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Lithium-Ion Battery Pack Robust State of Charge Estimation, Cell Inconsistency, and Balancing: Review

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ABSTRACT Lithium-Ion battery packs are an essential component for electric vehicles (EVs). These packs are configured from hundreds of series and parallel connected cells to provide the necessary power and energy for the vehicle. An accurate, adaptable battery management system (BMS) is essential to monitor and control such a large number of cells. Series and parallel connected cells also experience different production and operational conditions, which makes it challenging for the BMS to ensure the safe operation of each individual cell. The main functions of the BMS include battery state estimation, cell balancing, thermal management, and fault diagnosis. Robust estimation of the state of charge (SOC) is crucial for providing the driver with an accurate indication of the remaining range. This paper presents the state of art of battery pack SOC estimation methods along with the impact of cell inconsistency on pack performance and SOC estimation. Cell balancing methods, which are necessary due to cell inconsistencies, are discussed as well. Four categories of pack SOC estimation methods are presented, including individual cell, lumped cell, reference cell, and mean cell and difference estimation methods. The SOC estimation methods are compared in terms of algorithm type, computational load, and engineering effort to help practitioners decide which method best fits their application.

INDEX TERMS Lithium-ion battery packs, battery management systems, electric vehicles, cell inconsistency, state of charge, cell balancing.

I. INTRODUCTION

Recently lithium-ion battery packs have gained significant interest, especially for electric vehicle (EV) applications. Hybrid and electric vehicle battery packs are composed of series and parallel configurations of lithium-ion cells. The utilization of series and parallel connections allows for essentially any pack voltage and energy to be achieved; however, this adds more complexity for the battery management system (BMS) which monitors the cells and controls the pack [1]. Vehicles may have a very high number of small cells, such as one configuration of the Tesla Model S which has 7140 2.9 Ah cylindrical cells arranged in 16 modules, with each module consisting of 74 parallel cells and six series cells (74P6S) [2]. They may also have a smaller number of larger cells, like one configuration of the BMW i3 which utilizes

50 Ah prismatic cells arranged in eight modules consisting of 2 parallel and 12 series cells each (2P12S) [3]. The battery management system (BMS) must be able to monitor the state of charge and ensure balanced state of charge (SOC) for each series connected group of parallel cells in the pack. Fig. 1 shows the main components and key functions of the BMS.

Battery state of charge is defined as the ratio of coulombs of charge currently stored in the cell over the cell's total charge capacity. The SOC cannot be measured directly using sensors; hence, a robust SOC estimator must be implemented with the BMS to ensure accurate SOC values are reported to the driver [4]. Generally, the SOC of a battery can be estimated using different algorithms, including measurement-based, adaptive filters and observers, and data-driven algorithms. For the measurement-based algorithms, SOC is estimated based on measured physical quantities; typically integrated current [5], [6], open circuit voltage

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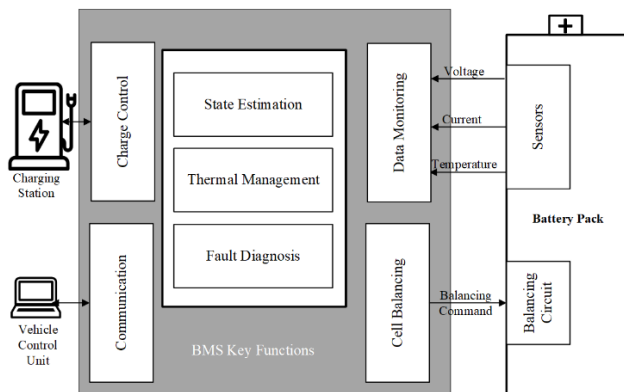


FIGURE 1. Battery management system key functions.

(OCV) [7], [8], or impedance [9], which are directly related to the cell SOC. Adaptive filters and observers estimate SOC using a battery model combined with measured physical quantities. Examples of these algorithms include the family of Kalman filters [10]–[14] and the particle filter [15], [16], least squares filter [17], [18], and adaptive Luenberger observer [19]. Data-driven algorithms, which are based on machine learning models, are often referred to as black-box models because they model LIB input-output relationships without the need for models representing the underlying physics or chemistry. Machine learning models are trained with measured data such as voltage, current, temperature, and state of charge. Recurrent and non-recurrent networks have been used to reliably and accurately estimate battery SOC [4], [20]–[22] and state of health (SOH) [4], [23] of the battery.

Battery cells, even when manufactured in the same batch, can have parameter variations of 1% or more. One study for example found resistance to vary by 0.3% and capacity to vary by 1.3% [24]. When cells are assembled in a pack bus bar and weld resistance can further exacerbate differences between cells. These factors contribute to inhomogeneous current, voltage, temperature, and cell characteristics during pack operation, and may cause further aging to the battery pack [10]. For example, in [25] 48 cells from the same batch were tested under identical conditions. A 10% capacity variation was found between the cells after 1000 cycles, and the cause of this variation was determined to be inconsistent manufacturing of the cells. Hence, some studies have presented a screening process for selecting homogeneous cells to group them in a pack [26], [27]. There are many methods for identifying inconsistencies in a battery pack from measured data, including signal processing, model, and data fusion-based methods which will be discussed in Section II.

When estimating SOC for a battery pack, the SOC of each cell must be considered due to inevitable variances in cell characteristics. Pack estimation algorithms utilize the discussed SOC estimation algorithms and may include additional features to minimize computational complexity or increase accuracy. The simplest class of pack estimation algorithms lumps all the cells into a single large cell and estimates SOC for the lumped cell, ignoring differences in

SOC of individual cells. An individual SOC estimator can also be used for each cell, but the computational complexity may be too high for the BMS. To address this, a reference cell may be selected for the pack, and then a higher bandwidth, more accurate SOC estimation method can be used for this cell. Lower bandwidth, less accurate SOC algorithms can then be used for the remainder of the cells, reducing the computational requirements. Pack SOC estimation methods can also utilize difference models, which estimate the difference in SOC of each cell from the mean cell SOC. Details of each of these types of methods, including implementation, advantages, and disadvantages are discussed in Section III.

