Reconfigurable Battery Systems: A Survey on Hardware Architecture and Research Challenges

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In a reconfigurable battery pack, the connections among cells can be changed during operation to form different configurations. This can lead a battery, a passive two-terminal device, to a smart battery that can reconfigure itself according to the requirement to enhance operational performance. Several hardware architectures with different levels of complexities have been proposed. Some researchers have used existing hardware and demonstrated improved performance on the basis of novel optimization and scheduling algorithms. The possibility of software techniques to benefit the energy storage systems is exciting, and it is the perfect time for such methods as the need for high-performance and long-lasting batteries is on the rise. This novel field requires new understanding, principles, and evaluation metrics of proposed schemes. In this article, we systematically discuss and critically review the state of the art. This is the first effort to compare the existing hardware topologies in terms of flexibility and functionality. We provide a comprehensive review that encompasses all existing research works, starting from the details of the individual battery including modeling and properties as well as fixed-topology traditional battery packs. To stimulate further research in this area, we highlight key challenges and open problems in this domain.

CCS Concepts: • **Computer systems organization** → *Embedded systems*;

Additional Key Words and Phrases: Reconfigurable battery systems, state of charge, state of health, cell imbalance

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1 INTRODUCTION

In recent years, the focus has been on smart utilization of batteries. Various control, optimization, and scheduling techniques have been discussed to improve the performance of batteries in order to achieve better operation and lifetime. Manufacturing as well as modeling problems restrict the availability of batteries in all sizes. That is why battery packs composed of several batteries, from a few to thousands, are commonly used to meet the specific load requirement. Battery packs present many challenges and opportunities for performance enhancement and optimum utilization as each battery is complex and has multiple nonlinear phenomena going on. In order to satisfy the reliability and safety requirements, battery packs generally have a management and monitoring system composed of many devices and features. For last two decades, a lot of effort has been put into improving the performance of battery packs, ranging from pack design to more advanced features such as cell balancing and energy management. Traditionally, these approaches dealt with a fixed configuration of battery packs; i.e., connections of different batteries within a pack were fixed. Ever-increasing demands of storing energy, with increases in the number of electronic devices including gadgets and cars, and perennial demands of longer operation time have generated many challenges. The requirements, challenges, and hence opportunities are available in all magnitudes: from tiny batteries on wearable devices and gadgets to batteries that weigh over 100 kilograms for electric vehicles (EVs).

In contrast to conventional battery packs, reconfigurable battery packs are flexible as the connections between the batteries can be reconfigured. In a reconfigurable battery system, the flexibility of battery topology enables reconfigurable batteries to vary their characteristics, i.e., voltage, currently available capacity, and so forth. This flexibility in architecture can be used to meet the desired load profile, resulting in fewer losses than power converters.

With the introduction of new possibilities by reconfigurable battery systems, there are new challenges as well, e.g., safe and optimal utilization. The rise of this new multidisciplinary cyber-physical field requires new understandings, governing principles, and techniques for optimal results. Extensive research has been conducted on reconfigurable battery systems recently. A good indication has been involvement of different, highly relevant industrial organizations such as Intel, Tesla Motors, Microsoft, and IBM Research, which shows the industrial demands of this rising field. A key advantage of reconfigurable systems is that by providing control freedom, expertise from other domains such as computer science can also be leveraged for innovative solutions, leading to performance enhancement.

To exploit the advantages of reconfigurable battery systems, a lot of techniques have been proposed, and a survey has been conducted in [25]. However, it focuses on battery management systems. In contrast, this article focuses on the hardware architectures of different reconfigurable battery systems and the functional comparison of these architectures, since recently many new hardware architectures for reconfigurable battery systems have been developed, and their uniqueness from a practical perspective and their benefits (and drawbacks) need to be scrutinized.

The aim of this article is to provide a comprehensive review of the hardware architectures of different reconfigurable battery systems. Moreover, we provide a comparison and detailed analysis of different reconfigurable architectures from functional and overhead perspectives. The article addresses key challenges, state-of-the-art technologies proposed by researchers, metrics used to quantify performance, and a comparison of these architectures. Finally, we discuss the applications and scenarios where significant advantages of reconfigurable battery systems have already been shown. An objective of this review is to highlight potential areas of research. To stimulate and motivate further research, we highlight important opportunities and challenges of the field. To the best of our knowledge, this is the first attempt to analyze and compare different hardware architectures used for reconfigurable battery systems.

