `LQT` charging strategy (Linear Quadratic Tracking).

tracking for charging can be considered as:

$$\begin{aligned} \min_{u_0,u_1,\cdots,u_{N-1}} \ & \frac{1}{2}\left(x_N - r_N\right)^\top S_N \left(x_N - r_N\right) \\ & + \frac{1}{2}\sum_{k=0}^{N-1}\left[\left(x_k - r_k\right)^\top Q\left(x_k - r_k\right) + u_k^\top R u_k\right], \\ \text{subject to} \quad & x_{k+1} = Ax_k + Bu_k,\ x_0, \end{aligned} \tag{15}$$

where $S_N \geq 0$, $Q \geq 0$ and $R > 0$. The optimal solution to the above problem is expressed as follows [19]:

$$K_k = (B^\top S_{k+1} B + R)^{-1} B^\top S_{k+1} A, \tag{16}$$

$$K_k^s = (B^\top S_{k+1} B + R)^{-1} B^\top, \tag{17}$$

$$S_k = A^\top S_{k+1}(A - BK_k) + Q, \tag{18}$$

$$s_k = (A - BK_k)^\top s_{k+1} + Qr_k,\ s_N = S_N r_N, \tag{19}$$

$$u_k = -K_k x_k + K_k^s s_{k+1}. \tag{20}$$

Following lines analogous to the development of `LQCwFTS`, the output-feedback tracker for charging can be created based on (16)-(20) through the employment of the Kalman predictor in (11)-(13). Specifically, (20) will use $\hat{x}_k$ rather than x_k, i.e.,

$$u_k = -K_k\hat{x}_k + K_k^s s_{k+1}. \tag{21}$$

Summarizing (16)-(19), (11)-(13) and (21) will yield the linear quadratic tracking strategy, or `LQT`, for charging, see Table 2. Similar to the aforeproposed `LQCwFTS`, the `LQT` can have much computation completed offline. Then only the Kalman state prediction and optimal tracking control (21) need to be computed during the actual control run.

It is noted that the control run of the `LQT` strategy will lead to a steady state where the gains K_k and K_k^s will be fixed. The steady state can be computed prior with knowledge of the discrete algebraic Riccati equation (DARE). In this case, the steady-state `LQT` strategy is named `SS-LQT`. The `SS-LQT` will enjoy further simplicity and computational efficiency in terms of its time and space complexities, thus more desirble for practical use.

4 Numerical Illustration

In this section, we present simulation examples to evaluate the performance of the proposed charging strategies. Let us consider a lithium-ion battery with known RC model parameters. Assume $C_b = 82$KF, $R_b = 1.1\text{m}\Omega$, $C_s = 4.074$KF, $R_s = 0.4\text{m}\Omega$, and $R_o = 1.2\text{m}\Omega$ [23]. It has a nominal capacity of 7Ah. The initial SoC is 30%. The user specifies that certain SoC must be achieved within certain duration.

Example 1 - Application of `LQCwFTS`*:* Suppose that charging should be completed in 2 hours. A series of target SoC values, 55%, 65%, 75%, 85% and 95%, are set for the simulation purpose. The sampling period $t_s = 1$s, so the number of data points is $N = 7200$. We apply the `LQCwFTS` method to carry out the charging tasks. For the control run, $Q_k = 0.1 \cdot (5 \times 10^7)^{k/N}$ and $R = 0.1$. The exponential increase of Q_k illustrates increasing emphasis on health as the charging goes on.

The computational results are illustrated in Figure 3. It is observed from Figure 3a that the different target SoCs are satisfied when the charging ends. The SoC increases approximately proportionally with time for the first 1.25 hours. Then the rate slows down gradually to zero as the charging objective is being approached. This is because of the large weight Q_k in the later stage for health protection. The charging current is kept at almost a constant level initially during each charging implementation, as illustrated in Figure 3b. For a higher target SoC, the magnitude is larger accordingly. However, the current drops quickly as the SoC grows further. The concerned health indicator, voltage different between C_s and C_b is characterized in Figure 3c. For each case, $V_s - V_b$ remains around a constant value in the first hour, despite high-frequency fluctuations due to noise. However, it decreases drastically as more charge is pumped into the battery, maximizing the health of the battery's internal structure. As a comparison, we force a constant current of 2.275A through the battery for 2 hours to reach 95% of the capacity. The voltage difference, as shown in Figure 3d, will be kept at a fixed level unsurprisingly. This, however, will cause more serious detrimental effects, because the battery's tolerance to the voltage difference will decrease rapidly with the SoC growth. Thus with this comparison, we argue that the `LQCwFTS` can offer a stronger health

