Journal of Power Sources 196 (2011) 10297–10304

Contents lists available at ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Optimal charge rates for a lithium ion cell

Saeed Khaleghi Rahimian, Sean Rayman, Ralph E. White*

Department of Chemical Engineering, University of South Carolina, Columbia, SC 29208, USA

ARTICLE INFO

Article history:
Received 4 March 2011
Received in revised form 5 July 2011
Accepted 6 July 2011
Available online 18 July 2011

Keywords:
Lithium-ion cell
Cell life
Optimal charge rates

ABSTRACT

The optimum charge rate for a lithium ion cell at each cycle is determined to maximize the useful life of the cell without using optimization algorithms. In previous work, we showed that by applying a dynamic optimization routine the number of cycles can be increased by approximately 29.4% with respect to the case with one optimal charge current [7]. The dynamic optimization results indicated that the optimum charge rates are the minimum currents at which the constraints for the useful life are satisfied. This is due to the minimum charge rate resulting in minimum side reaction rate and capacity fade. Useful cell life is defined as the number of cycles before the end of discharge voltage (EODV) drops below 3.0 V or the cell discharge capacity becomes less than 20% of the original discharge capacity. The new approach presented in this work is able to find the optimal charge rates in a few minutes while the previous optimization algorithm takes at least one day, and improves the useful cell life by approximately 41.6% with respect to using only one optimal charge current.

1. Introduction

Finding the optimal charge rates to maximize useful life of Li-ion cells is an important issue. The capacity of the Li-ion batteries decreases with the number of charge–discharge cycles due to undesirable side reactions. Since these batteries are used for tens to thousands cycles, depending on application, there is a demand to seek the best operating conditions to improve the cycling performance to minimize the capacity fade, and thereby increasing cell life. Some work has studied the effect of cycling conditions such as the end of charge voltage (EOCV), depth of discharge (DOD) and charging rate on capacity fade and cell life [1–3]. However, only a few studies have attempted to optimize the charge rates for battery longevity using optimization or heuristic algorithms. Methekar et al. applied the sequential dynamic optimization to find the optimal profile of charging current for a Li-ion battery [4]. They showed that if the battery is charged using the optimum profile estimated by dynamic optimization, more energy can be stored as compared with conventional charging protocol. In a similar work, Wang applied Optimal Control Theory techniques to maximize the efficiency of the battery charging process which is defined as the ratio of the energy accumulated in the battery over the actual energy supplied it [5]. However, these studies did not deal with the useful cell life. Recently, Bashash et al. used multiobjective genetic algorithm to obtain the charge pattern of a plug-in hybrid electric vehicle to simultaneously minimize the total cost of fuel and electricity and the battery life degradation. The results showed that the two objectives are conflicting and as a result a Pareto front of optimal charge patterns was formed [6].

We recently published a paper [7] in which the useful life of a lithium ion cell was maximized by optimization of charge currents, as a function of cycle number during cycling. The maximum number of charge rates used was twenty currents that were equally spaced in cycle numbers that improved the cell life by ~30% with respect to the case with single charge rate used. To obtain the optimal currents, Matlab's Genetic Algorithm and Direct Search Toolbox was used to solve the NLP (Nonlinear Programming) resulting from the sequential dynamic optimization method. Choosing twenty rates, the optimization needs to evaluate the objective function (number of cycles) more than 80,000 times and if the objective function evaluation takes only 1 s, at the best condition, it will take about one day to find the optimal profile. Moreover, only twenty optimal charge rates (the optimization was stopped at twenty decision variables because there was no enhancement of the objective function with respect to the case with ten decision variables) were found where each of them is applied for a number of cycles (the total number of cycles divided by twenty). Thus, it is not possible to find the optimal charge current at each cycle, unless the number of decision variables (charge rates) for optimization reaches the number of cycles. In this paper a new approach, shown in Fig. 1, is presented to find the best charge rate at each cycle that improves the useful life 10% more than the dynamic optimization in much less computation time.

* Corresponding author. Tel.: +1 803 777 3270; fax: +1 803 777 0973.
E-mail address: white@cec.sc.edu (R.E. White).