Unique features of this review article include:

- A concise background of individual batteries including modeling, properties, and tradeoffs is provided. There is an in-depth discussion on design goals that can be leveraged to optimize system performance.
- An overview of reconfigurable batteries is provided, followed by a summary of architectures that have been proposed.
- Existing architectures are analyzed and compared with respect to performance and losses. To the best of our knowledge, this is the first work to compare and highlight the differences (and limitations) of various architectures.
- A comprehensive overview is given of the challenges and future research opportunities in this field.

We use a bottom-up approach to gradually develop the case for reconfigurable batteries. First of all, we take a look at properties of individual batteries in Section 2. Important measures such as State of Charge (SoC) and State-of-Health (SoH) and the basic operating laws of batteries are discussed. In Section 3, we briefly discuss the alternative conventional approach of battery packs, i.e., those with fixed configuration. In Section 4, first we discuss overall design and all the hardware topologies that have been proposed in the literature, and then we provide the comparison of those topologies while discussing the differences and limitations. An analysis of these architectures with respect to flexibility and losses is presented in Section 5. Modeling and software methods are detailed in Section 6. Applications and opportunities of reconfigurable architectures are highlighted in Section 7. Section 8 concludes the article.

2 RECONFIGURABLE BATTERY: INDIVIDUAL CELL PROPERTIES

Before we discuss reconfigurable battery packs, let us first have an introduction to properties of individual cells. Batteries of all chemistries (i.e., different materials) have complex internal processes leading to different operational outcomes under various conditions. First we will have a look at the measures of storage, i.e., SoC and SoH, followed by a discussion on rate discharge effect and recovery effect. We will not cover different chemistries of batteries and problems related to their specific characteristics and construction: generally we will restrict our discussion to the commonly used lithium-ion (Li-Ion) batteries. Interested readers are referred to [74], which covers battery chemistries and their specific properties in detail.

2.1 Modeling

Battery modeling is a mature field now, thanks to dedicated efforts to develop accurate models that can predict responses of batteries under different circumstances. A brief summary of some commonly used methods is presented here, followed by a description of two battery models.

A kinetic battery model, which uses a controlled voltage source, is presented in [81]. This work was extended later on into a hybrid model in [57]. The proposed hybrid model has been used in some reconfigurable battery systems, such as [63]. The work in [100] highlights some electric models of batteries and then emphasizes the battery properties, which are discussed later. Even though electrical-equivalent models of batteries have long been developed, it is interesting to see modeling efforts aiming for cyber-physical codesign, such as [120]. The model in [120] is equivalent to the commonly used Rakhmatov-Vrudhula-Wallach model, which can be used for scheduling and policy development in the cyber part of the system. Capacity fading over time and temperature effects have been considered in the model presented in [33]. A dynamic model for a lithium-ion series battery pack based on the voltage-current relationship of individual cells and experimental validation of models with regard to voltage and current characteristics is presented in [36].

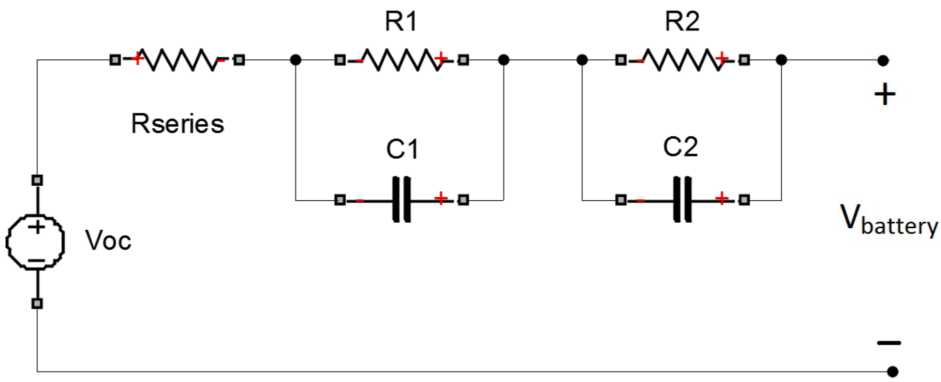

Fig. 1. Battery model: second-order equivalent electric circuit.

2.1.1 Second-Order Model. A commonly used second-order electric model (having two resistor-capacitor pairs) is presented in [21]. Unlike other methods, this model has one resistor-capacitor pair for a short-term instantaneous response and another for a long-term and slow response of current and voltage of batteries. It is also a common practice in many models to use only one resistor-capacitor pair, which implies having a single *time constant* of the systems that is generally used to emulate the long-term slow response of batteries. The equivalent electric model of a battery is shown in Figure 1.