Lithium-ion battery packs also require a means of adjusting or balancing individual cell SOC due to variations of the cells' characteristics and operating conditions.

Cell balancing methods can be categorized into two main methods, namely, dissipative and non-dissipative methods. Dissipative methods typically discharge a cell by applying a resistor across it and tend to be slow acting but low cost and compact. Non-dissipative methods utilize power electronic circuits to transfer energy between cells. They may act more quickly and conserve energy but increase the cost and size of the BMS. Dissipative and non-dissipative balancing methods are discussed and compared in detail in Section IV.

Overall, this paper presents the state of the art and current challenges for developing robust SOC estimation algorithms for lithium-ion battery packs, and considers cell inconsistency and balancing in relation to SOC estimation. The causes of inconsistent performance among cells in the pack along with their impact on the pack performance are discussed and modeled results are presented to depict how variances of cell capacity and resistance impact cell state of charge and current and voltage distribution. A detailed discussion of different battery pack SOC estimation methods is provided including algorithms used and the theory of operation of each method. Cell balancing methods are also compared in terms of the active elements, advantages, and disadvantages of each method. The rest of the paper is organized as follows; in section II the consistency analysis of lithium-ion battery packs is discussed and in section III battery pack SOC estimation algorithms and methods are presented. In section IV, the range of cell balancing methods are discussed and finally the conclusions and recommendations are presented in section V.

II. CONSISTENCY ANALYSIS FOR LITHIUM-ION BATTERY CELLS AND PACKS

Ideally each battery cell leaving a manufacturing line would perform identically throughout its life. Many factors cause cells in a pack to age at different rates though, such as variances in manufacturing processes and uneven temperature distribution. These factors tend to cause cells to age unevenly over time, as described in Fig. 2, make managing a battery pack over its life difficult. In this section, the causes of inconsistent performance among cells in a pack are discussed along with their impact on pack performance.

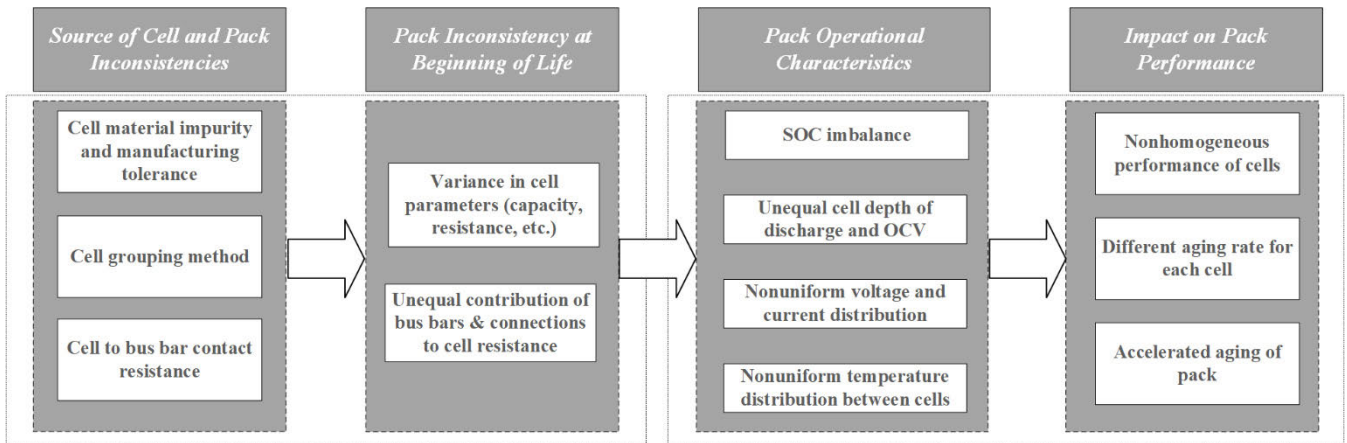


FIGURE 2. Lithium-Ion battery packs inconsistency production and operational causes and effects.

Modeling is also used in this section to depict how variances of cell capacity and resistance impact cell state of charge and voltage and current distribution.

A. INCONSISTENCY OF CELL MANUFACTURING AND WELDING PROCESSES

Inconsistent cell characteristics originate at the production stage. Impurities in active materials and tolerance in human and automated manufacturing processes contribute to cell performance variations [24], [28]–[30]. Typically, these factors result in each cell having slight differences in capacity and resistance. For example, in one very comprehensive study, quantity 1100 Sony US26650FTC1 3 Ah cylindrical LiFePO₄-graphite cells were tested [24]. For cells produced in the same batch, the standard distribution of discharge capacity and dc resistance was found to be around 0.3% and 1.3% respectively. Diagnostic tests, such as the wavelet-based method proposed in [31], may be used quickly measure cell parameters so cells can be sorted into similar groups prior to assembly of packs. While the differences between cells are typically small, they may have a significant impact on pack performance over time as will be discussed in the next subsection.

When cells are assembled into a pack, series and parallel connections are made with conductive bus bars. The connection between the cells and the bus bars are most often made via a welding process. The welding process has a significant impact on the overall resistance of the pack. Since all welds are not identical, the welding process also contributes to differences in resistance between cells. In one study, cylindrical cell to bus bar connection methods including press contact, resistance spot welding, ultrasonic welding, laser beam welding, and soldering were investigated and found to have resistances of 0.154, 0.167, 0.169, 0.130, and 0.080 mΩ respectively [28]. Depending on the connection type, resistance can vary by as much as 0.02 mΩ, which would cause around a 0.1% variance in resistance for a cylindrical cell with 20 mΩ nominal resistance [28]. Unequal cell to bus bar resistance has been found to cause uneven heat generation

in battery packs [29] and to contribute to unequal current sharing between parallel connected cells, especially at higher c-rates [30].

B. IMPACT OF INCONSISTENCIES ON PACK PERFORMANCE

Inconsistencies in initial cell resistance and capacity, as well as resistance variance introduced by cell to bus bar connections, all contribute to inhomogeneous current, voltage, temperature, and aging in battery packs. Many studies have investigated the impact of these inhomogeneities and quantified their impact.