0378-7753/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2011.07.019

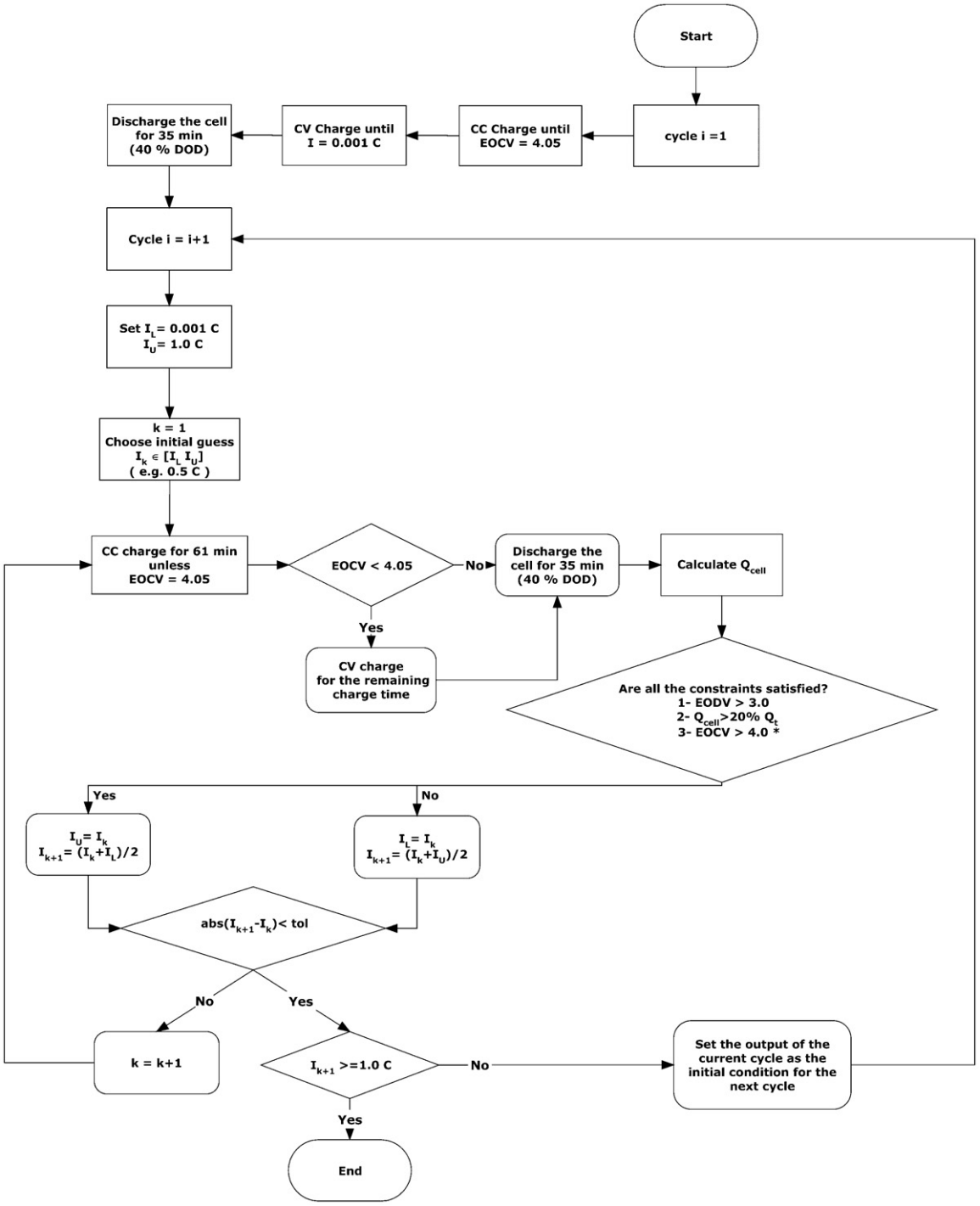

Fig. 1. The new approach flowchart (please refer to Section 4 for explanation).

2. Lithium-ion cell simulation

A single particle (SP) physics based model, which includes capacity fade, was applied to simulate the cell performance under low-earth-orbit (LEO) cycling conditions [7]. The main assumptions associated with the SP model are as follows:

- The concentration of the electrolyte and the potential in the solution phase is constant and uniform for all time across the cell sandwich (cathode, separator, anode).
- Positive and negative electrode potentials depend on time only.
- The model considers the capacity fade by a continuous occurrence of a side reaction (reduction of ethylene carbonate) only during the charge near the surface of the negative electrode. Moreover, the state of the charge (SOC) of the positive electrode is diminished during cycling.
- The concentration of Li ions in the spherical particle is estimated using a two term polynomial approximation.

The mathematical formulation of the SP model is briefly restated here. More details can be found in our previous work [7]. A volume

Nomenclature

c_e	electrolyte concentration (mol cm^{-3})
$c_{i,\max}$	maximum solid phase for each electrode ($i = p,n$) (mol cm^{-3})
$D_{s,i}$	solid phase diffusion coefficient of Li^+ for each electrode ($i = p, n$) (cm^2 s^{-1})
F	Faraday's constant (C mol^{-1})
I	current (C-rate)
I_{app}	applied current (A)
I_L	minimum allowed rate (C-rate)
I_U	maximum allowed rate (C-rate)
i_{0f}	exchange current density for the film formation reaction (A cm^{-2})
J_i	the current density to each electrode ($i = p$, n) (A cm^{-2})
J_s	side reaction rate (A cm^{-2})
k_f	film specific conductivity (S cm^{-1})
k_i	rate constant for each electrode ($i = p$, n) (A cm$^{2.5}$ mol$^{-1.5}$)
M_f	molecular weight of film (g mol^{-1})
N_{cycle}	total number of cycles
Q_0	initial cell capacity (Ah)
Q_{dis}	discharge capacity (Ah)
$Q_{\max}$	maximum capacity of the cell (Ah)
Q_{cell}	cell capacity at each cycle (Ah)
Q_p	charge capacity (Ah)
Q_S	capacity loss (Ah)
Q_t	total original discharge capacity (Ah)
R	gas constant (J mol^{-1} K^{-1})
R_{film}	film resistance (Ω cm^2)
R_i	particle radius for each electrode ($i = p$, n) (cm)
R_{SEI}	resistance of the Solid Electrolyte Interphase layer (Ω cm^2)
S_i	electroactive surface area for each electrode ($i = p, n$) (cm^2)
T	temperature (K)
tol	specific tolerance (e.g. = 1e−6)
U_i^θ	open circuit potentials for each electrode ($i = p$, n) (V)
$U_{ref,f}$	open circuit potential for film formation reaction (V)
$x_{i,avg}$	ratio of the solid average concentration to the maximum solid concentration for each electrode ($i = p$, n)
$x_{i,surf}$	ratio of the solid surface concentration to the maximum solid concentration for each electrode ($i = p$, n)
$\alpha_{a,i}$	cathodic transfer coefficient
$\alpha_{c,i}$	anodic transfer coefficient
$\alpha_{c,f}$	cathodic transfer coefficient for the film formation reaction
δ_{film}	film thickness (cm)
η_i	overpotentials for the lithium ion intercalation reaction for each electrode ($i = p$, n) (V)
η_s	side reaction over potential (V)
θ_1	loss of SOC
ρ_f	film density (g cm^{-3})
ϕ_i	potential for each electrode ($i = p$, n) (V)