Here, the RC pairs $R_1 - C_1$ and $R_2 - C_2$ represent the short- and long-term responses that are observed in real batteries. R_{series} is the series resistance (also called internal resistance) and V_{OC} is the open-circuit voltage of the battery. Let us define the state vector as $[v_1 \quad v_2 \quad SOC]^T$. Here, v_1 and v_2 represent the voltage drop across C_1 and C_2, respectively. Based on this state vector, we can write the battery dynamics as the linear system shown in Equation (1):

$$\begin{bmatrix} \dot{v}_1 \\ \dot{v}_2 \\ \dot{SoC} \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1C_1} & 0 & 0 \\ 0 & -\frac{1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ SoC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ -\frac{1}{3600C} \end{bmatrix} \cdot i + E \cdot v_n, \tag{1}$$

where C_p is the total rated storage capacity of battery in ampere-hours. Vector v_n represents the noise that is being added in the system and matrix E relates the noise to the system state. Vector v_n is defined as $[n_{v_1} \quad n_{v_2} \quad n_{SoC} \quad n_{voltage}]^T$: it contains noise in states (v_1, v_2, and SoC) and measured voltage.

As universally acknowledged, the relationship between open-circuit voltage v_{OC} and SoC is nonlinear, which makes it difficult to directly consider voltage as system output. Battery voltage can be represented as a nonlinear function of SoC as shown in Equation (2):

$$v_{oc} = f(SoC). \tag{2}$$

This relationship can be found out experimentally. When battery current is i, the output voltage can be written as

$$y = f(SoC) + v_1 + v_2 + R_{series} \cdot i. \tag{3}$$

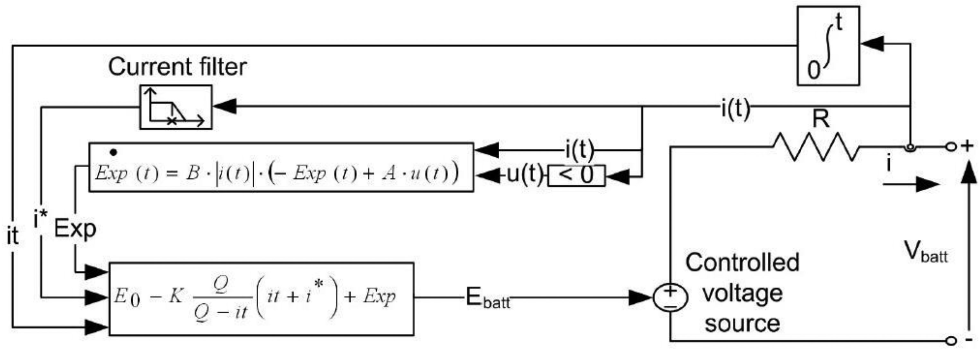

Fig. 2. Battery model implementation in Simulink [115].

A linearized output equation can be obtained by using Taylor series and ignoring higher-order terms, as shown in Equation (4):

$$y = \begin{bmatrix} 1 & 1 & \dfrac{\partial f(SoC)}{\partial SOC} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ SoC \end{bmatrix} + R_{series} \cdot i + F \cdot v_n, \tag{4}$$

where matrix F relates the noise vector to the observed output. Matrices A, B, C, and D can be taken from Equations (1) and (4).

2.1.2 Simplified Nonlinear Model. An alternative battery model is presented in [115], which relies on a first-order scheme. This model has been widely used and this is the battery model implemented in MATLAB and Simulink. Even though that paper discusses models of other types of batteries, we restrict the scope to Li-Ion batteries. Interested readers are referred to [57, 115] for equations about other battery types. The charge model of Li-Ion battery is given in Equation (5):

$$V_{battery} = V_{OC} - R \cdot i - K \frac{C}{it - 0.1 \cdot C} \cdot i^* - K \frac{C}{C - it} \cdot it + A \cdot exp(-B \cdot it), \tag{5}$$

where V_{OC} is the open-circuit voltage (volts), R is the internal resistance (ohms), i is the current and i^* is the filtered current (amperes), C is the total capacity (ampere-hours), K is the polarization constant or resistance (ohms), and it is the used capacity (ampere-hours). A and B are used to model the exponential zone: A is the amplitude of the exponential zone (volts) and B is the time constant inverse ($(ampere - hours)^{-1}$).