For example, a 3S3P configured pack with cell resistance and capacity varying by 5% was found to have an 8% SOC imbalance and 3°C variance in temperature across the pack after a full discharge [32]. After 310 days of cycling, the variance of capacity and resistance between the cells grew to 10% and 25% respectively, demonstrating that over time variance between cells tends to grow. In another study, a 20% mismatch in resistance and capacity of parallel connected cells was found to reduce pack lifetime by 40%, showing the importance of having consistent cell characteristics [33].

Differences in cell resistance also contribute to uneven current and voltage distribution among parallel and series connected cells. In [34], low temperatures were found to exacerbate this issue, with two parallel connected cells with a 13% difference in resistance having a 50% difference in current at 5°C. In [35], the current of parallel connected cells was found to not be directly proportional to their relative capacities, leading to imbalanced state of charge during operation. Differences in cell capacity also cause nonuniform voltage and temperature distribution, as was observed for an 8S pack with 2.5% variation in capacity between cells which led to a 0.8% variation in terminal voltage between cells during a cycle [36].

The cooling system for a battery pack can also drive uneven temperature distribution. If the cooling media, typically air or liquid, significantly increases in temperature as it flows across the pack or does not cool some parts of the pack

as effectively as others, there will be a temperature distribution across the cells. In [37] the liquid cooling system caused a 4°C temperature variation between cells in a 4S pack and resulted in a 1% variation in voltage between the cells during operation. Non-uniform temperature was shown to cause a 25% difference in current for two parallel connected cells in [38], and to cause 5% additional aging for a temperature distribution of 5°C in [39]. Cooling systems should therefore minimize the temperature variation across the pack, ideally keeping the hottest and coolest parts of the pack within a few degrees Celsius of each other.

C. IDENTIFICATION OF PACK INCONSISTENCIES

Inconsistencies in the pack will result in differences in voltage, current, and temperature between cells. Cell resistance, capacity, and other characteristics can be estimated from measured voltage, current and temperature data. There are many methods for identifying inconsistencies in a battery pack from measured data, including signal processing, model, and data fusion-based methods. For signal processing approaches time domain voltage and current data, which is typically collected using lab-based tests, is used to extract pack inconsistency features [40], [41]. Model based methods utilize adaptive filters to fit equivalent circuit models to measured data and to estimate important features of each cell during operation, such as resistance and capacity [42], [43]. Data fusion methods directly quantify the cell inconsistency using mathematical theories without the need for a cell model, and include information entropy [44], principal component analysis [45], and copula theory [46]. All of these methods can be helpful for managing battery pack performance over time, and for determining if a battery pack meets manufacturing consistency and performance specifications.

D. MODELED IMPACT OF RESISTANCE AND CAPACITY VARIATION ON CELL CURRENT, VOLTAGE AND SOC

To illustrate how resistance and capacity variation between cells effects the distribution of voltage and current in a battery pack, several different cases are modeled in this section. The cells are modeled with a simple equivalent circuit model (ECM) developed in Simulink, which includes state of charge dependent open circuit voltage in series with a resistance. Fig. 3 and Fig. 4 show the impact of the variance of cell resistance on the performance of battery packs with three series and three parallel connected cells. The modeled cells have identical capacity and OCV-SOC characteristics and a 20% resistance variance, as labeled in the figures. Fig. 3 shows that a 20% resistance variance in a 3S battery pack leads significant differences between terminal voltage even though SOC is the same at each point in time. Fig. 4 shows that when the cells are connected in parallel, the resistance variance leads to imbalanced current and therefore imbalanced SOC during the charge. Once the charge stops, the cells SOC will equalize due to the self-balancing effect [10], but these circulating currents will cause some extra loss.

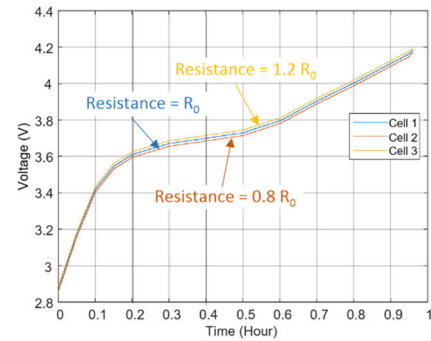


FIGURE 3. Impact of 20% internal resistance mismatch on voltage sharing of 3 series connected cells during constant current charge.

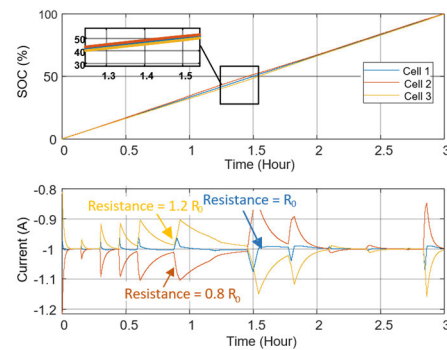


FIGURE 4. Impact of 20% internal resistance mismatch on SOC and current sharing of 3 parallel connected cells during constant current charge.

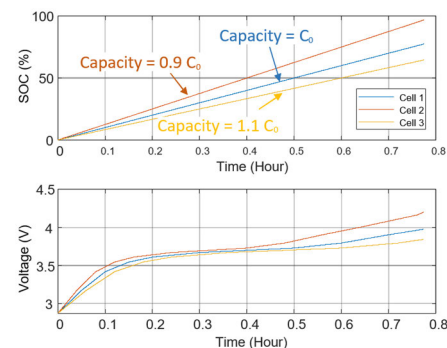


FIGURE 5. Impact of 10% capacity mismatch on SOC and voltage sharing of 3 series connected cells during constant current charge.

Fig. 5 and Fig. 6 show the impact of the cell capacity variance on the performance on a 3S and a 3P battery pack, respectively. The cells are assumed to have identical internal resistance and OCV-SOC characteristics and a 10% capacity variance as indicated in each figure. The figures show cell capacity variance has a significant impact on the SOC of series connected cells, an imbalance that would have to be corrected for through cell balancing methods like those discussed in Section IV.