average technique is applied to predict the diffusion of the lithium ions for the cathode ($LiCoO_2$ with no Ni) and the carbon anode:

$$\frac{dx_{p,avg}}{dt} = \frac{-3J_p}{FR_p c_{p,\max}}$$

$$x_{p,surf} - x_{p,avg} = \frac{-J_p R_p}{5FD_{s,p} c_{p,\max}}$$

$$J_p = \frac{I_{app}}{S_p}$$

$$\frac{dx_{n,avg}}{dt} = \frac{-3J_n}{FR_n c_{n,\max}}$$

$$x_{n,surf} - x_{n,avg} = \frac{-J_n R_n}{5FD_{s,n} c_{n,\max}}$$

$$J_n = \frac{-I_{app}}{S_n} - J_s$$

where $x_{i,avg}$ is the ratio of the solid average concentration to the maximum solid concentration for each electrode ($c_{i,max}$), $x_{i,surf}$ is the ratio of the solid surface concentration to the maximum solid concentration. J_s, the side reaction rate is calculated by using Tafel kinetics:

$$\begin{cases} J_s = -i_{0f} \exp\left(\dfrac{-\alpha_{c,f} F}{RT}\eta_s\right) & \text{[charge]} \\ J_s = 0 \quad \text{[discharge]} \end{cases}$$

$$\eta_s = \phi_n - U_{ref,f} - \frac{I_{app}}{S_n} R_{film}$$

R_{film} is defined as:

$$R_{film} = R_{SEI} + \frac{\delta_{film}}{k_f}$$

and the rate at which the film thickness increases is calculated by:

$$\frac{d\delta_{film}}{dt} = \frac{-J_s M_f}{\rho_f F}$$

The Butler–Volmer kinetic expression is used to predict the rates of the lithium ion deintercalation and intercalation reactions for each electrode:

$$J_i = k_i (c_{i,\max} - x_{i,surf} c_{i,\max})^{0.5} (x_{i,surf} c_{i,\max})^{0.5} c_e^{0.5} \times \left[\exp\left(\frac{\alpha_{a,i} F}{RT}\eta_i\right) - \exp\left(\frac{-\alpha_{c,i} F}{RT}\eta_i\right)\right]$$

The overpotentials for the lithium ion intercalation reaction for the anode and cathode are given as:

$$\eta_p = \phi_p - U_p^\theta$$

$$\eta_n = \phi_n - U_n^\theta \mp \frac{I_{app}}{S_n} R_{film} \left(\begin{Bmatrix} -\text{charge} \\ +\text{discharge} \end{Bmatrix}\right)$$

The SOC of the positive electrode updated at the end of each charging process as follows:

$$\theta_{p,N} = \theta_{p,N-1} - \theta_{1,N-1}$$

where θ_1 is the loss of SOC obtained by dividing the capacity loss to the maximum capacity of the cell (subscript $N-1$ indicates the previous cycle):

$$\theta_1 = \frac{Q_S}{Q_{\max}}$$

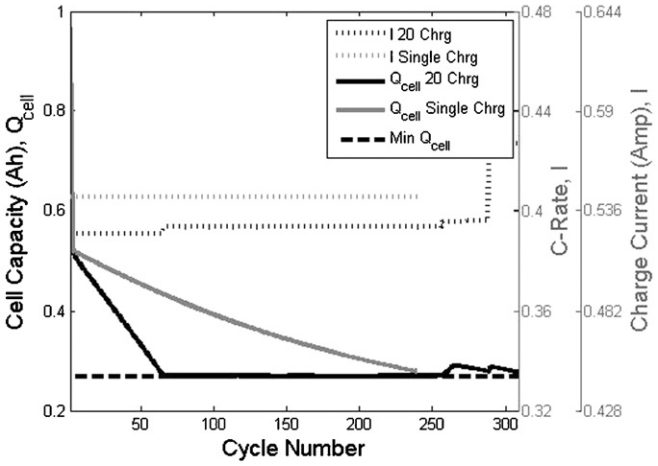

Fig. 2. Remaining cell capacity at the end of discharge versus cycle number for single and 20 charge currents [7].

