Journal of Power Sources 349 (2017) 94–104

Contents lists available at ScienceDirect

Journal of Power Sources

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

Simulation of lithium ion battery replacement in a battery pack for application in electric vehicles

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HIGHLIGHTS

- Simulation of cell replacement in a battery pack that is subjected to aging.
- Cell replacement can prolong the lifetime of the battery pack significantly.
- Detailed analysis of varying degradation rates on the pack state of health.
- Detailed analysis of how often the battery pack needs to be inspected.
- Simulation show similar trends for LFP and LMO battery chemistry.

ARTICLE INFO

Article history:
Received 29 November 2016
Received in revised form
19 February 2017
Accepted 1 March 2017
Available online 11 March 2017

Keywords:
Reconfigurable battery pack
Cell change out
Lithium ion
Electric vehicle
Simulation
Battery degradation

ABSTRACT

The design and optimization of the battery pack in an electric vehicle (EV) is essential for continued integration of EVs into the global market. Reconfigurable battery packs are of significant interest lately as they allow for damaged cells to be removed from the circuit, limiting their impact on the entire pack. This paper provides a simulation framework that models a battery pack and examines the effect of replacing damaged cells with new ones. The cells within the battery pack vary stochastically and the performance of the entire pack is evaluated under different conditions. The results show that by changing out cells in the battery pack, the state of health of the pack can be consistently maintained above a certain threshold value selected by the user. In situations where the cells are checked for replacement at discrete intervals, referred to as maintenance event intervals, it is found that the length of the interval is dependent on the mean time to failure of the individual cells. The simulation framework as well as the results from this paper can be utilized to better optimize lithium ion battery pack design in EVs and make long term deployment of EVs more economically feasible.

1. Introduction

The use of lithium-ion batteries (LIB) in vehicles is becoming increasingly prevalent and their market share is only projected to grow. Lithium-ion (Li-ion) batteries are considered to be the best battery choice for most applications at this time due to their high energy-density and high power-density. However, over time, the battery pack in an electric vehicle (EV) will age, decreasing its capacity to store energy (i.e. capacity fade) and losing its ability to deliver maximum power (i.e. power fade), until it is eventually not suitable for use in a vehicle [1].

It is generally accepted that the end of life (EOL) of a vehicle battery pack can be defined as the time when its maximum capacity fades to 80% of its nominal maximum capacity [2]. As it stands, a vehicle battery pack is either disposed off or repurposed for stationary applications at EOL [3]. However, due to cell-to-cell variations or position within the pack, not all the cells will degrade at the same rate. This can be due to variation in cell resistance, uneven thermal management of the pack, differences in active material and several other factors that are characteristic of the manufacturing process and pack configuration [4]. Therefore, this implies that in a battery pack that has reached its EOL, one can find cells that have lost more or less than 20% of their nominal capacity. Using a routine preventative maintenance strategy, degraded cells may be identified so that they can be replaced to prolong the service life of the pack as a whole. Also, any cell that may have failed for any other reason could also be replaced. This

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http://dx.doi.org/10.1016/j.jpowsour.2017.03.010

will require consideration in the design phase of the battery pack, pack configuration or assembly, as well as consideration within the battery management system (BMS). In order to prolong the primary in-service lifetime of the battery pack, damaged cell or modules can be replaced with new ones.

This concept of routine maintenance and refurbishment is an established practice in the automotive industry in which a system, such as an engine, is not replaced entirely upon failure, but has certain parts replaced with regular maintenance. For some systems, the replacement of every component on a certain interval can extend the system's life indefinitely [5–7]. The American automotive remanufacturing industry is a multi-billion dollar industry for fossil fuel vehicles, and the economic, environmental and legislative benefits of remanufacturing are well-documented [5]. Therefore, it is of interest to investigate this model as it pertains to future technologies such as LIB's in vehicles by changing out degraded cells in the battery pack as they fail without replacing the entire pack. The goal of this is to maintain the capacity and available power of the battery pack above a defined EOL criterion.

Significant efforts have been made in going from single-cell battery models to pack-level models, taking into account cell to cell variability [8–10]. With respect to state-of-charge SOC estimation, many new considerations and challenges arise at the battery pack level [11–17]. For example, Sun et al. [17] employed an average pack model and model bias correction, taking into account model and parameter uncertainty in order to estimate state of charge. The shift in focus towards the battery pack from the cell is important, because it is the battery pack that is implemented in electric vehicles (EVs), and it is the battery pack that must be accurately monitored and modelled. A battery pack configuration that is rigid is not advantageous to EV manufacturers since the performance of cells in series is limited by the weakest cell. Therefore, the idea of reconfigurable and/or maintainable battery packs have gained attention in recent years, where if certain cells or modules fail, they can be replaced or removed from the battery pack circuit.

Although a few studies in literature have explored the idea of reconfigurable battery packs, little research currently exists on simulating a battery pack with the concept of cell change out, and none on a vehicle scale. Adany et al. [18] have conducted preliminary work in switchable configurations, where the battery management system (BMS) removes a cell that is deemed to negatively impact the rest of the battery pack. Ugle et al. [19] proposed a metric called worthiness of replacement, a quantitative measure of whether a battery module that has degraded needs to be replaced with a new one. Although not specifically addressed by Ugle, nor examined in detail in this work, the concept of battery change-out could be applied to a single cell, a group or 'gang' cells, a 'string' of cells, or a 'module'. Ganesan et al. [20] investigated the idea experimentally in the context of state-of charge (SOC) estimation, and showed that the concept can extend the useful life of a battery pack. However, the investigation by Ganesan et al. lacked the scope that the current work will attain in terms of battery pack size and lifetime. Similarly, although there have been numerous articles that have proposed a comprehensive battery simulator that take into account degradation [21–23], none of these studies have examined the effects of replacing a damaged cell with a new one. The goal of this paper is to provide a simulation framework for cell replacement in a battery pack for electric vehicles. The simulation results will then be used to examine how quickly the cells need to be replaced in order to maintain the state of health of the battery pack above a certain threshold. If the model simulations show that cell change-out extends pack life indefinitely while maintaining pack performance at steady-state, the concept would be of interest to EV and battery manufacturers for its economic benefits. The change-out concept would hopefully lead to a reduced load of batteries on the recycling and disposal infrastructure as a 'good' or long lasting cell would remain in service for an extended period of time. This environmental benefit could also be legislatively advantageous if LIB disposal policy becomes strict [24].

The paper is divided as follows: Section 2 will describe the experimental set-up used to obtain data for building the battery pack model. Section 3 will discuss how the battery pack simulation framework was established. It will explore the development of the voltage response model at the cell and pack level as well as an empirical degradation model. It will then explain how these different components can be integrated to develop a cell change out simulator. Section 4 will look at the simulation results as well as discussion and conclusions will be provided in Section 5.