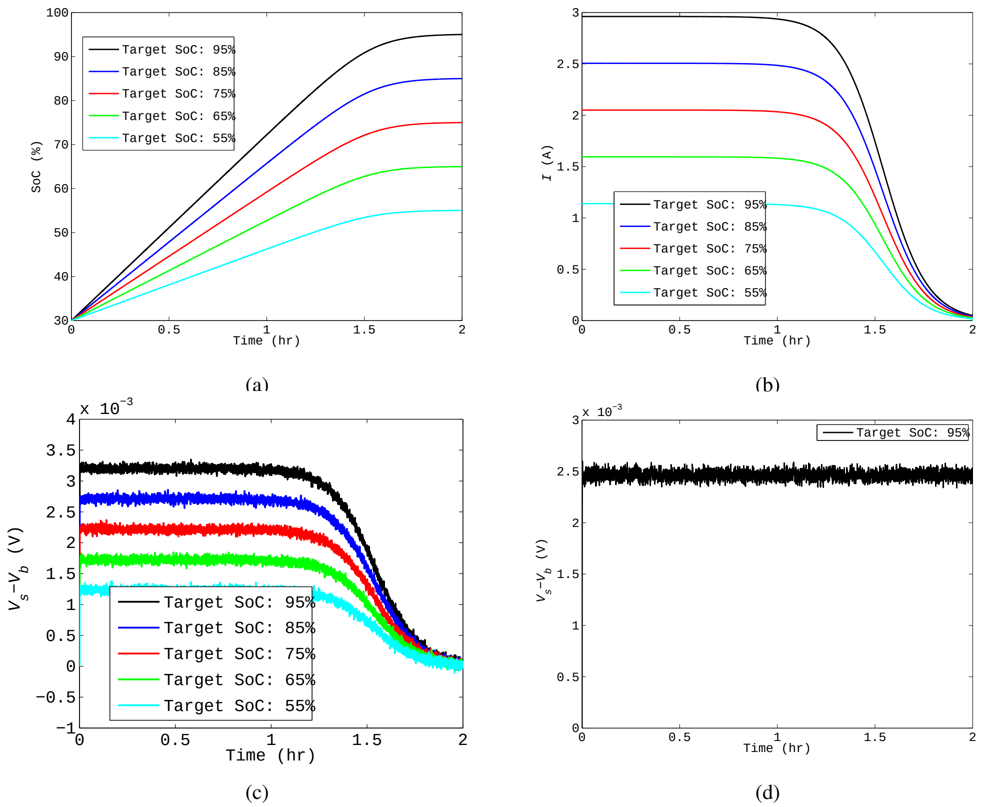

FIGURE 3: Example 1 - Application of `LQCwFTS` to charge the battery from 30% to 55%, 65%, 75%, 85% and 95%: (a) the SoC trajectories; (b) the charging current profiles; (c) the voltage differences as health indicator; (d) voltage difference due to constant current charging to 95% SoC.

protection during charging.

Example 2 - Application of `SS−LQT`*:* We consider the use of `SS−LQT` for charging in this example. The problem setting is the same as in Example 1. The charging trajectories are generated prior based on the objectives. For simplicity and convenience, we assume that the desired trajectory for x_1 and x_2, denoted as r_b and r_s, is

$$r_{j,k} = \frac{1-e^{-kt_s/\tau_j}}{1-e^{-Nt_s/\tau_j}}(r_{j,N}-r_{j,0})+r_{j,0},$$

for $j=b$ or s, $k=1,2,\cdots,N-1$, where $r_{j,0}$ is the initial charge, $r_{j,N}$ the target charge, and τ_j the time coefficient for $j=b$ or s. Note that $r_{j,0}$ and that $r_{j,N}$ can be calculated from the initial SoC and user-specified target SoC. The resultant trajectories have a steep increase followed by a gentle slope, which are reasonable in view of health protection. Letting $\tau_b=\tau_s=Nt_s/4$, V_s and V_b are enforced to be equal. Thus at the trajectory design stage, we put the minimization of the detrimental effects well into consideration.