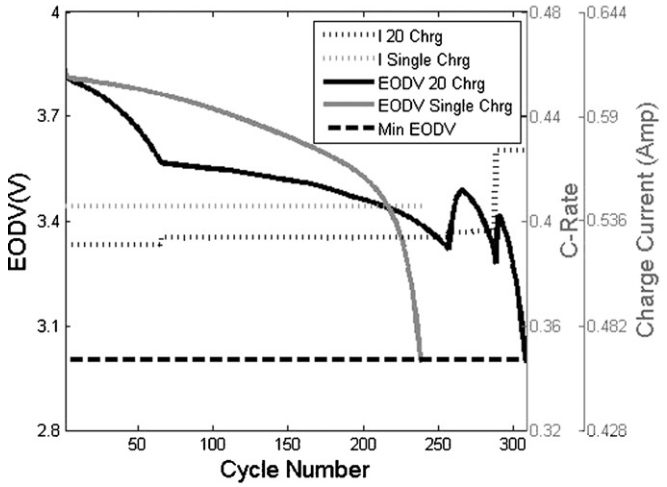

Fig. 3. EODV versus cycle number for single charge and 20 charge currents [7].

$$Q_s = -\int_0^{t=\text{charge time}} (J_s S_n)dt$$

$$Q_{\max} = \int_0^{t=\text{charge time}} I_{app}dt \quad \text{(first cycle)}$$

The cell capacity at each cycle is obtained as follows:

$$Q_{Cell} = Q_0 + \sum_{i=2}^{N_{cycle}} (Q_p(i) - Q_{dis}(i))$$

where Q_0, Q_p and Q_{dis} are the initial cell capacity, the charge capacity and discharge capacity, respectively.

LEO cycling [3], which contains the following steps, was applied for the cell simulation after the cell is completely charged initially:

(1) Constant current discharge (0.6857 C-rate (40% DOD)) for 35 min discharge time. Unless the voltage drops below 3.0 V or the cell capacity reaches the 20% of the total discharge capacity, go to step 2.
(2) Constant current charging (up to 1 C rate) for 61 min charge time. If the voltage reaches the EOCV (4.05 V), go to step 3, if not go to step 1.
(3) Constant voltage (4.05 V) charging for the remaining charge time, go to step 1.

3. Dynamic optimization results

To apply the dynamic optimization, the number of cycles obtained for one optimal charge rate is rounded up to 320 [7]. Then a constant charge rate was used for each subdomain which is obtained by dividing the assumed total number of cycles (320) by N equally spaced cycle number. MATLAB® Genetic Algorithm and Direct Search Toolbox [8] were used to find the optimal charge rates as follows. First, direct search approach was applied to increase the objective function rapidly. Then the resulting point was considered as one of the children for the initial population in the genetic algorithm. If the objective function was improved by the genetic, the procedure is repeated; otherwise the optimization algorithm stops [7].

To compare the results of the dynamic optimization and the new method, the best profile obtained by the optimization using single charge rate and twenty charge rates are presented in this work as well as [7]. Figs. 2–4 show the variation of the cell capacity, the end of charge voltage (EODV) and the end of discharge voltage (EOCV) respectively as a function of cycle number for single and twenty charge rates. Because the optimal charge rate during cycling for the case with twenty currents (black dotted line) is below the optimum single (gray dotted line), the cell capacity for twenty charge rates (black solid line) decreases more rapidly than the cell capacity for single charge rate until it reaches the minimum allowed cell capacity (dashed line) at cycle 60, as shown in Fig. 2. As a result next rate is increased as to not violate the capacity constraint. However, the new rate is still below the optimal single rate up to cycle 260 to reduce the side reaction rate and capacity fade and consequently to enhance the useful cell life. After cycle 260, the capacity constraint makes the charge rate increase above the optimal single rate and finally the EODV constrain determines the number of cycles, as presented in Fig. 3. While the EOCV is constant at 4.05 V for the case with single rate, the EOCV for the case with twenty rates decreases gradually to 3.985 V during the first 60 cycle and after that increases to 4.046 V up to cycle 260 and finally becomes constant at 4.05 V for the remaining cycles, as shown in Fig. 4. The EOCV variation during cycling can be described that no constraints were used in the optimization algorithm to keep the EOCV constant and the low charge rates causes the EOCV decreases. The total number of cycles obtained by using single charge current is 238 and the optimum current is 0.4055 C-rate. Using twenty charge currents increases

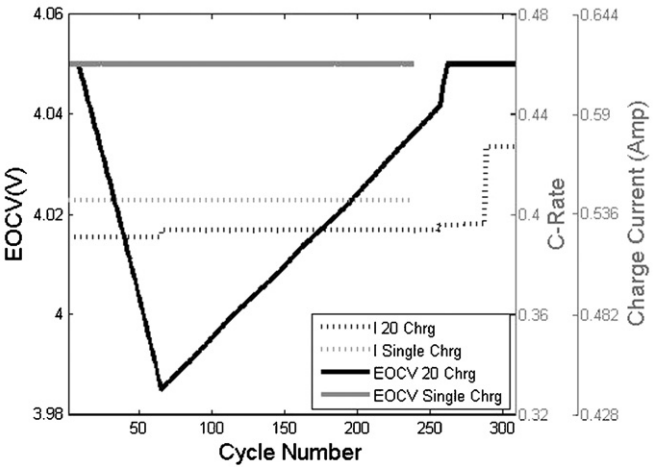

Fig. 4. EOCV versus cycle number for single charge and 20 charge currents [7].

the number of cycles to 309, 29.4% increase with respect to one optimum current.