2. Experimental

The two different battery chemistries used in this study were Lithium Iron Phosphate (LFP) and a mixed cathode chemistry of lithium nickel magnesium cobalt oxide (NMC) and lithium magnesium oxide (LMO). Both were automotive patterned cells with a pouch configuration. Experimental data was collected in order to develop a robust battery pack model, where each battery in the pack has a slightly different voltage profile and degradation rate. This was accomplished by testing four different LFP cells and four different NMC/LMO cells. The variation in the parameters obtained from these cells were then used to develop a distribution that was applied to stochastically generate the parameters for each individual cell in the battery pack simulation. The manufacturer specifications for each battery are given in Table 1.

2.1. Experimental set-up and procedure

All tests were carried out using a BioLogic EC-Lab VSP multichannel potentiostat/galvanostat. The equipment is equipped with 4 channels, where each channel can provide a maximum of 400 mA. In order to test the pouch cells, a 100Amp booster was attached, allowing a maximum current of 100 Amps and a voltage range of 0 V–5 V.

In order to determine the parameters of the equivalent circuit model, the following procedure was applied: The cell was initially charged at 1C constant current to its upper voltage limit followed by constant voltage charge until the current was below C/25. The hybrid pulse power characterization test (HPPC), proposed by the Department of Energy (DOE), was then carried out at 10% intervals from 100% to 0% SOC. The HPPC test consists of a 1C discharge for 10 s, a 40 s rest period and a ¾ C charge for 10 s. Constant current 1C discharge was applied to move to different SOC levels and a 1 h rest was conducted in between HPPC tests in order to ensure that the battery reached equilibrium.

The open circuit voltage (OCV) curve was determined by subjecting the cells to a C/25 discharge current for 25 h followed by an hour of rest and a C/25 charge current for another 25 h. The OCV curve was then calculated by taking the average of the charge and

Table 1
Manufacturer specifications for the batteries tested.

Parameter	Value	
Cathode Chemistry	Lithium Iron Phosphate (LFP)	Lithium Nickel Magnesium Cobalt Oxide (NMC)/Lithium Magnesium Oxide (LMO)
Type of Cell	Pouch	Pouch
Nominal Capacity (Ah)	20	15
Rated Voltage Range (V)	2.00–3.65	2.80–4.15

discharge curves.

3. Model development/simulation framework

The cell-level voltage response model and pack-level simulation framework were the exact same for each battery chemistry. The only difference between battery chemistries were the circuit parameter values in the model and the degradation model chosen for the simulation. The decision to test the simulation with different battery chemistries was made to determine the robustness of the change-out concept.

3.1. Cell-level voltage response model development

The cell-level model was built on the concept of an equivalent circuit model (ECM) due to constraints in computation time. The Thevenin equivalent circuit model was used to represent cell voltage response since the model provided a good balance of accuracy and computational efficiency. This ECM was also chosen based on its merits in representing fundamental characteristics of LFP and NMC/LMO batteries [25,26]. The equivalent circuit model consists of the R_o parameter, which represents the internal resistance of the cell and RC parameters R_{Th} and C_{Th}, which model the transient voltage response to changing current. The voltage source of the ECM represents the open-circuit voltage (OCV) of the cell and is varied with SOC. The ECM is shown in Fig. 1.

The equivalent circuit model can be written in the form of a differential equation as shown below.

$$\frac{d(U_{Th})}{dt} = -\frac{U_{Th}}{R_{Th}C_{Th}} + \frac{I_L}{C_{Th}} \tag{1}$$

$$U_L = U_{oc} - U_{Th} - I_L R_o \tag{2}$$

The parameters R_o, R_{Th} and C_{Th} can be determined using the procedure outlined in Section 2.1. For a given current and state of charge, solution of Equations (1) and (2) can yield the terminal voltage.

3.2. Degradation model development

The voltage response model needs to be coupled with a degradation model in order to adequately predict the degradation profile of a battery pack. During the simulation of the battery pack, the degree of degradation of the particular cell will continuously be evaluated based on its charge history. Several cycling aging models have been proposed in the literature, including both empirical and fundamental approaches. Generally, cycling aging models consider the effects of charge throughput, depth of discharge (DoD), current rate and average cell SOC [2,27,28] on capacity and power fade.

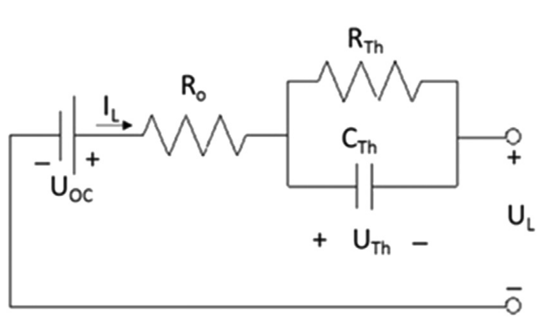

Fig. 1. Thevenin equivalent circuit model used for voltage response in the cell change out simulator.

The empirical degradation model based on concepts originally proposed by Schmalstieg et al. [27] was used in this work to model degradation in the LFP cells. The model considers the effects of the depth of discharge of the cell as well as the average voltage of the cell throughout the current profile. The model was simplified slightly to depend only on cycling aging factors and neglect calendar aging.

Equations (3)–(5) show the degradation equations modeling capacity fade and resistance increase. The terms β_{cap} and β_{res} represent fitting parameters and were calculated in the same form, shown in Equation (5), but with different values of *a*, *b*, *c* and *d* [27].

$$CAP_{cyc} = 1 - \beta_{cap}\sqrt{Q_{processed}} \tag{3}$$

$$Res_{cyc} = 1 + \beta_{res} Q_{processed} \tag{4}$$

$$\beta_{cap/res} = a\left(V_{avg} - b\right)^2 + c + d{*}DoD \tag{5}$$

The term CAP_{cyc} represents the ratio of current cell capacity to the initial cell capacity. A ratio of one occurs when there is zero amp-hours processed, which indicates a new cell. This value decreases over time due to degradation of the cell. In a similar way, Res_{cyc} represents the ratio of the current cell resistance to the initial cell resistance. As the resistance increases over time, the ratio increases. The equivalent circuit model, shown in Equations (1) and (2) can be solved for a given current profile in order to determine the average voltage used in Equation (5). The depth of discharge (DoD) can be estimated from the coulomb counting block in Fig. 2.