With the reference trajectories available, the `SS−LQT` strategy is applied to charging. The increase of the actual SoC over time is demonstrated in Figure 4a. All the targets are met. In each case, the SoC grows at a fast rate when the SoC is at a low level but at a slower rate when the SoC becomes higher. Figure 4b shows the current produced by `SS−LQT`. The current usually begins with a large magnitude but decreases quickly. The voltage difference, given in Figure 4c, has the similar trend. It is relatively high when the charging starts, but reduces fast. The state tracking for the task of 95% SoC is shown in Figures 4d and 4e. It is observed that tracking of r_b by x_1 exhibits high accuracy. Tracking of r_s by x_2 becomes accurate increasingly, despite deviation in the first hour. Meanwhile, the further the target SoC is approached, the smaller the tracking error becomes.

In Examples 1 and 2, different charging current profiles are noticed for the same charging task. This is caused by the charging trajectories adopted for the `SS−LQT` and the selection of the weight matrices Q and R. Such a difference does not compromise

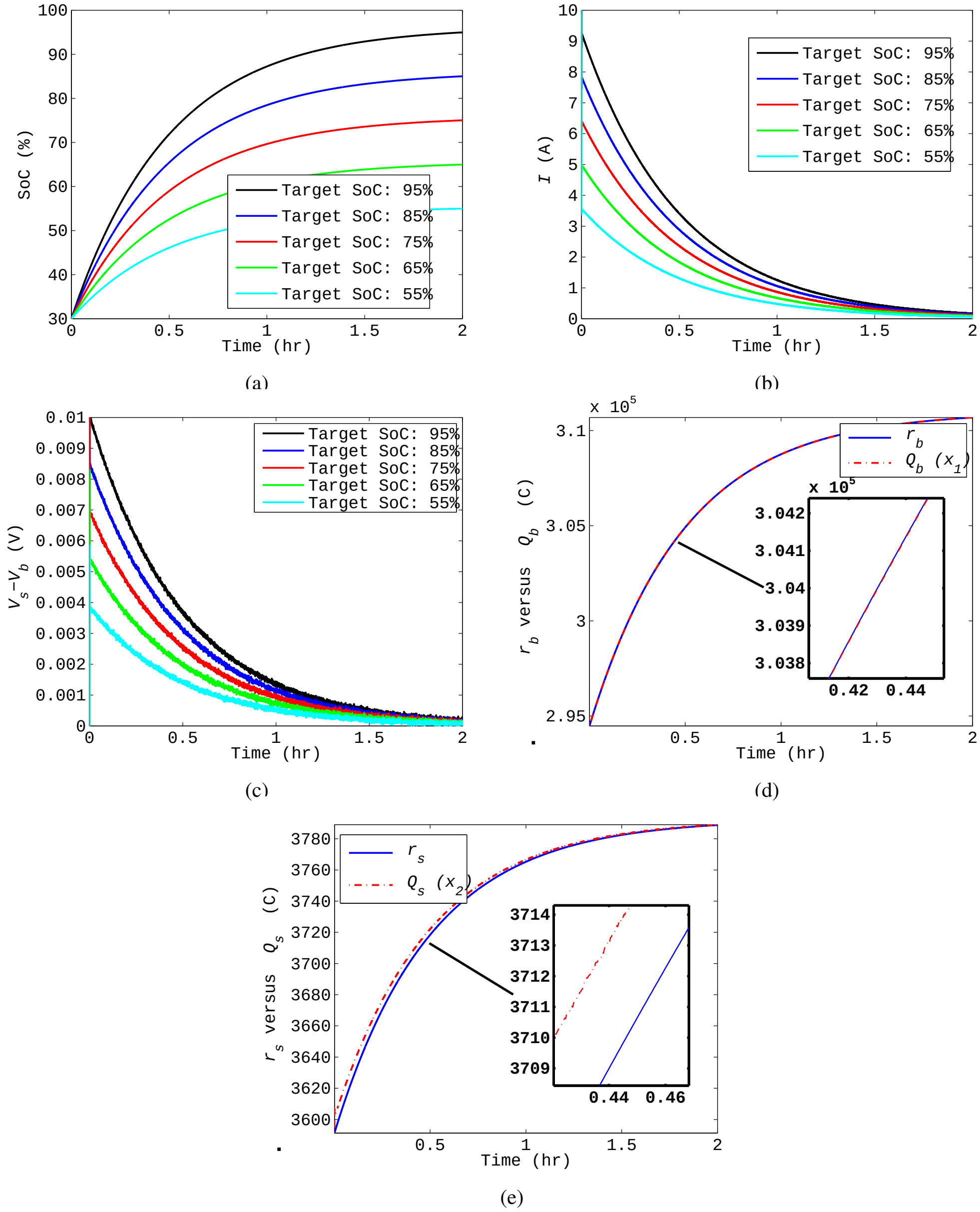

FIGURE 4: Example 2 - Application of `LQT` to charge the battery from 30% to 55%, 65%, 75%, 85% and 95%: (a) the SoC trajectories; (b) the charging current profiles; (c) the voltage differences; (d) tracking of x_1 (i.e., Q_b) for 95% target SoC; (e) tracking of x_2 (i.e., Q_s) for 95% target SoC.

the value of the proposed charging strategies. Further experimental evaluation and validation of the strategies will be pursued in our future work.

5 Conclusions

Effective battery charging management is of vital importance for the development of EVs, though it has not received attention deserved. In recent years, fast charging control has gained some interest. However, the problem of health-aware and user-involved charging has not been explored in the literature. In this paper, we propose a set of novel charging strategies, which aim to accomplish user-defined charging objectives with awareness of the harms to health. They are developed in the framework of linear quadratic control. Compared with most existing fast charging techniques, they do not require the time-consuming real-time optimization. The usefulness of the proposed strategies is evaluated via a simulation study. This work can also find uses in consumer electronics and other applicaitons and will provide further incentives for the study of intelligent charging management.

REFERENCES