4. New approach

The optimization results from prior work [7] indicate that the best charge current is the minimum rate at which, the cell capacity constraint (>20% of the total discharge capacity) and the EODV constraint (>3.0) are not violated. Thus, finding the optimal charge rate at each cycle by seeking a charge current where the cell capacity and the EODV constraints are not violated without using any optimization algorithm appears to be possible. The new proposed procedure, shown in Fig. 1, is as follows (the cell is initially fully charged):

(1) Discharge the cell for 35 min with 40% depth of discharge (DOD).
(2) Set the minimum rate at 0.001 C-rate and the maximum rate at 1.0 C-rate
(3) Choose an initial guess for the charge rate between the minimum (e.g. 0.001 C-rate) and maximum (e.g. 1.0 C-rate) allowed rates (e.g.0.5 C-rate)
(4) Constant Current Charge for 61 min. If the EOCV reaches 4.05 V go to step 5, otherwise go to step 6.
(5) Constant Voltage Charge for the remaining charge time.
(6) Discharge the cell for 35 min with 40% DOD and calculate the cell capacity and the EODV.
(7) If one of the constraints is violated, set the minimum rate as the current charge rate and the next current as the half of the sum of current rate and the maximum rate. Otherwise, set the maximum rate as the current rate and the next current as half of the sum of the current rate and the minimum rate.
(8) Repeat steps 4–7 until the difference between the current rate and the minimum rate or maximum rate becomes less than a specific tolerance (e.g., tol = 1e−6).
(9) Set all the dependent variables (e.g. the solid average concentrations, the solid surface concentration, electrode potentials, etc.) of the current cycle as the initial condition for the next cycle.
(10) Repeat steps 2–9 until the charge rate reaches the maximum rate.

5. Results and discussion

It is worthwhile to show how the cell capacity and the EODV vary with the charge rate for the first and the second cycle. Fig. 5 presents the cell capacity and the EODV as a function of the charge rate for the first and second cycle. The results in Fig. 5 indicate the cell capacity and the EODV at the minimum rate are 0.435 Ah and 3.762 V, respectively, which are greater than their minimum allowed values (minimum capacity = 0.268 Ah, minimum EODV = 3.0 V). Thus, the new approach gives the minimum charge rate as the best rate for the first cycle. For second cycle, choosing the minimum rate violates the cell capacity constraint, consequently it is necessary to increase the charge current. The minimum rate at which the cell capacity is greater than the minimum allowed cell capacity obtained by the optimization method is 0.272 C-rate. By following the above procedure, the optimal charge rate profile is obtained during the cycling. The optimal charge rate and the cell capacity as a function of the cycle number obtained by the new approach that improves the number of cycles to 337, 41.6% increase with respect to one optimal charge rate, shown in Fig. 6. Variation of the EODV and the EOCV with the cycle number is presented in Fig. 7. During the cycles 2–310 the cell capacity constraint determines the optimal value of the charge rate. However, since the EODV would drop below

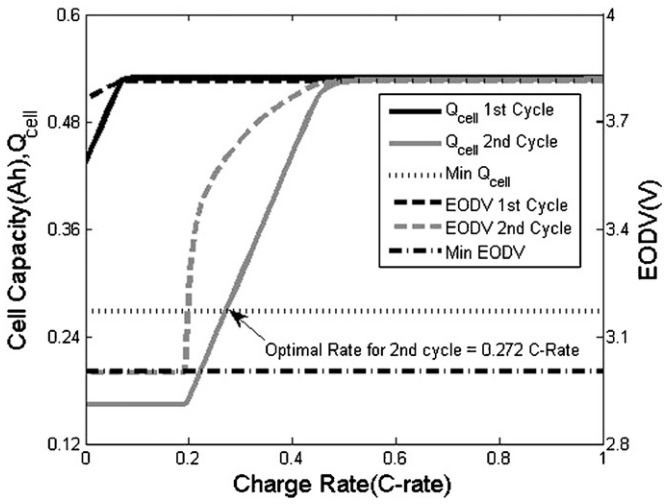

Fig. 5. Remaining cell capacity at the end of discharge and EODV versus charge rate for the first and second cycles.

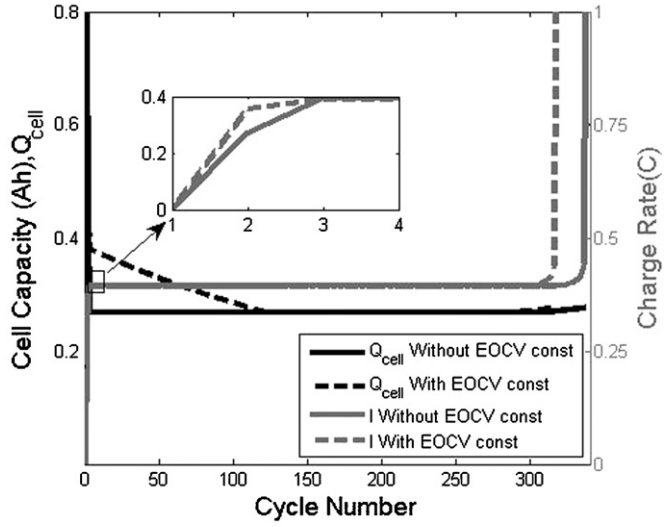

Fig. 6. Remaining cell capacity at the end of discharge and charge rate versus cycle number obtained by new approach with and without EOCV constraint.