The degradation model proposed by Cordoba-Arenas et al. [29] formed the basis of the degradation model applied to the NMC/LMO chemistry. It also considered average SOC and charge throughput, but neglected depth of discharge (DoD). It additionally considers C-rate and temperature, although the temperature was taken to be constant 298 K in the simulation. This degradation model is governed by Equations (6)–(9), where $R = 8.314\ \mathrm{J\ K^{-1}\ mol^{-1}}$.

$$CAP_{loss} = a_c{*}\exp\left(\frac{-E_{ac}}{R_g T}\right){*}Q_{processed}^{z} \tag{6}$$

$$Res_{inc} = a_r{*}\exp\left(\frac{-E_{ar}}{R_g T}\right){*}Q_{processed} \tag{7}$$

$$a_c = \alpha_c + \beta_c{*}Ratio^e + \gamma_c(SOC_{\min} - SOC_{0c})^f \tag{8}$$

$$a_r = a_r + \beta_r(SOC_{\min} - SOC_{0r})^q + \gamma_r{*}\exp[g(CR_0 - CR) + h(SOC_{\min} - SOC_{0r})] \tag{9}$$

The terms a_c and a_r represent the capacity and resistance severity factors that depend on C-rate (*CR*), the minimum SOC ($SOC_{\min}$), and the ratio between the time spent depleting and regenerating charge (*Ratio*). The terms *e*, *f*, *z*, α_c, β_c, γ_c, SOC_{oc} α_r, β_r, γ_r, SOC_{or}, CR_o, *g*, *h*, *and q* represent constants in the fitting equation, while E_{ac} and E_{ar} are the cell activation energy for the capacity fade and resistance increase processes respectively. The output from the models Cap_{loss} and Res_{inc}, represent the percent capacity loss [%] and resistance increase [%] respectively.

The above models, developed by Schmalstieg et al. [27] and Cordoba-Arenas et al. [29] were used for two main reasons. First, using an empirical model instead of a theoretical one is essential for reducing computational time, which can become a significant issue when simulating a large number of cells, especially with stochastic considerations. Secondly, both models contain fitting parameters

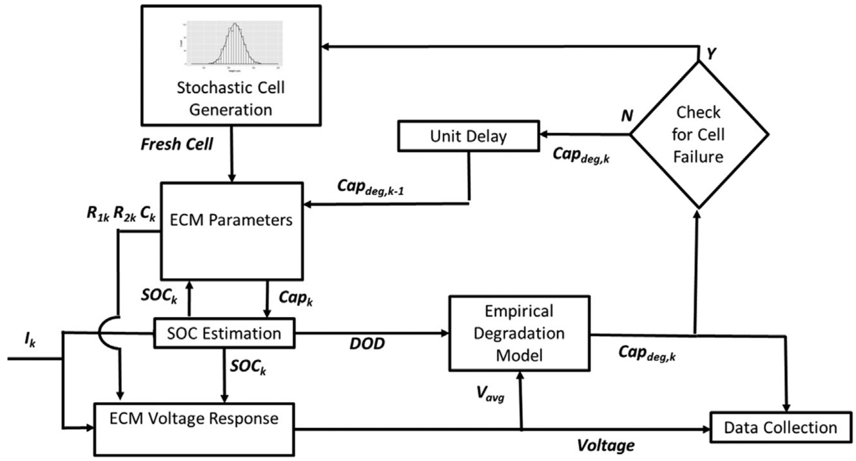

Fig. 2. Framework of the cell change-out simulator for a battery pack.

that can be varied stochastically allowing one to develop a more realistic battery pack, where certain cells degraded more quickly than others. Note that in this work variation in the degradation associated with location of the cell within a pack was not considered, but left to future works (e.g. different cells will experience different thermal histories). The variability of the cells is a factor that will be considered in the simulation, and the effects of having cells that have a high degree of variability will be discussed with respect to cell change out.

3.3. Pack level voltage model

The pack-level model acts to aggregate results from an array of single cell models and to summarize the overall performance of the pack. It assumes a series orientation for all of the cells contained in an array of cells and simplifies a series of n Thevenin-based ECM to a single Thevenin-based ECM with n RC circuits. The pack-level model also outputs pack-level voltage, OCV, and SOC information with respect to the current profile, which is then used to evaluate the performance of the overall pack as it degrades.

The other role of the pack-level model is to consistently update cell-level circuit parameters in the pack. This ensures that the overall pack model reflects realistic series pack performance, in which all cells are subjected to the same current profile. It should be noted, however, that variation in degradation rate of each cell will result in variance in cycling characteristics for each cell such as DoD and SOC.

3.4. Simulation framework

The simulation framework proposed in this paper combines the cell level voltage response model, the cell level degradation model and the pack level model. The simulation procedure was conducted in MATLAB using object-oriented programming. Working in an object-oriented environment allows one to emulate individual cells that have unique characteristics. In this study, the pack used for the simulation was made up of 40 randomly generated cells in series. Therefore, the scale of the simulation was more one of a ‘module’ than a full EV ‘pack’. The cells in the pack would vary in their equivalent circuit resistances and capacitance values as well as in how quickly they degrade. By stochastically varying these parameters, the simulation provides a more realistic prediction on how the pack would degrade over time. The battery pack was subjected to a charge/discharge cycle of 1C, between 20 and 80% average SOC. As the cells varied in capacity, the current profile was generated based on the average capacity of all the cells in the pack, in order to scale the 1C duty. Note that one cycle refers to one complete charge and discharge from 20% to 80% SOC. Therefore, if the cell was discharged from 80% SOC to 50% SOC and charged back up to 80% SOC, this would only be considered as half a cycle. The framework used for the simulation is illustrated in Fig. 2.

At the beginning of the simulation, 40 new cells were created, each with its own unique parameters for the voltage response and degradation. Each cell has a meantime to failure (MTTF), which is defined as the amount of time it takes for the product, in this case a particular lithium ion battery cell, to reach its end of life. Stochastic variation was introduced by generating a distribution from the experimental data collected on the four LFP cells and four NMC/LMO cells and drawing the equivalent circuit model parameters from the distribution. Degradation rate was varied by stochastically varying the parameters in the degradation model equations for both LFP and NMC/LMO (i.e. Equations (3)–(9)). Variations in capacity, cell parameters and degradation are well-documented in the literature [4,10].

For a given current and array of cells in the battery pack, the first step is to calculate the state-of-charge (SOC) of each cell. One of the simplest SOC estimation methods is based on the notion that one can count the coulombs entering and leaving the battery. The equation for calculating the SOC is:

$$SOC = SOC_0 + \frac{1}{C_n}\int \frac{I}{3600}dt \tag{10}$$

Where I is the current measured in coulombs/second, and C_n is the maximum battery capacity. The simulation starts from an SOC value of 80% for each cell and by integrating the amount of current, the current SOC value can be determined.

Using the ECM model described in Equation (2), the voltage for each of the cells in the pack is determined. Note that each battery in the simulator will produce a slightly different voltage response due to variations in the individual cells. The degradation model then takes the voltage and state-of-charge for the cell as an input in order to calculate the capacity fade.