The discharge model of the Li-Ion battery is shown in Equation (6):

$$V_{battery} = V_{OC} - R \cdot i - K \frac{C}{C - it} \cdot (it + i^*) + A \cdot exp(-B \cdot it), \tag{6}$$

where the terms having polarization constant K are used to model the changing behavior of effective polarization resistance in Li-Ion batteries. The overall implementation of the discharge model is shown in Figure 2.

We can see that the battery voltage is determined by the expression shown in Equation (6), current i, and filtered current i^*. Also, the exponential zone depends on A and B. For discharge mode, the implementation is the same as shown in Figure 2, and the only difference is the calculation of battery voltage (E_{batt}): now it is calculated according to Equation (6).

2.2 State of Charge

SoC is defined as a measure of charge in a battery with respect to overall storage capacity. It is a unitless quantity generally measured from 0 (fully discharged) to 1 (fully charged), or alternatively from 0% to 100%. The SoC of a battery, at time t, having storage capacity C (units: ampere-hours) can be represented as

$$SoC = SoC_i - \frac{1}{3600C} \int_0^t i(\tau) d\tau, \tag{7}$$

where SoC_i is the initial storage capacity of the battery and i is the current (amperes). The general convention is to consider current as *positive* when the battery is being charged and *negative* while charging. Note that we need to know the initial SoC, as shown in Equation (7).

SoC estimation is a challenging problem for several reasons: the initial SoC may not be known, noise in sensors, and degradation of the total capacity C of the battery. The battery capacity fades over time by charge-discharge cycles and there is self-discharge in batteries (a process where stored charge is lost over time, especially in low temperatures). All these factors give rise to the problem of SoC estimation.

There are two basic physical quantities that can be used (individually or combined) to estimate the SoC: current (i) and voltage (V). The method relying solely on current is referred to as *Coulomb Counting* and can be mathematically written as Equation (7). This method is based on current and the voltage of a cell is fully ignored. The disadvantage of this method is that error accumulates over time and becomes significantly large. Alternatively, some traditional approaches were based on voltage information. This is difficult because of a highly nonlinear SoC-voltage relationship, especially for Li-Ion batteries. Also, the SoC-voltage curve is flat for most of the region: there is a very small change in voltage after a much larger change in SoC, which makes it difficult to use voltage as a basis for SoC estimation. Limited information and the contribution of multiple factors, including noise in measurements and model inaccuracy, make it difficult to rely on only one of current or voltage. Because many methods of SoC estimation exist in the literature, from very simple ones to highly sophisticated ones, we briefly review some relevant literature here.

An estimation method based on Coulomb counting is presented in [93]. A voltage-based method for SoC estimation was presented in [116]. This work dealt with complexities such as hysteresis (difference in voltage levels at the same SoC while charging and discharging). It was also discussed that the SoC for a few of the battery types such as nickel-metal hybrid can be difficult to estimate. A closed-form analytical expression for SoC estimation based on both current and voltage was presented in [102]. A fuzzy logic approach for SoC was presented in [106] that required training data, which is challenging to replicate because changing properties depend on various conditions. An approach based on a complex neural network restricted to lead acid batteries was presented in [17]; it also has a complex network design and computations. An SoC estimation technique based on a genetic algorithm and hybrid neural network for series-connected modules (battery cells) was introduced in [70]. This complex method has promising results, but the method has high computational cost. In [87], a mathematical model that can predict the SoC and remaining operation time for lead acid batteries is presented in [87], but it suffers from low accuracy. Parameters of batteries have been put through different tests in a study presented in [56]. An algorithm introduced in [44] combines the weighted sum of common voltage-based SoC estimation techniques and Coulomb counting. A Kalman filter-based technique for SoC estimation was discussed in [94]. An extended Kalman filter (EKF)-based estimation method is presented in [22]. The paper provides the design of the estimation technique along with detailed simulations and experimental results. However, determination of actual SoC and its comparison with estimated SoC is not shown.

2.3 State of Health

SoH is a measure to quantify the ability of a battery to store charge with respect to its original design storage capacity (both in ampere-hours). SoH is a unitless quantity and generally ranges from 0 to 1, or equivalently from 0% to 100%. Here 0 means a battery cannot store any charge now and 1 implies that it is able to store full capacity according to its design. For example, an SoH of 0.8 for a battery whose design capacity was 1 ampere-hour means now it can store only 0.8 ampere-hour. Due to capacity fading of batteries caused by various phenomena including cycle and calender aging, it is important to keep track of SoH as it tells about the actual capacity of a battery. A review of impedance-based measurement methods for SoH is presented in [48].