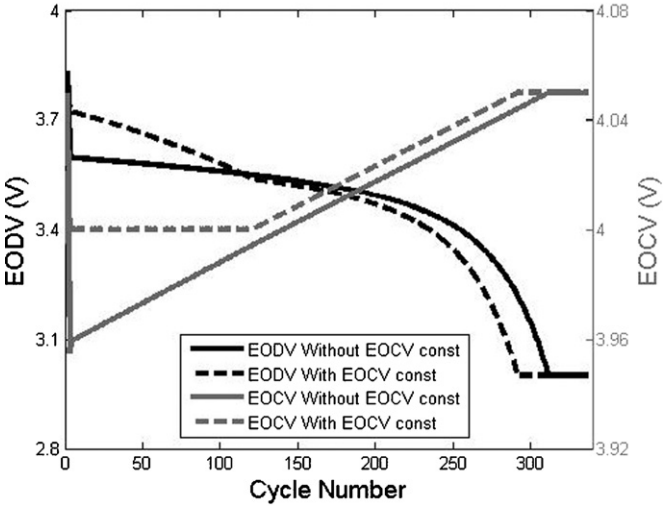

Fig. 7. EODV (black) and EOCV (gray) versus cycle number obtained by new approach with and without EOCV constraint.

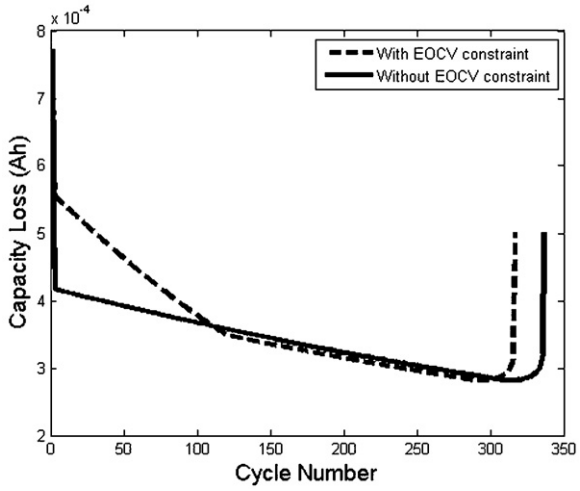

Fig. 8. Cell capacity loss during charge versus cycle number by new approach with and without EOCV constraint.

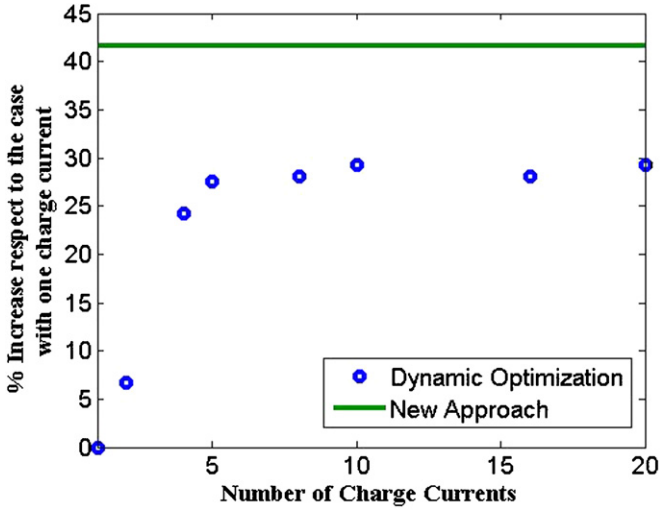

Fig. 9. %Increase in number of cycles respect to the case with one charge current.

its minimum allowed value if the same current at cycle 310 was applied for the next cycle, the charge rate increases to satisfy the EODV constraint. The increase in current continues until the current reaches the upper bound value (1 C-rate) which results in growth of the reserved cell capacity after cycle 310 until the cell dies as illustrated in Fig. 6. Since no constraint was used to keep the EOCV constant during cycling, the voltage dropped below 4.05 V at the end of charge as indicated in Fig. 7. However, the EOCV constraint can be included in the algorithm without any difficulties. Adding the constraint that keeps the EOCV greater than 4.0 V (*constraint in Fig. 1), decreases the number of cycles to 317, a 33.2% increase with respect to one optimal charge rate. This is due to increase in charge rate in some cycles to not allow the EOCV dropping below the constraint. In this case the number of cycles is still greater than the dynamic optimization result while in dynamic optimization the EOCV drops below 4.0 V as observed in Fig. 4. The optimal charge rate and the cell capacity for this case are depicted in Fig. 6 while the EODV and the EOCV are shown in Fig. 7. As can be seen, between cycles two and 120 the charge rate is determined by the EOCV constraint and between cycles 121 and 291 by the capacity constraint. For the remaining cycles, the EODV dictates the optimal value of the charge current. Fig. 6 also indicates that the charge rate for the case with EOCV constraint is much greater (0.1133 C-rate) at cycle 2 and less (0.0004 C-rate in average) than the charge rate for the case with no EOCV constraint for the next 289 cycles. This causes more capacity loss for the case with EOCV constraint as shown in Fig. 8.

The computation time for the new approach is 228 s on a Dell Precision T7500, with 2 Quad Core 2.53 GHz Zenon Processors CPUs and 12.285 GB of RAM, the same machine used in our previous work.

The percent increase in number of cycles with respect to the case with one charge current for dynamic optimization using different number of charge rates and the new approach is shown in Fig. 9. Note that improvement of the objective function is not a monotonic function of the number of charge currents. A monotonic increase in the number of cycles would occur if the number of cycles were divided by the same initial number (e.g. 2, 4, 8,. . . or 5, 10, 20,. . .).