The capacity of each of the cells in the entire pack will be checked at discrete intervals to ensure that all the cells are above the cell failure limit. The interval at which cell degradation was checked and cells were replaced will be referred to as maintenance event interval and cells that have capacity below a critical value will be removed and replaced with new ones. The number of cells replaced during a maintenance event will be referred to as

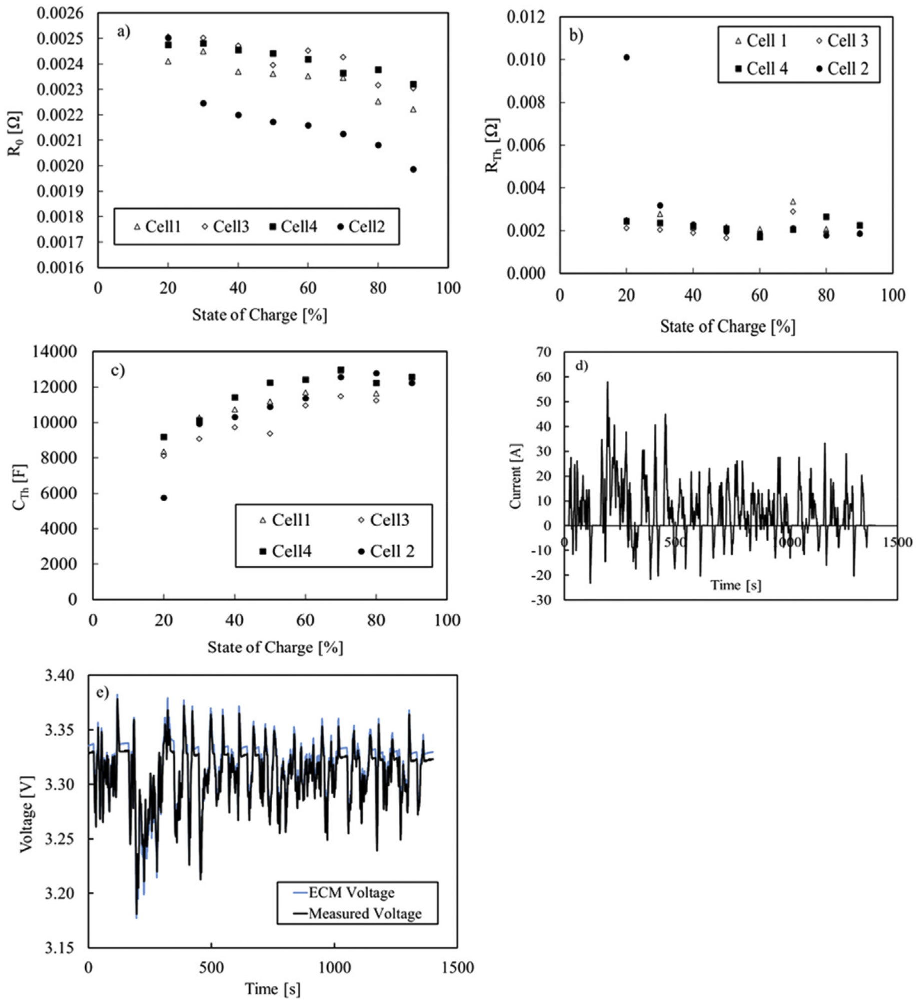

Fig. 3. (a–c) Equivalent circuit model parameters estimated (R_o, R_{Th} *and* C_{Th}) estimated for four LFP cells; (d) current profile of the UDDS cycle used for model validation (e) comparison of ECM voltage with the measured voltage for a UDDS drive cycle.

replacement rate. This concept is widely used in remanufacturing models, where a “perfectly maintained system” is one where the replacement check is done continuously and “discretely maintained system” refers to a system that is checked at discrete intervals. Note that the maintenance event interval is an important parameter in this discussion since in electric vehicle applications, the replacement of cells or modules in a battery pack utilized in an electric vehicle can only be carried out at discrete intervals. For example, in a typical vehicle, the cells or modules might be inspected for degradation during the car's regular seasonal maintenance check.

One of the consequences of discretely maintained systems like EV battery pack is that irregular checks could theoretically miss the exact moment at which a cell exceeds its EOL capacity fade, and the cell would not be replaced until the next scheduled check for replacement took place. Therefore, the state-of-health (SOH) of the battery pack could fall below 80% since an individual cell could fall below 80% in between checking intervals. Therefore, the individual cells need to be replaced when their capacity fade is above 80% in order to ensure that the entire pack does not degrade past 80%. Although not specifically examined in detail, the concept of battery change-out could be applied to a single cell, a group or ‘gang’ of 3–5 cells, or a ‘string’ of 5–10 cells, or a ‘module’ of 20–40 cells, depending on the design of the pack.

The capacity of each of the cells is recorded throughout the simulation procedure and a pack capacity is determined based on the capacity of the weakest cell. The ratio of the degraded cell capacity of the weakest cell with the nominal cell capacity allows for the estimation of state of health for the pack as shown in Equation (11).

$$SOH_{pack} = \frac{\min(Cap_{cell1}, Cap_{cell2}, \ldots, Cap_{cellN})}{NominalCellCapacity} * 100 \quad (11)$$

The nominal cell capacity is the initial capacity of the specific battery. Although power fade is another metric that is often used to model state of health, previous works [29,30] have shown that, for LFP and NMC/LMO batteries, the effect of resistance rise (via power fade) on cell performance is not significant compared to that of capacity fade.

4. Results and discussion

4.1. Cell level voltage model validation

Following the HPPC procedure taken by Scott [31], the ECM parameters were determined at various SOC's for 4 LFP cells. The results are plotted in Fig. 3(a–c). It was concluded that the parameters were constant enough in the range of SOC that would be simulated so the parameters were not varied with SOC. This simplification improved computational time and the stability of the model. The C/25 charge-discharge cycles allowed for the calculation of nominal cell capacities as well as helped in developing the OCV curve.

Examining Fig. 3(a–c), it can be seen that for all four LFP cells, the same trend is observed for the parameters R_0, R_{Th} and C_{Th}. In terms of the internal resistance R_0, it can be seen that the value decreases as the SOC increases. The resistance in the RC pair, represented by R_{Th} was found to be constant while the capacitance in the RC pair, represented by C_{Th}, was found to increase as the SOC increased. The variation in the parameters for the four LFP cells was used to generate the varying ECM parameters for the cell change out simulator.