The magnitude and types of cell inconsistency and their impact on the performance on the battery pack should be considered when developing battery pack estimation methods. Pack SOC estimation methods must be able to identify the SOC of each cell, even for example when the cells'

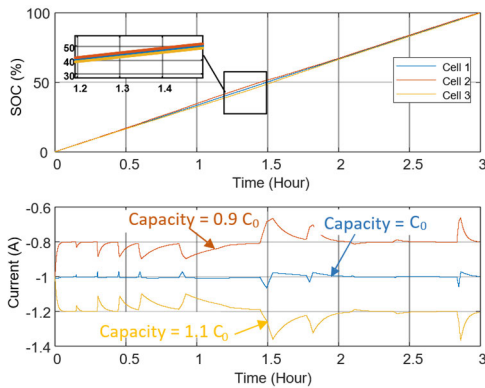


FIGURE 6. Impact of 10% capacity mismatch on SOC and current sharing of 3 parallel connected cells during constant current charge.

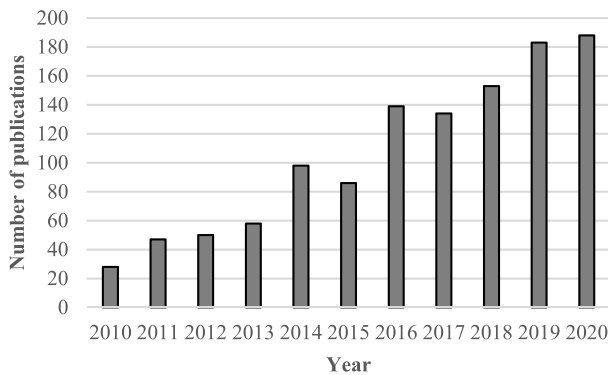


FIGURE 7. Number of publications each year for keywords “state of charge” and “Lithium-ion batteries” searched in the IEEE library.

terminal voltage is different due to resistance variation. Cell inconsistency may also lead to inhomogeneous degradation of the cells and accelerated aging of the pack.

III. SOC ESTIMATION OF LITHIUM-ION BATTERY PACKS

Estimating the state of charge for a lithium-ion battery pack is challenging because each series connection of parallel cells will have slightly different characteristics, such as capacity, resistance, or temperature. SOC estimation algorithms, which have been the subject of increasing interest in the literature (see Fig. 7), must be able to account for differences in cell characteristics and report an SOC value for the pack. Several algorithms of estimating cell SOC are discussed in Section III-A. These algorithms are then applied within pack SOC estimation methods like those which are compared and contrasted in detail in Section III-B.

A. SOC ESTIMATION ALGORITHMS

Generally, SOC can be estimated using different algorithms, including measurement-based, adaptive filters and observers, and data-driven algorithms. In the measurement-based algorithms, SOC is estimated based on measuring some physical quantities which are directly related to the cell SOC namely; coulomb counting [5], [6], OCV [7], [8], and electrochemical impedance stereoscopy (EIS) [9]. For coulomb counting, SOC is estimated by integrating battery current [5], [6]. SOC

can be estimated directly open circuit voltage, but OCV can only be directly observed after an hour or more of non-use [7], [8]. Battery impedance measured with EIS, which applies a sinusoidal voltage or current to the battery and measures the response, can also be used to estimate the battery SOC [9].

Adaptive filters and observers estimate SOC as a function of measured terminal voltage, current, and temperature, and are a more practical solution because they can estimate SOC during operation and correct for current sensor and other errors. These algorithms utilize a battery ECM or electrochemical model as part of the estimation process. The Kalman filter [10]–[14], particle filter [15], [16], least squares filter [17], [18], and adaptive Luenberger observer (ALBO) [19] are all commonly used to estimate battery SOC. The family of Kalman filters includes the extended Kalman filter (EKF) [10], fuzzy-based EKF [11], adaptive Kalman filter (AKF) [12], sigma point Kalman filter (SPKF) [13], and unscented Kalman filter (UKF) [14]. Generally, the Kalman filter estimates SOC via coulomb counting and an equivalent circuit model which is fit to the measured data. The filter is tuned to adjust how much it trusts the model and measurements.

The particle filter or so-called sequential Monte Carlo (SMC) filter utilizes a Monte Carlo sampling method to extract particles from the posterior probability distribution, update their weights, and thus estimate battery SOC [15], [16]. The least-squares filter is a statistical algorithm in which regression analysis is used to determine the best-fit line for a given dataset. Least squares filters have been used with battery models to estimate battery SOC [17] and capacity [18]. Adaptive observers such as the ALBO, which updates observer gain each time step to match the stochastic nature of SOC estimation [19], can also be used to estimate SOC.

Another category of SOC estimation algorithms is based on data-driven algorithms such as neural networks, deep learning, and support vector machine algorithms. These algorithms treat the battery as a black box, and learn the relation between measured values and SOC. The models are trained with data recorded during operation, such as voltage, current, temperature, and state of charge which is the objective function. Recurrent and non-recurrent networks have been used to estimate SOC. [20]–[22] and state of health (SOH) as well. [4], [23].

B. BATTERY PACK SOC ESTIMATION METHODS

Battery pack SOC estimation methods must consider all the inconsistencies which are common in battery packs, while also not placing too much computational load on the BMS. Pack SOC estimation methods therefore aim to simplify the estimation process and improve accuracy by lumping the cells together as a single large cell, by estimating SOC of some cells at a lower update rate, or by estimating cell SOC difference compared to a mean cell. These SOC estimation methods, along with the simplest method of just estimating

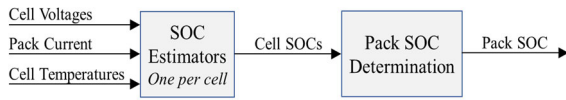


FIGURE 8. Individual cell SOC estimation method.



FIGURE 9. Lumped cell SOC estimation method.

SOC for each individual cell, are discussed in the following sections.