In the previous work [7] the exchange current density was set to 1.0e−10 A cm^{-2} to exaggerate the side reaction rate to decrease the cell life and their computation time by reducing the number of cycles that must be simulated to achieve end of life. To compare the new approach with the dynamic optimization for more practical condition, the previous Li-ion cell model was applied with the exchange current density for the film formation reaction equal to 2.5e−12 A cm^{-2} [3]. Variation of the number of cycles with one charge rate is shown in Fig. 10 which indicates the number of cycles reaches to 16,122 cycles at the best charge rate, 0.4 C-rate. Fig. 10 also shows the stiffness of the objective function near the optimal point that restricts the use of deterministic (gradient based) optimization routines. This is the reason nondeterministic methods including the genetic and the pattern search algorithms were applied in prior work [7]. However, the computation time for these methods is much greater than the deterministic optimization routines. The new approach, presented in this paper, deals with the computation time difficulties while improving the objective function (cell useful life) more than the previous optimization method.

To compare the computation time, the dynamic optimization was applied to obtain the optimum single charge current by using 0.5 C-rate as the initial point for the pattern search algorithm that converged to the optimum point in 25 iterations. MATLAB® Parallel Computing Toolbox was applied every iteration to evaluate the objective function twice simultaneously except for the first iteration where only one evaluation was performed. Then, the genetic algorithm used the pattern search result as one of the 20 children for the initial population. At each generation six objective function evaluations were done simultaneously using the Parallel Computing Toolbox. Since the genetic algorithm was not able to improve the objective function after the stall generations limit (was set 20),

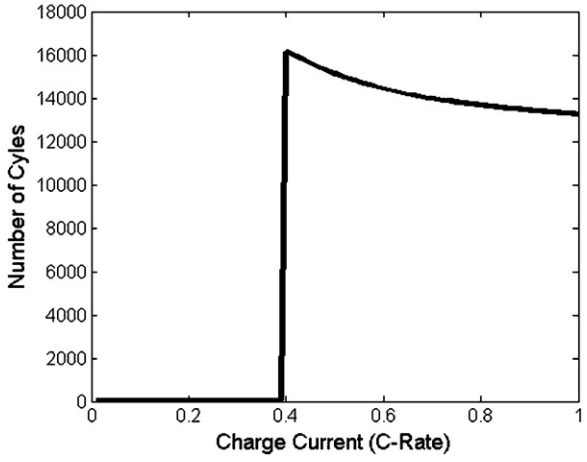

Fig. 10. Variation of the number of cycles with one charge rate for the practical case.

Table 1
Comparison between the new approach and the dynamic optimization for the practical case.

Method	Number of cycles	%Increase[a]	Number of CPU cores used	Computation time (h)	Computation time per one CPU core (h)
Dynamic optimization ($N=1$)	16,122	0	6	43.66	217.13
Dynamic optimization ($N=2$)	16,631	3.16	6	81.58	444.63
Dynamic optimization ($N=4$)	17,839	10.65	6	419.68	2512.4
New approach	20,027	24.22	1	7.26	7.26

[a] In number of cycles with respect to the case with one charge current.

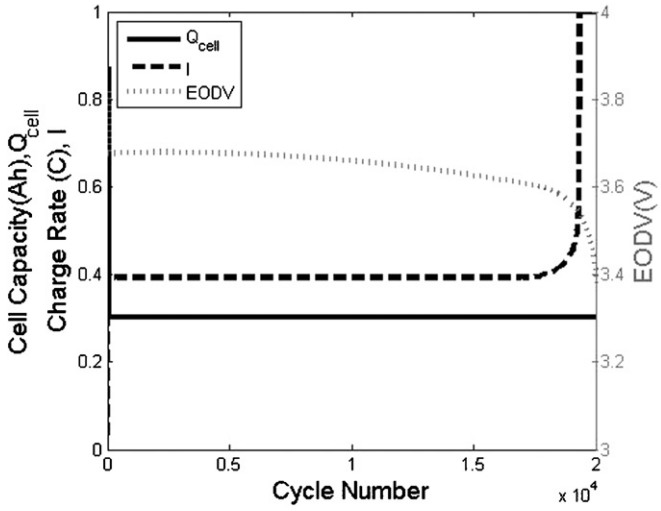

Fig. 11. Remaining cell capacity at the end of discharge, charge rate and EODV versus cycle number obtained by new approach for the practical case.

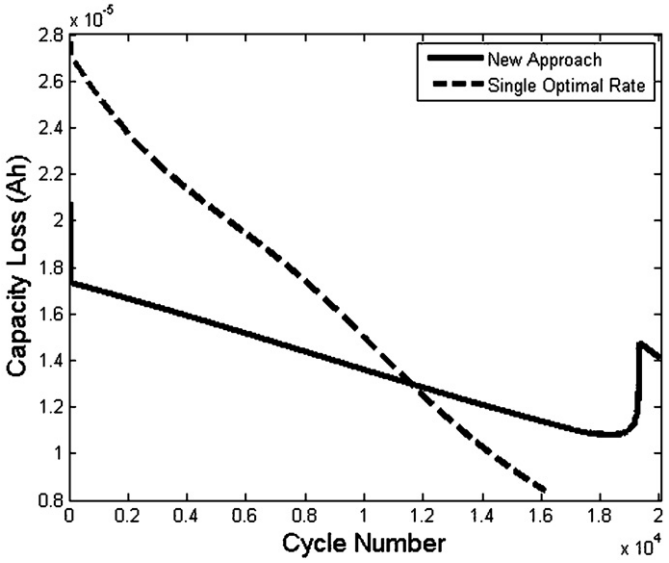

Fig. 12. Cell capacity loss during charge versus cycle number using single optimal charge rate and new approach for the practical case.

the optimization algorithm stopped. The total computation time for finding the best single charge rate took about 43.66 h (approximately 217.13 h if the PC had run only one CPU core). The dynamic optimization algorithm was also used to obtain the two and four optimal charge rates and the results are presented in Table 1.