Urban Dynamometer Driving Schedule (UDDS), is a drive cycle that is used to represent driving conditions in the city. Since the change out concept will be used for an electric vehicle battery pack, it is important to validate the voltage response model using a drive cycle. Fig. 3 (d), shows the current from a UDDS drive cycle that was applied to a new lithium iron phosphate battery. The experimental values obtained were compared to the values obtained from the ECM model. From Fig. 3(e), it can be seen that there is a good agreement between the model and experiment for the drive cycles. The maximum model error was calculated to be 1.56%. Although adding additional RC pairs would lower the model error, for the purpose of simulating cell change-out, these values were deemed to be adequate.

4.2. Cell level degradation

Having selected the degradation model proposed by Schmalstieg et al. [27], the model was parameterized to degradation rates found in the literature for LFP cells. Degradation rates were found to be highly varied, because the cycling conditions used by different sources were very different. Degradation rates found in the surveyed literature for cycling conditions similar to the simulation (1C current, 60% DOD) are summarized in Table 2.

For the purpose of this simulation, the approximate meantime to failure of the LFP cells was taken to be 4000 cycles. Given the rated capacity of the LFP cells (20 Ah) and the DoD of the simulation cycles, this corresponded to 96000 Ah of charge throughput. Ahmadi et al. [1] proposed an empirical capacity fade model based on charge throughput for constant cycling conditions. Collection of long-term degradation data was not in the scope of this work, which focuses on introducing the cell change-out concept and showing its feasibility.

The predictive model proposed by Ahmadi et al. [1] was sufficient for the purposes of this paper as it adequately describes capacity fade in an electric vehicle until the capacity fade reaches 20%. Therefore parameters in the degradation model for capacity fade were determined by fitting the degradation equation shown in Equations (3) and (5) to the curve obtained by Ahmadi et al. [1] using least-squares regression. The results are shown in Fig. 4.

Although the model is not able to fully capture the initial exponential growth of the capacity prediction model, the two curves do align once the charge throughput is greater than

Table 2
Summary of relevant degradation rates for LFP batteries.

Cycling Conditions	Cell Life (# of Cycles)	Source
Current unspecified, 60% DOD	4000–5000	[32]
0.7C, 100% DOD	4000	[33]
2C, 50% DOD	3000–4000	[34]

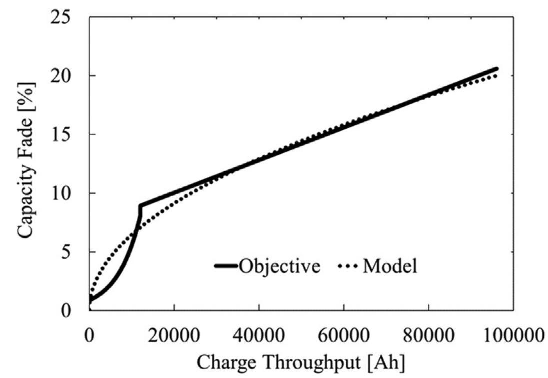

Fig. 4. Parameterized degradation curve used in the model compared with the objective degradation function.

40,000 Ah, which is important as cell change out will normally occur towards the end of the cycle. In a similar way, the parameters for resistance increase can be identified according to LFP data from Zhang et al. [28]. The estimated empirical parameters for capacity fade and resistance increase are described in Table 3 for lithium iron phosphate.

The same approach can be applied for NMC/LMO cells, where the mean time to failure is 4000 cycles. The parameter values for the capacity fade and resistance increase models are summarized in Table 4.

It should be noted that although it is possible to use the degradation model from Ref. [1] directly, the degradation model of [27] was used in this paper for three reasons.

1. One of the main goals of this paper is to provide a simulation framework for cell replacement that can be used by other researchers for understanding the feasibility of this concept for different battery chemistries. Part of this framework is selecting a degradation model that is computationally efficient and to illustrate how this model can be coupled with the voltage response model in order to simulate cell change out.
2. The degradation model that was selected has inputs of average voltage (or SOC) and depth of discharge, in addition to charge throughput. When degradation data is available, this model can be used to determine capacity fade under different operating conditions.
3. The chosen degradation model has fitted parameters a, b, c and d, which can be varied stochastically in order to generate variability among different batteries and these models can be coupled to power fade models.

4.3. Simulation results – variability in degradation

One of the first simulations that will be discussed in this paper is the effect of variability in degradation rate on the cell change-out

Table 3
Parameters for the LFP cell degradation model.

Parameter	Capacity Fade	Resistance Rise	Units
a	0.00142	$2.780*10^{-5}$	$\sqrt{Ah*V}^{-1}$
b	3.274	3.199	V
c	0.00119	$-2.237*10^{-5}$	$\sqrt{Ah}^{-1}$
d	$-9.219*10^{-4}$	$7.361*10^{-5}$	$\sqrt{Ah}^{-1}$

Table 4
Parameters for the NMC/LMO cell degradation model.

Parameter	Value
E_{ac}	$2.16*10^4$ [J mol^{-1}]
E_{ar}	$4.76*10^4$ [J mol^{-1}]
z	0.516
α_c	144.5 [Ah^{-z}]
β_c	420.1 [Ah^{-z}]
γ_c	$9.39*10^3$ [Ah^{-z}]
e	0.343
f	3
α_r	$3.46*10^5$ [Ah^{-z}]
β_c	$1.29*10^9$ [Ah^{-z}]
γ_r	$3.96*10^3$ [Ah^{-z}]
q	6
g	1.02
h	1.75
SOC_{0c}	0.24
SOC_{0r}	0.23
CR_0	4.43

results. Depending on the type of battery and the battery pack manufacturer, there can be a significant difference in how quickly one cell degrades when compared to another. Therefore, the effect of varying degradation on the feasibility of cell change-out is a topic that needs to be addressed. This was investigated by changing the standard deviation of the distributions from which the degradation model parameters came from. Standard deviation of 10%, 5% and 2% of the mean value were tested.

As previously mentioned, the simulation of the battery pack was carried out for 40 cells for a total of 15,000 charge-discharge cycles between 20% and 80% state of charge. The simulation protocol illustrated in Fig. 2 was utilized in order to generate the simulation results. In this particular simulation, it was assumed that the battery pack is a "perfectly maintained system", which means that the battery pack was checked continuously (or at a very small maintenance event interval) in order to determine whether one or more of the cells had degraded. The minimum capacity for which a cell will be replaced was taken to be 85% of its nominal capacity for this particular simulation.

The capacities of each individual cell, the pack capacity, the end-of-charge and end-of-discharge voltages, and the voltage profiles were recorded throughout the simulation. The charge throughput history of each cell was updated at the end of each cycle, as it is required for updating the degradation status of the cells.

The simulation results are summarized in Fig. 5 below. Fig. 5 a shows the state of health of the battery pack as a function of number of cycles with three different simulations carried out with different variability in the degradation parameters. The meantime to failure of the cell was taken to be 4000 cycles for this simulation presented in this section. In addition, the plot of the number of batteries replaced as a function of number of cycles is shown in Fig. 5b, for different degradation parameter variability.