1) INDIVIDUAL CELL ESTIMATION

A straightforward method of pack SOC estimation is to implement a single SOC estimator for each individual cell, like those described in section III-A. The pack SOC is then determined as a function of the individual cell SOC's, with for the simplest case the minimum cell SOC used to represent pack SOC during discharging and the maximum cell SOC used during charging, as described in (1) and shown in Fig. 8. Because each SOC estimation algorithm instance may utilize significant computation resources, this method is not always practical. Other pack estimation methods aim to reduce computational load and potentially improve estimation accuracy as well.

$$SOC_{pack} = \begin{cases} SOC_{min\ cell}, & \text{during Discharging} \\ SOC_{max\ cell}, & \text{during Charging} \end{cases} \quad (1)$$

2) LUMPED CELL ESTIMATION

If the cells in a battery pack have similar characteristics, then it may be suitable to simply consider the pack to be one large cell and to estimate SOC as a function of the overall pack voltage, V_{pack} , and current, I_{pack} , as illustrated in Fig. 9. Many such lumped cell models have been proposed in the literature, such as in [10] where the parameters for a pack ECM were determined offline using a genetic algorithm and SOC was estimated each time step with an EKF. In [19] a similar approach was taken, and pack ECM parameters were determined with an hybrid pulse power characterization test and an ALBO was used to estimate SOC. Incorporating aging into SOC estimation is also important, as was done in [11] using a fuzzy-based EKF for estimating SOC at various stages of aging.

Since SOC is a direct function of open circuit voltage, it is also possible to consider algorithms which eliminate the battery pack current sensor, a costly component. The study in [47] proposed such a current sensor free solution, where reasonable SOC estimation accuracy was achieved for a pack.

The main advantages of lumped cell methods are their simplicity, and they may be a good option for less dynamic applications where the SOC imbalance of cells is not expected to be large. However, this method can lead to accelerated

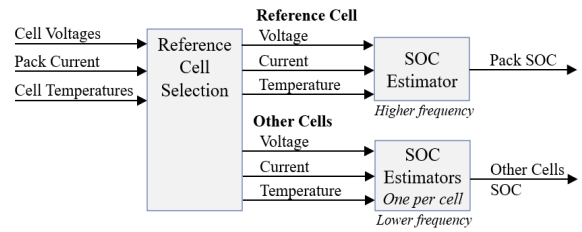


FIGURE 10. Reference cell SOC estimation method.

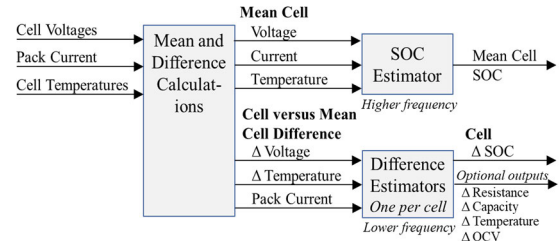


FIGURE 11. Mean cell and difference SOC estimation method.

ageing of the weakest cell in the pack and of a poor estimation of pack SOC if cell characteristics vary too much.

3) REFERENCE CELL ESTIMATION

As an alternative to lumping all the cells together a single cell from the pack, referred to as the reference cell, can be selected to represent the pack performance. The SOC of the reference cell is then estimated using a higher bandwidth, more accurate SOC estimation method. The remaining cells may have a simpler, lower bandwidth SOC estimation method applied as is shown in Fig. 10, allowing for a good pack SOC estimate without the need to have a full performance estimator for each cell. The reference cell is typically chosen based on the weakest cell, i.e., the cell with the lowest voltage during discharge and highest during charging, as is done in [48]–[50]

In [48], the lowest voltage cell is selected as the reference cell and two proposed modified nonlinear predictive filters (NPF) are used, one executed at a higher frequency and a second at a lower frequency, to provide two different estimates of reference cell SOC. The proposed NPF is a modified optimal state estimator implemented for nonlinear systems. However, the process noise can take any form and is estimated with optimal state. In [49] the lowest voltage cell was also selected as the reference cell, and an online variable factor recursive least squares filter was used to estimate the reference cell parameters for an EKF SOC estimation method. The work in [50] expands beyond that in the other studies by proposing a dual time-scale EKF method which estimates SOC of the weakest reference cell at a higher frequency and SOC of the remaining cells at a lower frequency.

4) MEAN CELL AND DIFFERENCE ESTIMATION

The individual, lumped, and reference cell methods all approach SOC estimation in a similar way, using cell or pack measurements as inputs and outputting cells or pack SOC. For mean cell and difference estimation another approach is taken. Mean cell SOC is estimated based on the mean of all the cell voltages and temperatures as shown in Fig. 11. For

TABLE 1. A comparison of SOC estimation methods in lithium-ion battery packs and the corresponding algorithms accuracy.

SOC Method	Pack Configuration	Algorithm	Cell characteristics				Dataset	Error
			variance					
			R	C	T	OCV		
Lumped cell SOC estimation	3S [10]	EKF					DST ¹	0.26 % RMSE
	16S [19]	ALBO					FUDS ²	2.5% MAXE
	120S [11]	Fuzzy-based					NEDC ³	0.82% RMSE
		EKF					FTP ⁴	
	12S [47]	OCV	x				N/A	N/A
Reference cell SOC estimation	6S [48]	NPF	x				UDDS ⁵	2% MAXE
	4S [49]	EKF	x		x	x	FUDS	0.5 RMSE 20°C
	6S [50]	EKF	x	x			DST	2.34-2.37% RMSE
Mean cell and difference SOC estimation	96S [51]	EKF				x	Complex pulse current+ FTP	4% MAXE
	8S [14]	UKF	x				CC ⁶ Discharge	1.83% RMSE
	96S [42]	OCV	x				N/A	3% MAXE
	12S [52]	EKF	x			x	NEDC	2% MAXE
	12P7S [13]	SPKF	x	x	x		N/A	0.5 MAE at 20°C
	4S [53]	SPKF	x	x			UDDS	1% MAXE
	4S [27]	AEKF	x	x	x	x	UDDS+DST	1% MAXE
	6S [54]	EKF			x	x	UDDS+DST	2% RMSE 10°C
	12S [55]	AEKF		x			DST	2% MAXE

x: means covered in the study, DST¹: Dynamic stress test, FUDS²: Federal urban driving schedule, NEDC³: New European drive cycle, FTP⁴: Federal test procedure, UDDS⁵: Urban dynamometer driving schedule, CC⁶: Constant current,

TABLE 2. Performance comparison of SOC estimation methods.