Finally, the new approach was also used to predict the optimum charge rate during cycling for the practical case. Fig. 11 presents the cell capacity, the charge rate and the EODV versus cycle number obtained by the new method. The results shown in Fig. 11 indicate that the new approach improved the number of cycles to 20,027, a 24.22% increase with respect to the case with single optimum charge rate. Fig. 11 also indicates that the optimal charge current is only determined by the cell capacity constraint and the EODV never reaches to the minimum value at 3.0 V. To illustrate how the new approach improves the cell useful life with respect to the case with single optimal charge rate, the cell capacity loss during charge (the model assumes no capacity loss during discharge) as a function of cycle number is shown in Fig. 12. As can be seen, the capacity loss for the single optimal rate is more than the new approach capacity loss up to cycle 11,615, about 72% of the total number of cycles for the single rate, that makes the cell dies more rapidly.

The computation time was about 7.26 h, about 17% of the time required for dynamic optimization, where only one CPU core was involved. Table 1 compares the new approach improvement and the computation time with respect to the dynamic optimization.

The advantages of the new method with respect to the dynamic optimization algorithm [7] are as follows:

(1) The new method finds the optimal charge rate at each cycle; while the optimization seeks the best charge current for certain number of cycles (total number of cycles divided by number of decision variables). Thus, the useful life of the cell is improved more than the optimization by this method (more than 10%).
(2) The computation time is greatly reduced by this approach. It takes a few hours while the optimization algorithm with 4 number of charge rates takes more than 15 days, Table 1. Also there is no guarantee that the optimization finds the global optimum.
(3) To use the optimization algorithm for online applications, it is required to predict the entire useful cell life based on prior cycling data. The new method only requires the prediction of the next cycle by using prior cycling data. Thus, the result of the new approach depends only on the next cycle prediction while the optimization results rely on the cell life prediction.
(4) The number of decision variable in the new method is one (current cycle charge rate) and the constraints are evaluated for one cycle. While the number of decision variables in the optimization algorithm can be much greater and the objective function and constrains are evaluated for the total cell life.
(5) The new approach gives the global optimum of the optimization method when the number of decision variables limits to the number of cycles. To verify this claim, the optimal charge rates attained by the new technique are set as the initial guess for the dynamic optimization. The optimization algorithm was not able to improve the cell useful life after approximately one million function evaluations; as a result the new approach charge currents are likely the optimal profile.
(6) The new approach allows us for use of more any rigorous models (e.g. Pseudo two dimensional [9]) for on-line applications without prohibitively the computation time to find the best charge rates.

Although the new approach in this work was used to find the optimal charge current for a lithium ion cell with LEO cycling, it can be applied for other battery design, cycling protocol, lithium ion chemistries, rechargeable batteries, etc. The proposed algorithm

assumes that the capacity fade, the cell capacity and the EODV increase as the charge rate increases. Thus the optimal charge current is the minimum rate at which the capacity fade is minimized while the cell capacity and EODV constraints are met.

6. Conclusion

A new approach was developed to provide the optimal charge rates to maximize the useful life of a Lithium-ion cell without using optimization framework. The best charge current is determined as the minimum rate where all the cell life constraints are satisfied. During the useful cell life the cell capacity and the EODV are required to be greater than their minimum allowed values. The cell capacity and the EODV are both a monotonic ascending function of the charge current; as a result the optimal charge current can be obtained by some iterations of the charge–discharge processes for each cycle. The new method improves the predicted cell life in a few minutes by ∼42% with respect to the case when only one optimal charge rate is used during the useful life, while the dynamic optimization is able to increase the predicted number of cycles by ∼30% in more than one day at best conditions. Thus, the new technique enables us to find the best charge profile in online application in reasonable computation time by using any rigorous model for the cell simulation.

Acknowledgment

This work was supported by the NRO, NRO-000-09-C0056.

References

[1] P. Ramadass, B. Haran, P.M. Gomadam, R.E. White, B.N. Popov, J. Electrochem. Soc. 151 (2) (2004) A196.
[2] G. Sikha, P. Ramadass, B. Haran, R.E. White, B.N. Popov, J. Power Sources 122 (2003) 67.
[3] J. Lee, Y.K. Anguchamy, B.N. Popov, J. Power Sources 162 (2006) 1395.
[4] R. Methekar, V. Ramadesigan, R.D. Braatz, V.R. Subramanian, ECS Trans. 25 (2010) 139.
[5] J. Wang, SAE International, 2010-01-1238.
[6] S. Bashash, S.J. Moura, J.C. Forman, H.K. Fathy, J. Power Sources 196 (2011) 541.
[7] S. Khaleghi Rahimian, S.C. Rayman, R.E. White, J. Electrochem. Soc. 152 (12) (2010) A1302–A1308.
[8] http://www.mathworks.com/.
[9] T.F. Fuller, M. Doyle, J. Newman, J. Electrochem. Soc. 141 (1) (1994) 1–10.