Examining Fig. 5a, it can be seen that regardless of the variability in the cell degradation, the state of health of the battery pack reaches steady state after 15,000 cycles. These findings have been shown to hold true by Refs. [6,7], who developed reliability models for the remanufacturing of a system with parts that can be replaced after failure. The results from this group showed that the average age of parts in a system can be maintained below their failure age indefinitely by remanufacturing. However, the findings by Refs. [6,7] cannot necessarily be applied to the battery pack since the capacity (analogous to age) of a serial battery pack is limited entirely by its weakest cell; the average age of the cells is not a consideration. Therefore, the findings from this study are important to EV manufacturers as it shows that by employing a cell replacement strategy, the state of health of the battery pack can be maintained indefinitely.

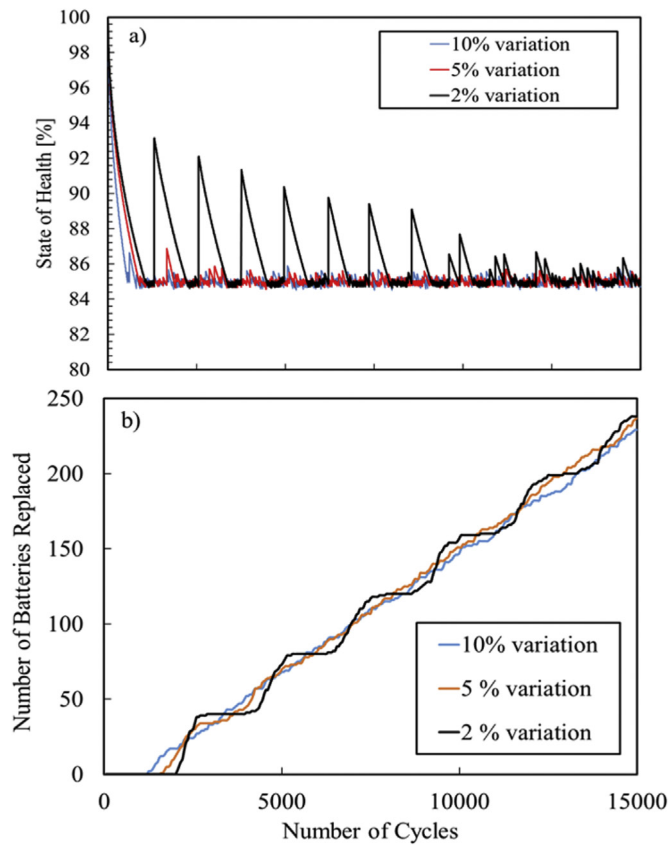

Fig. 5. (a) The effect of variability in the degradation parameters on the state of health of the battery pack during cell change out simulation; (b) The number of batteries replaced during the cell change out simulation when degradation parameters are varied.

The results from this simulation also show that regardless of the variability in the cell degradation parameters, by using the cell change out concept, the state of health of the battery pack does not fall below 80%. A lower degree of variability results in larger oscillations in state of health as shown in Fig. 5. This is due to the fact that a lower degree of variability means most of the cells will reach the maximum state of health value required for cell replacement at the same time, resulting in the large oscillations seen in Fig. 5. The effect of variability is also reflected in Fig. 5b, where it can be seen that when the degree of variability is low, a large number of batteries need to be replaced at once. However, a higher variability in the degradation parameters is found to require constant replacement of batteries. This is not possible in an EV since servicing of the battery pack can only be carried out at discrete intervals. The section below will examine how quickly the cells needs to be checked in order to ensure the battery pack is maintained above the critical capacity fade level.

4.4. Simulation results - degradation rate and maintenance event interval

As previously mentioned, it is not possible to conduct cell change-out continuously as soon as one cell reaches its minimum capacity. Rather, the cell change out concept can only realistically be done at discrete intervals. The following section examines the relationship between the rate at which the cells degrade and how quickly the cells need to be replaced in order to ensure that the pack capacity does not drop below 80%. This is an important factor to considered for EV manufactures as this allows them to develop guidelines on how quickly the car needs to be taken in for service and what degree of degradation in the individual cell is acceptable.

Once again, the simulation of the battery pack was carried out by developing a battery pack of 40 cells in series and carried out at 1C charge/discharge for a total of 30,000 cycles. The first simulation was carried out for cells with a meantime to failure of 4000 cycles. As noted previously, since the goal of cell change out concept is to ensure that the pack capacity does not fall below a minimal threshold value, it is important to change out the individual cells that are at a capacity higher than this value in order to ensure the pack SOH always remains above the threshold value. This higher threshold for the individual cells will be referred to as minimal cell capacity and a value of 15% capacity fade will be used in this simulation. The results are shown in Fig. 6 below.

Fig. 6 (a) shows simulation results for cell change out for three different scenarios: when there is perfect replacement (replacement every 100 cycles), replacement every 1000 cycles and replacement every 2000 cycles. The dashed line represents 80% state of health for the pack, where the battery pack normally has to be replaced.

The results show that when the maintenance event interval is 1000 cycles, the battery pack is maintained at a state of health that is above the 80% mark. However, at 2000 cycles, the state of health value dips below the required threshold. Therefore, this means that for this particular battery chemistry and battery life, the degraded cells must be replaced at least at a discrete interval of 2000 cycles in order to ensure the capacity fade of the battery pack does not exceed 20%. These results are important since they illustrate that by using simulation, car manufacturers will be able to determine how quickly the battery pack in an electric vehicle needs to be serviced in order to prolong the pack life.

In addition to capacity fade, the voltage of the battery pack will also decrease (power fade) as the battery is cycled. Fig. 6(b) shows the pack voltage at the end of discharge, recorded every 500 cycles. The initial decrease in voltage is due to an increase in resistance as the battery pack is cycled. The voltage of the battery pack increases when a maintenance event occurs where damaged batteries are replaced. Similar to the state of health of the battery, the pack voltage is found to reach a steady state value as the number of cycles increases.

It is also important to consider the number of cells that need to be replaced during a maintenance event. Fig. 6(c) shows 30 consecutive maintenance events and the number of cells that have been replaced during each event. The results in Fig. 6(c) show that as the number of maintenance events increase, the number of cell that are replaced during these events appears to reach a steady state value.

The same simulation was carried out only this time the assumed meantime to failure of the cell was decreased to 2000 and 1000 cycles. The degradation data for an EV battery pack obtained by Ref. [1] was still utilized, only the data was scaled to match the lower MTTF of the cell. The results are shown in the two figures below.