	Individual cell	Lumped cell	Reference cell	Mean cell and difference
Number of SOC algorithms	n	1	(1) + (n-1)	1 SOC + n SOC difference
Cell SOC estimation	Yes	No	Yes	Yes
Computational load for BMS	High	Low	Medium	Low
Engineering effort to develop algorithm	Low	Low	Medium	High

each individual cell, the difference in SOC, ΔSOC , compared to the mean cell is estimated as a function of the difference between the individual and mean cell voltage, ΔV_{cell} , and temperature, ΔV_{temp} , using simplified cell difference models. An accurate, higher bandwidth method is used for estimating the mean cell SOC, and a simpler, lower bandwidth method is used to estimate the ΔSOC values. As a result, mean cell and difference estimation methods typically estimate cell SOC and thus the pack SOC as mentioned in (1) with good accuracy and low computational complexity compared to other methods.

The cell difference models, which capture the difference in SOC between each cell and the mean cell, may also include the difference in internal resistance, capacity, temperature, polarization voltage, and OCV. Cell difference models are often equivalent circuit models with parameters such as delta

open circuit voltage and delta resistance. The model parameters are determined by fitting the model to measured cell voltage difference data.

Many mean cell and difference SOC estimation methods have been proposed in the literature, including [13], [14], [42], [51]–[53] which utilize mean cell voltage and a few which alternatively select the most average cell to represent the mean cell [27], [54], [55]. The work in [51] presented a dual timescale method using an EKF to estimate mean cell SOC at a higher frequency and a method using OCV to estimate cell SOC difference at a lower frequency. In [14] and [42], which uses an UKF and the OCV respectively, the cell difference models also account for cell resistance deviation, leading to more precise SOC estimation. Cell charge and discharge resistance was considered in [52], an EKF was used to estimate both mean cell and cell difference SOC. Another method in [13] utilized even more detailed cell difference models which include deviation in temperature, internal resistance, and capacity, and utilizes a SPKF to estimate mean cell SOC at a higher frequency a second SPKF to estimate cell SOC difference at a lower frequency. An SPKF was also used to estimate mean cell SOC in [53], and a delta filter was used to estimate cell SOC difference via a difference model considering cell resistance and capacity differences.

The aforementioned studies all perform cell SOC difference estimation online, but this estimation can also be done using offline methods as in [27], [54], [55]. While Kalman filters are most commonly used for mean cell and difference

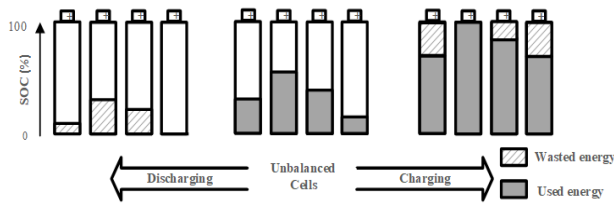


FIGURE 12. The impact of the SOC imbalance on 4-cell battery pack during charging and discharging scenarios.

estimation, researchers have investigated other estimation methods as well. For example in [27] an AEKF filter was used to estimate mean cell SOC and cell SOC difference. Machine learning has been utilized as well, including in [54] and [55] which both use Kalman filters along with neural network based bias correction methods to determine cell to cell variations.

5) COMPARISON OF PACK SOC ESTIMATION METHODS

Table 1 presents a comprehensive comparison of the battery pack SOC estimation methods discussed in this section. The table lists the algorithm type, the cell variance characteristics considered, datasets used, and the corresponding SOC estimation root mean square error (RMSE), mean absolute error (MAE), and/or maximum error (MAXE). The variance in the cells' characteristics may resistance (R) and capacity (C) and their impact on the cells' temperature (T) and open circuit voltage (OCV). All of the algorithms are demonstrated to have quite reasonable error, RMSE a few percent or less or MAXE 5% or less. Error may be higher for a given application though, so it could be beneficial to evaluate several different algorithms and methods before selecting one.

The performance of the different pack SOC estimation methods are also compared qualitatively and quantitatively in Table 2. The individual cell and reference cell methods require the most individual SOC estimation algorithms, and therefore have higher computational load for the BMS. The lumped cell method only has a single SOC estimation algorithm, and the mean cell and difference method utilizes simplified difference models to estimate individual cell SOC, resulting in both methods having the lowest computational load for the BMS. The engineering effort to develop the algorithm is a qualitative value, indicating how much time and resources are needed to implement the algorithm. The individual and lumped cell methods require the least engineering effort to develop, since both only require standard SOC estimation algorithms while the reference and mean cell and difference methods require the development of specialized estimation methods for cells other than the reference or mean cell.

IV. SOC BALANCING METHODS FOR LITHIUM-ION BATTERY PACKS

Because the cells in a battery pack have non-uniform properties, as was discussed in Section II, it is necessary to have a method of balancing the pack to prevent cell SOC differences

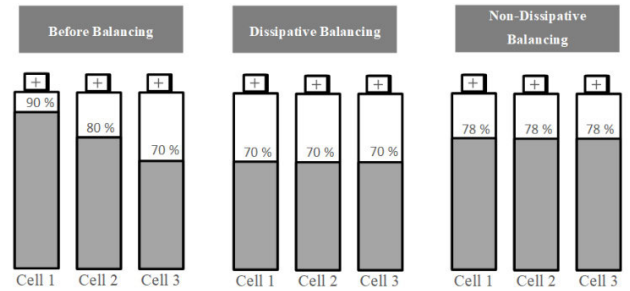


FIGURE 13. A comparison between dissipative and non-dissipative cell balancing methods.

from growing over time. If the difference in SOC between cells becomes too large, the usable capacity will be substantially reduced due to the fullest cell limiting the maximum charge and the emptiest cell limiting the minimum charge, as illustrated in Fig. 12. Cell balancing is typically a very slow process, with resistive balancing circuits dissipating a few hundred milliwatts of power from the most charged cells. Non-dissipative cell balancing circuits, which transfer energy from more charged to less charged or lower capacity cells, can also be used to extend the usable capacity of a battery pack. Non-dissipative balancing circuits are considerably more complex and expensive though and must be fairly high power to offer a meaningful improvement in battery pack performance. In cases of large SOC imbalance, as shown in Fig. 13, non-dissipative balancing will prevent the need to simply convert excess charge to waste heat. Lithium-ion battery cells have such minimal self-discharge though that they typically require very little balancing over time, minimizing any efficiency benefits from non-dissipative methods. Despite this there is still substantial interest in balancing methods for lithium-ion battery packs, including the dissipative and non-dissipative methods highlighted in the remainder of this section.