[1] Rahn, C. D., and Wang, C.-Y., 2013. *Battery Systems Engineering*. Wiley.

[2] Young, K., Wang, C., Wang, L., and Strunz, K., 2012. "Electric vehicle battery technologies". In *Electric Vehicle Integration into Modern Power Networks*, R. Garcia-Valle and J. P. Lopes, eds. Springer.

[3] Hatzell, K., Sharma, A., and Fathy, H., 2012. "A survey of long-term health modeling, estimation, and control of lithium-ion batteries: Challenges and opportunities". In Proceedings of American Control Conference, pp. 584–591.

[4] Moura, S., Chaturvedi, N., and Krstic, M., 2013. "Adaptive partial differential equation observer for battery state-of-charge/state-of-health estimation via an electrochemical model". pp. 566–571.

[5] Smith, K., Rahn, C., and Wang, C.-Y., 2010. "Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries". *IEEE Transactions on Control Systems Technology,* ***18***(3), pp. 654–663.

[6] Lin, X., Perez, H., Siegel, J., Stefanopoulou, A., Li, Y., Anderson, R., Ding, Y., and Castanier, M., 2013. "Online parameterization of lumped thermal dynamics in cylindrical lithium ion batteries for core temperature estimation and health monitoring". *IEEE Transactions on Control Systems Technology,* ***21***(5), pp. 1745–1755.

[7] Wang, Y., Fang, H., Sahinoglu, Z., Wada, T., and Hara, S., 2015. "Adaptive estimation of the state of charge for lithium-ion batteries: Nonlinear geometric observer approach". *IEEE Transactions on Control Systems Technology,* ***23***(3), pp. 948–962.

[8] Suthar, B., Ramadesigan, V., De, S., Braatz, R. D., and Subramanian, V. R., 2013. "Optimal charging profiles for mechanically constrained lithium-ion batteries". *Physical Chemistry Chemical Physics,* ***16***(1), pp. 277–287.

[9] Spotnitz, R., 2003. "Simulation of capacity fade in lithium-ion batteries". *Journal of Power Sources,* ***113***(1), pp. 72 – 80.

[10] Bergveld, H., Kruijt, W., and Notten, P., 2002. *Battery Management Systems: Design by Modeling*. Springer.

[11] Klein, R., Chaturvedi, N., Christensen, J., Ahmed, J., Findeisen, R., and Kojic, A., 2011. "Optimal charging strategies in lithium-ion battery". In Proceedings of American Control Conference, pp. 382–387.

[12] Yan, J., Xu, G., Qian, H., and Song, Z., 2011. "Model predictive control-based fast charging for vehicular batteries". *Energies*, pp. 1178–1196.

[13] Moura, S., Chauturvedi, N., , and Krstic, M., 2013. "Constraint management in li-ion batteries: A modified reference governor approach". In Proceedings of American Control Conference, pp. 5332–5337.