When the meantime to failure of the cell is taken to be 2000 cycles, the minimum maintenance event interval also decreased to 1000 cycles. The trend holds when the MTTF is decreased even further to 1000 cycles, as shown in Fig. 7, where at a maintenance event interval of 500 cycles the state of health dips below 80%. For this particular chemistry, it appears that a ratio of meantime to failure to maintenance interval of 2 is required in order to ensure the pack is able to meet its capacity demands.

These results from Figs. 6 and 7 show that in order to decrease

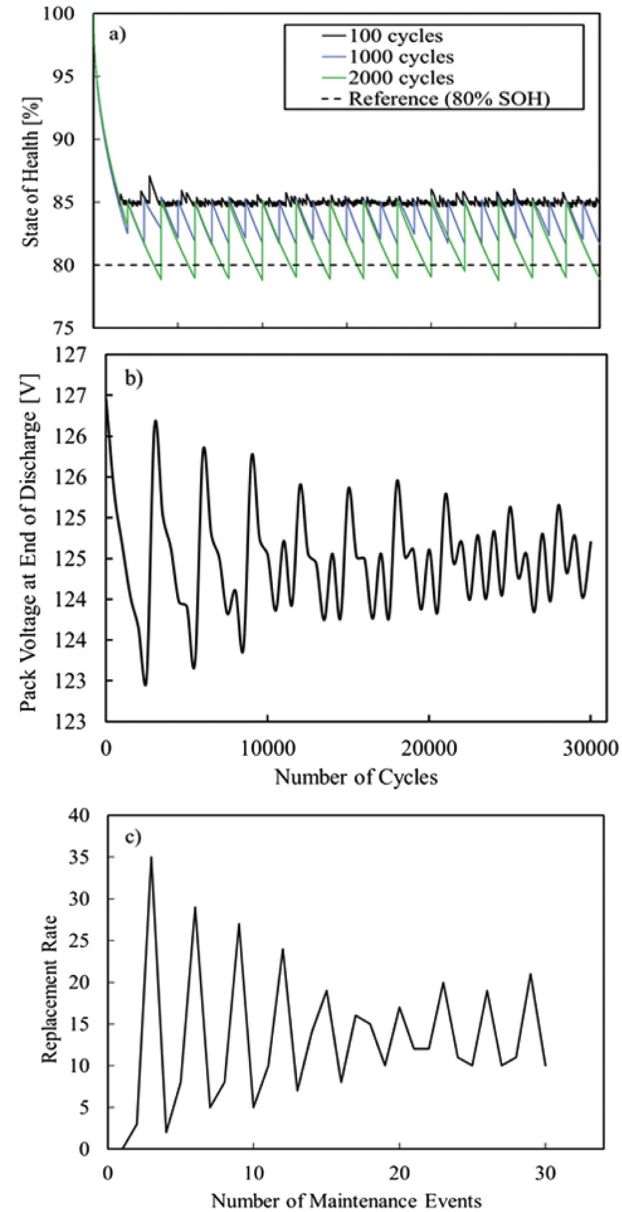

Fig. 6. (a) The simulated state of health for a battery pack that has a meantime to failure of 4000 cycles, where the cells are replaced at discrete intervals of 100, 1000 and 2000 cycles; (b) The pack voltage at the end of discharge for a lithium ion battery pack with a meantime to failure of 4000 cycles and maintenance event interval of 2000 cycles; (c) The replacement rate (or number of cells replaced) during each maintenance event for a lithium ion battery pack with a meantime to failure of 4000 cycles and maintenance event interval of 2000 cycles.

the number of maintenance events (or the number of replaced batteries), the meantime to failure needs to be increased. The meantime to failure for a particular battery depends on the battery chemistry as well as the operating conditions under which the battery pack is used. Therefore, the simulator presented in this paper can be utilized to assess the feasibility of a particular battery for cell change out. Also, discrete change-out of the individual cell at lower minimum capacity threshold is viable, where the EOL chosen should be tuned to the meantime to failure of the cell and how often the cell can be checked for replacement. If a longer monitoring interval is selected, an earlier cell EOL will be required.

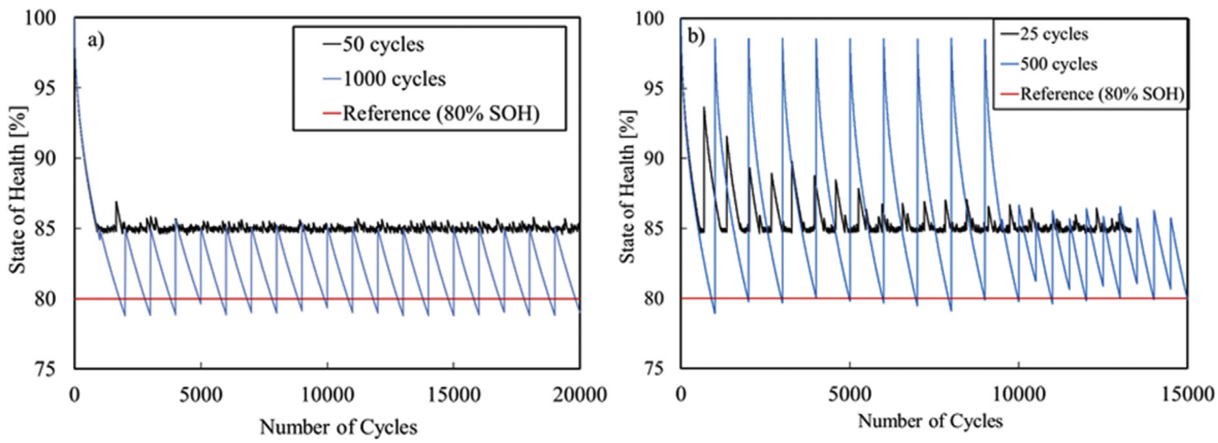

Fig. 7. The simulated state of health for a battery pack that has a meantime to failure of (a) 2000 cycles, where the cells are replaced at discrete intervals of 50 and 1000 cycles; (b) 1000 cycles, where the cells are replaced at discrete interval of 25 and 500 cycles.

4.5. Simulation results — comparison of LMC/NMC chemistry

The simulation results described above were obtained for a battery pack primary composed of lithium iron phosphate (LFP) battery cells. In order to test the robustness of the cell change out application for electric vehicles, the change out concept was implemented on a different chemistry; this time a mixed cathode chemistry of NMC/LMO. It is important to understand whether the trends obtained in the above section for LFP is observed for other battery chemistries such as NMC/LMO. The meantime to failure for NMC/LMO cells was deliberately chosen to be the same as that of LFP cells and the standard deviation used in generating the stochastic degradation parameters was also chosen to be 5% of the mean for both cases. New parameters for the ECM were developed based on HPPC tests carried out for NMC/LMO cells and the degradation model shown in Equations (6)–(9) was applied. It should be noted that the same degradation curve used for LFP is used for NMC/LMO cells to fit the degradation model. The results from Ref. [29] shows a similar trend to that observed in Fig. 4 for LFP and therefore the assumption is deemed to be sufficient for the purposes of this paper.