A. DISSIPATIVE BALANCING METHODS

Most EV manufacturers use dissipative resistive balancing circuits in their battery packs due to their reliability and simplicity. Switched shunt resistors [56] are most commonly used, but it is also possible to use fixed resistors which are always connected to the cells [57]. The fixed resistors cause the pack to naturally balance over time, since the highest voltage cells will have higher resistor current, but there are always losses even when the pack is fully balanced making it a rather undesirable method [58]. In the switched shunt resistor method [56], each cell is associated with a balancing resistor and a switch to connect it to the cell, typically a MOSFET. Most battery cell voltage measurement chips are able to directly control each balancing switch, and some even have the switches integrated into the chip and just require an external resistor. The BMS balances the pack by enabling the discharge resistors on the most charged cells.

B. NON-DISSIPATIVE BALANCING METHODS

Non-dissipative balancing utilizes capacitors [59], [60], inductors [61], [62], transformers [63]–[65], and various

common power electronic converter topologies [66]–[70] to transfer the energy among the cells within the pack. Energy is transferred from more charged to less charged cells, preventing the waste of energy present for dissipative methods. Non-dissipative balancing can achieve relatively high balancing speed [71] and high efficiency [72], which are the main advantages of this method. However, this method involves many components that add more cost and complexity to the balancing circuits [73].

1) CAPACITOR-BASED BALANCING

In this method, capacitors are utilized to transfer the energy between adjacent cells or from the pack to the cell, thus achieving cell balancing. All implementations are based off the same concept, a capacitor is charged while connected in parallel with a higher voltage cell and discharged while connected in parallel with a lower voltage cell. For double-tiered switched capacitor balancing, there is one capacitor per cell and two switches, and the capacitors are switched between adjacent cells at a 50% duty cycle to achieve equal voltage among cells [59]. For single switched capacitor balancing, a single capacitor is used with a group of cells along with five switches plus one switch per cell, allowing the capacitor to be connected in parallel with any of the cells [60]. The switches are controlled intelligently to move energy between cells until balancing is achieved. The double-tiered capacitor method has a faster balancing time and can more easily be modularized while the single switched capacitor method has fewer components [74].

2) INDUCTOR-BASED BALANCING

For inductor-based methods, one or more inductors are utilized for cell balancing [61], [62]. The single-inductor balancing system utilizes one inductor to transfer the energy between the pack to the weakest cells [61]. The control system selects the weakest cell with the lowest SOC level to transfer the energy through activating the corresponding switches. The multi inductor method utilizes $n - 1$ inductor for balancing n cells, [62]. The controller senses the voltage difference of the two neighboring cells, then a control signal is applied to the switches with the condition that the higher cell must be switched on first to transfer the energy to the weakest cell. The inductor-based cell balancing methods have a relatively higher balancing speed and efficiency. However, they have higher switch current stress as compared to the remaining methods [74].

3) TRANSFORMER-BASED BALANCING

Transformers can be utilized to perform isolated transfer of power between cells and the pack and individual cells. The variations of this approach include the use of multiple transformers [63], transformers with multiple secondary windings [64], and a single transformer switched among cells [65]. The multiple transformers method [63] utilizes several transformers where all the primary windings are connected in parallel, and each of the secondary windings are connected to

a separate cell via a diode. The primary winding is connected across the pack voltage via a switch, and power is transferred from the pack to the cells by switching at 50% duty cycle. For the multi-secondary windings transformer method [64], the multiple transformers used for the previous method are replaced by a single multi secondary winding transformer and the balancing approach is the same. However, in this method, the number of cells is limited by the feasible number of secondary windings [74], [75]. For the single transformer method the secondary winding is switched between cells to charge the weakest cells until balancing is achieved [65]. The switched transformer method is more compact, but to ensure good equalization between cells it requires a more complex control process than the other transformer based methods [75].

4) COMMON CONVERTER TOPOLOGY-BASED BALANCING

Common dc-dc converter topologies can also be used for balancing, such as bidirectional buck-boost [66], bidirectional Cuk [67], bidirectional flyback [68], full-bridge [69], and quasi-resonant [70] converters. Typically, one converter per cell is utilized, and the converters transfer power between adjacent cells. Rather than simply allowing the voltage of cells to be matched like many of the prior methods discussed, the converters can control the flow of power in any way the BMS commands allowing more flexibility for managing SOC of the cells.

The bidirectional buck-boost converter is utilized in [66] to transfer energy between two adjacent battery cells. Another bidirectional converter, the Cuk converter, has the same principle of operation but utilizes capacitors as the energy transfer elements instead of inductors [67]. The bidirectional flyback converter, which is derived from the buck-boost converter [68], utilizes a transformer and fewer components to achieve cell balancing. The bidirectional converters have the advantage of transferring energy into or out of cells. The multi-module full-bridge converter is a fully controlled converter that transfers the energy from the cell to the adjacent cell or from the pack to the weakest cell [69]. This method has the advantage of it can be scaled for higher power applications. Zero-current quasi-resonant or zero-voltage quasi-resonant converters can also be used to achieve cell to cell balancing [70]. The resonant circuits are tuned to achieve zero switching current and voltage which reduces the switching loss. Overall, the converter-based cell balancing methods achieve high efficiency and good balancing speed; however, they are more expensive and require a more complex control system [74], [75].

C. COMPARISON OF BALANCING METHODS

Table 3 presents a comparison between the different cell balancing methods, including the number of active elements and advantages and disadvantages of each method [71]–[75]. Overall, dissipative balancing is a reliable, lower cost, and simpler cell balancing method. However, this approach is inefficient as the energy is released in resistors in the form

TABLE 3. A comparison of cell balancing methods in lithium-ion battery packs where n is the number of cells in the pack.