[14] Perez, H., Shahmohammadhamedani, N., and Moura, S., 2015. "Enhanced performance of li-ion batteries via modified reference governors and electrochemical models". *IEEE/ASME Transactions on Mechatronics*, p. to appear.

[15] Wai, R., and Jhung, S., 2012. "Design of energy-saving adaptive fast-charging control strategy for Li-Fe-PO4 battery module". *IET Power Electronics,* ***5***(9), pp. 1684–1693.

[16] Bashash, S., Moura, S. J., Forman, J. C., and Fathy, H. K., 2011. "Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity". *Journal of Power Sources,* ***196***(1), pp. 541–549.

[17] Hoke, A., Brissette, A., Maksimovic, D., Pratt, A., and Smith, K., 2011. "Electric vehicle charge optimization including effects of lithium-ion battery degradation". In Proceedings of IEEE Vehicle Power and Propulsion Conference, pp. 1–8.

[18] Hoke, A., Brissette, A., Maksimovic, D., Kelly, D., Pratt, A., and Boundy, D., 2013. "Maximizing lithium ion vehicle battery life through optimized partial charging". In Proceedings of IEEE PES Innovative Smart Grid Technologies, pp. 1–5.

[19] Lewis, F. L., Vrabie, D. L., and Syrmos, V. L., 2012. *Optimal Control*, 3rd ed. Wiley.

[20] Duncan, T., Guo, L., and Pasik-Duncan, B., 1999. "Adaptive continuous-time linear quadratic gaussian control". *IEEE Transactions on Automatic Control,* ***44***(9), pp. 1653–1662.

[21] Duncan, T., 2013. "Linear-exponential-quadratic gaussian control". *IEEE Transactions on Automatic Control,* ***58***(11), pp. 2910–2911.

[22] Lee, J. H., Lee, K. S., and Kim, W. C., 2000. "Model-based iterative learning control with a quadratic criterion for time-varying linear systems". *Automatica,* ***36***(5), pp. 641 – 657.

[23] Johnson, V. H., Pesaran, A. A., and Sack, T., 2000. "Temperature-dependent battery models for high-power lithium-ion batteries". In Proceedings of 17th Electric Vehicle Symposium.

[24] Johnson, V. H., 2002. "Battery performance models in ADVISOR". *Journal of Power Sources,* ***110***(2), pp. 321–329.

[25] Sitterly, M., Wang, L. Y., Yin, G., and Wang, C., 2011. "Enhanced identification of battery models for real-time battery management". *IEEE Transactions on Sustainable Energy,* ***2***(3), pp. 300–308.

[26] Pinsona, M. B., and Bazant, M. Z., 2013. "Theory of SEI formation in rechargeable batteries: Capacity fade, acceler-

ated aging and lifetime prediction". *Journal of the Electrochemical Society,* ***160***(2), pp. A243–A250.

[27] Woodford IV, W. H., 2013. "Electrochemical shock: Mechanical degradation of ion-intercalation materials". PhD thesis, Massachusetts Institute of Technology.

[28] Bandhauera, T. M., Garimellaa, S., and Fullerb, T. F., 2011. "A critical review of thermal issues in lithium-ion batteries". *Journal of the Electrochemical Society,* ***158***(3), pp. R1–R25.

[29] Bryson, Jr., A. E., and Yu-Chi Ho, 1975. *Applied Optimal Control*. Taylor & Francis Group.

[30] Fang, H., Zhao, X., Wang, Y., Sahinoglu, Z., Wada, T., Hara, S., and de Callafon, R. A., 2014. "Improved adaptive state-of-charge estimation for batteries using a multi-model approach". *Journal of Power Sources,* ***254***, pp. 258–267.

[31] Fang, H., Wang, Y., Sahinoglu, Z., Wada, T., and Hara, S., 2014. "State of charge estimation for lithium-ion batteries: An adaptive approach". *Control Engineering Practice,* ***25***, pp. 45–54.

[32] Fang, H., Wang, Y., Sahinoglu, Z., Wada, T., and Hara, S., 2013. "Adaptive estimation of state of charge for lithium-ion batteries". In Proceedings of American Control Conference, pp. 3485–3491.

[33] Fang, H., Zhao, X., Wang, Y., Sahinoglu, Z., Wada, T., Hara, S., and de Callafon, R., 2014. "State-of-charge estimation for batteries: A multi-model approach". In Proceedings of American Control Conference, pp. 2779–2785.