The simulation was once again carried out for 30,000 cycles for the perfect replacement case as well as discrete replacement case. For the discrete replacement example, a maintenance event interval of 2000 cycle was used for checking to determine whether the individual cell needs to be replaced. The results are summarized below.

The findings from Fig. 8 show that regardless of the chemistry of the battery, the state of health of the battery pack does reach steady state if the pack undergoes regular maintenance events where degraded cells are replaced. How quickly the state of health reaches steady state differs between the two chemistries, and on the mean time to failure assumed for the cells. As Fig. 8 shows, NMC/LMO chemistry has a greater degree of oscillation and takes longer to reach its steady state value using cell change out. This is an important consideration since a larger degree of oscillations in the state of health of the battery pack can have implications on how quickly the cells need to be checked for replacement i.e. how frequent pack maintenance events should be. Finally, the results illustrate that the cell change out concept is able to maintain battery SOH indefinitely with regular maintenance events where degraded cells are changed out regardless of the battery chemistry.

Besides the somewhat common LFP and NMC/LMO battery chemistries, novel chemistries have been proposed in Refs. [35,36]. While these Lithium–Vanadium and Sodium-based chemistries were not considered in this work, the fact that the ultimate result of the simulation was consistent between different degradation models and cathode chemistries suggests that the change-out concept would hold for any battery chemistry. The frequency of maintenance events and the SOH threshold for these would need to be adjusted for new battery types, an adjustment that would be based on eventual experimental data. Future work could be carried out by considering these new battery chemistries as well as other battery configurations such as prismatic and spiral wound cells.

It should be noted that the battery pack used in this study is composed of cells connected in series. Therefore, the overall

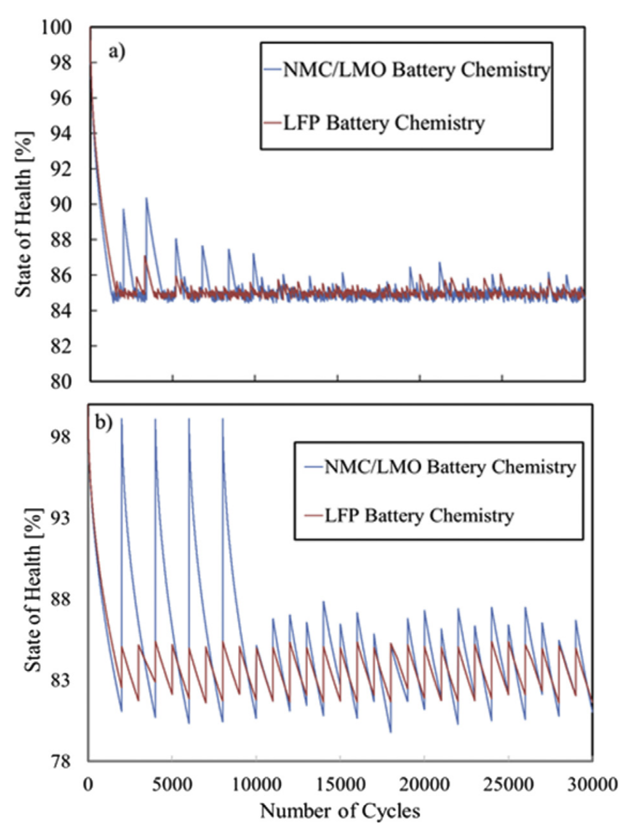

Fig. 8. The simulated state of health for a battery pack that has battery cells with a chemistry of LFP and NMC/LMO for the (a) perfect replacement and (b) discrete replacement cycles.

performance of the battery pack was limited by the most degraded battery. The old batteries act as a limit on how much of the new batteries' capacity is used during cycling. Future work will be carried out in developing a battery pack composed of multiple battery strings in parallel. When using such a battery pack, the interaction effect between a new and old battery would be greatest since the resistance rise in one string would lead to more current being diverted to other strings. Applying the cell change out concept for this particular battery pack would be something that will be considered in future works.

Finally, this work recognizes the limitations of this degradation model, as large sets of degradation data is difficult and time consuming to collect. However, the overall change-out concept presented in this work can be modelled with any degradation model including models that are specific to certain chemistries or cell configurations. Naturally the more specific and validated the degradation model is, the better the prediction of the overall pack life. Thus, another research group with their own degradation model can use this approach for simulating cell change out.

5. Conclusions

Various studies in literature have carried out simulations of battery packs, while few have discussed the concept of cell change-out. This paper attempts to combine the two concepts by creating a battery pack model and utilizing the model to understand the concept of cell change-out. The battery pack model is developed by modeling each individual cell using a Thevenin equivalent circuit and an empirical degradation model. The individual cell parameters in the voltage response model as well as the parameters in the degradation model can vary stochastically in the simulation. The individual cells that have degraded below 80% capacity in the simulation are changed out during maintenance events resulting in an overall cell replacement rate that appears to reach steady state as the number of maintenance events increase. The overall pack performance also reaches steady state with the replacement of individual degraded cells during maintenance events. The paper provides a simulation framework for conducting cell change out and from the simulation results, the following conclusions can be observed:

- By changing out individual cells that have dropped below their minimum capacity, the overall state of health of the battery pack can be maintained indefinitely above a target specification of 80% pack capacity;
- The maintenance event rate at which the cells are replaced is directly related to the average mean time to failure assumed for the individual cells which is simulated using stochastic parameters. As expected a higher mean time to failure results in a longer period between maintenance events required to maintain the state of health. Therefore, by using the simulation protocol outlined in this paper, the optimal maintenance period for a particular pack can be established;
- The results show that regardless of the chemistry, the cell change out concept will result in a battery pack that reaches steady state performance with regular maintenance.

The contributions from this paper illustrates that if at some point the concept of cell change-out does become economically feasible, applying this approach would ensure that the battery pack operates for a much longer period of time in service.

Acknowledgement

The authors would like to acknowledge the Natural Sciences and Research Council of Canada (NSERC 261669-2013-RGPIN) for the funding required to complete this project.

Abbreviations

CC/CV	Constant current/constant voltage
DoD	Depth of discharge
ECM	Equivalent circuit model
EOL	End of life
EV	Electric vehicle
HPPC	Hybrid pulse power characterization
LMO	Lithium magnesium oxide
LFP	Lithium iron phosphate
LIB	Lithium ion battery
Li-ion	Lithium ion
MTTF	Meantime to failure
NMC	lithium nickel magnesium cobalt oxide
OCV	Open circuit voltage
SOC	State of charge
SOH	State of health

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