	Method	Active elements	Advantage	Disadvantage
Dissipative balancing	Fixed resistors [57]	n resistors	Easy to implement, low cost	Low balancing speed, continuous heat dissipation and pack discharge
	Switched resistors [56]	n resistors, and n switches	high balancing speed, relatively lower loss	More cost, limited to low power due to need to dissipate loss
Capacitor-based balancing	Double tiered switched capacitors [59]	n capacitors, and $2n$ switches	Adequate balancing speed, modularity, simple control	High number of switches, high cost
	Single switched capacitor [60]	1 capacitor, 1 resistor, and $n+5$ switches	Fewer components, more efficient	Low balancing speed
Inductor-based balancing	Single inductor [61]	1 inductor, $2n$ switches, and $2n$ diodes	Satisfactory balancing speed, higher efficiency	Complex control, high cost
	Multi-inductor [62]	$n-1$ inductors, $2n-2$ switches	Good balancing speed, less control complexity	High cost
Transformer-based balancing	Multiple transformers [63]	n transformers, 1 switch, and n diodes	Good modular design, good balancing speed	Very high cost, less efficient, large size
	Multi windings transformer [64]	1: n transformer, 1 switch, and n diodes	relatively compact	less efficient, limited number of cells
	Switched transformer [65]	1 transformer, $n+6$ switches, and 1 diode	Lower magnetic losses, relatively compact	High cost, complex control is needed
Common converter-based balancing	Buck-boost converter [66]	n converters	Good efficiency, satisfactory balancing speed.	Larger size, cost, complex control is needed
	Cuk converter [67]	$n-1$ converters	Good balancing speed, satisfactory efficiency	Complex control is needed, relatively large size
	Flyback converter [68]	1 converter, $2n$ switches, and 1 transformer	Fewer components, less complex control, fast balancing speed	Transformer needed
	Multi-module full-bridge converter [69]	n converters	Can be scaled to high power applications, good balancing speed	Large size, high cost, complex control is needed
	Quasi-resonant converter [70]	$n-1$ converter	Easy to implement, relatively higher efficiency	Higher cost, and size

of heat without being transferred to other cells. The non-dissipative cell balancing methods can be fast and energy efficient as compared to the dissipative balancing methods. The comparison between the different non-dissipative balancing methods shows that there is no single method that is clearly the best, since each method has a different combination of cost, balancing speed, control complexity, and overall simplicity.

Common converter-based cell balancing methods may be very promising in the future if the power conversion and control circuits can be optimized to reduce size and cost sufficiently.

V. DISCUSSION AND RECOMMENDATIONS

A robust SOC estimation algorithm and BMS must handle the inconsistencies between cells which are inevitably present in a battery pack. Cells produced in the same batch may have capacity and resistance variation around 1%, and the method of connecting bus bars to cells may add a further 1% resistance variation. These inconsistencies may also be exacerbated due to thermal variations within the pack and aging processes, resulting in cell capacity and resistance varying by more than 10% at end of life. Cell sorting, advanced welding techniques, and improved bus bar and thermal design

methods may be applied to reduce variation between cells throughout the life of the pack, reducing the challenge for pack SOC estimation algorithms and the need for higher power cell balancing.

SOC estimation algorithms, including measurement based, filters, observers, and machine learning methods, form the basis for pack SOC estimation methods. The most computationally efficient pack SOC estimation methods estimate SOC at the fastest rate for a single reference or mean cell, and then estimate SOC or the SOC difference for the other cells with a simpler, slower updating algorithm. These methods require more engineering effort to develop than methods which simply apply a full performance SOC estimation algorithm to each cell. Importantly any pack SOC estimation method must handle the differing characteristics of each cell throughout the life of the pack. Mean cell and difference methods, which fit a cell difference model to the difference in voltage between a cell and the mean cell, show particular advantage in identifying small differences in SOC between cells and therefore have significant promise for improving the robustness of pack SOC estimation.

Cell balancing is necessary due to the differences in cell capacity which are present at the time of manufacture and throughout the life of the pack. Pack SOC

estimation algorithms which estimate the SOC of each cell are needed so the BMS can command the balancing circuitry to equalize charge throughout the pack. Resistive balancing remains the most common method of balancing SOC, but there are also many different non-dissipative methods for transferring energy between greater and lesser charged cells. The non-dissipative methods may utilize capacitors, inductors, or transformer-based power converters, and could potentially transfer enough energy to a weak cell to extend the range of an electrified vehicle. More research is needed to quantify how non-dissipative methods could benefit battery pack performance over the life of the pack.

There are many opportunities to further improve the robustness of pack SOC estimation algorithms. Machine learning, for example, has been shown to offer significant potential for cell SOC estimation, but has not yet been optimized specifically for pack SOC estimation. Also while studies have focused on developing pack SOC estimation methods which are more computationally efficient, these methods have not been deployed to a BMS and compared in a comprehensive manner, so it remains uncertain how much benefit reference cell or mean cell and difference models would have. Furthermore, it is difficult to fairly compare different pack SOC estimation algorithms since each study utilizes different datasets. A standardized dataset and evaluation method, which includes a realistic spread in cell parameters and has data to end of life, would help researchers compare algorithms more systematically.

VI. CONCLUSION

There is significant variation in the capacity and resistance of cells in a battery pack due to cell manufacturing tolerances, welding or interconnect methods, and bus bar design in the battery pack. As the battery pack ages, differences between cells grow due to non-uniformities in the pack, including non-uniform temperature distribution. Battery pack SOC estimation algorithms must consider these differences between cells and report a pack SOC value which considers the most and least charged cells. A robust algorithm will estimate the SOC of each cell, typically by either estimating the SOC of each cell individually or through methods like mean cell and difference algorithms which estimate the SOC of one cell and the difference in SOC between the remaining cells. Pack SOC estimation algorithms should not only estimate SOC accurately but must also not be too computationally intensive or difficult to design and implement. The differences between cells also necessitates that some method of balancing be implemented. Resistive balancing, where energy of more charged cells is dissipated in a resistor, remains the most common method. Many different power electronics converter-based methods, which transfer energy between cells, have been investigated by researchers as well and will likely see increased adoption if they can be shown to increase pack life without adding significant size or expense to the BMS.

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