Weak battery cells can be identified on the basis of SoH. Generally SoH is acquired by comparing fully charged capacity with the rated nominal capacity. Other methods involving internal resistance/impedance, ability to accept a charge, rate of self-discharge, charge-discharge cycles, and so forth have been adopted. Because of the nature of the problem, most methods of SoH estimation also predict the SoC as well. These techniques are generally limited to nickel-cadmium and lead-acid batteries. A method based on Coulomb counting for SoH prediction is presented in [43, 84].

2.4 Battery Life

Capacity fading is a commonly occurring phenomenon that causes a reduction in the storage capacity of the battery, i.e., reduced SoH. Several factors contribute to reduction in fading, including lithium deposition during overcharge, decomposition of electrolytes, and film formation on electrodes [2]. These side processes have been studied and modeled but generally are dependent on the type and chemistry of battery. As discussed earlier, SoH is a measure of the remaining capacity of battery. However, we need to quantify the *longevity of the battery* as well. *Cycle count* is a common method of specifying the process of capacity fading during the life cycle of a battery. A cycle is defined to be a complete process of charging and discharging the battery. A common way to assess the longevity of the battery is to measure (and predict for the future) the remaining capacity after a particular cycle count.

Among many usage conditions causing capacity fade (such as overcharge and undercharge), we feel the need to specify a common cause that is relevant to subsequent discussion. According to work in [2, 102], the capacity fading is mainly due to film growth on the electrode, which is caused by cell oxidation. The process of film growth can be written as

$$\frac{\partial \delta}{\partial t} = \frac{i_k M}{L \alpha \rho F},$$

where δ represents the film thickness and i_k is the rate (current) of reaction [102]. Parameters M, L, α, ρ, F are constants for any specific battery. The important thing here to note is that when the current is higher (heavy load or fast charging), the process of capacity fading (by film formation) is faster, which will lead to reduced cycle count.

For design algorithms, understandably the goal should be to have maximum longevity in terms of cycle count with as high capacity (SoH) as possible.

2.5 Rate Discharge Effect

The rate discharge effect, governed by Peukert's law, is a common phenomenon that exists in all battery types. In a nutshell, it states that if we increase the discharge rate (current), the *energy* output of the battery will decrease. This is counterintuitive because the law of conservation of energy states otherwise. However, this occurs due to limitations of internal electrochemical reactions of the battery. Peukert's law is expressed as [74]

$$C_p = i^k t, \tag{8}$$

where i is the current (amperes), C_p is the rated storage capacity (ampere-hours), and t is the operation time (hours). Ideally, in the absence of such effect, the operation time should have been $t = \frac{C_p}{I}$, which is represented as $k = 1$ in Equation (8). But in reality, all batteries have $k > 1$, so $t < \frac{C_p}{I}$.

This law dictates an important objective for algorithms: minimize the current of individual batteries. The rate discharge effect has been studied for fixed architecture systems in [6], where internal loss of energy is evaluated. Work in [16, 74] investigated the effect of higher discharge rate on battery storage capacity and temperature rise, respectively. This phenomenon has been leveraged in reconfigurable systems to enhance performance, such as [38, 52, 53, 117]. This property gives an important goal for algorithms: minimize the current of batteries to increase operation time.

2.6 Recovery Effect

After discharge, when a battery is rested, the electrochemical processes lead to voltage recovery of the battery [74]. So the voltage of the battery, which has dropped because of a high discharge rate (current), will rise if it is provided some rest. Recovery of voltage is greater after a higher discharge rate because during the rest period, the battery has the possibility to recover from polarization effects, which have a higher impact when the load is heavy [74]. Other than increased voltage, such rests (sometimes referred to as the process of intermittent discharging) also increase the service life of the battery.

A mathematical method to model the recovery effect is proposed in [52]. Key factors affecting the recovery effect include discharge rate c, discharge time t_d, and rest time t_r. Based on these parameters, a correlation function can be defined as $F_r : c \times t_d \times t_r \to V_{out}$, where V_{out} represents output voltage. To find F_r, multivariate linear regression can be used for every value of t_r. This will formulate a set of functions. Clearly our goal is to maximize recovery efficiency factor η (which represents the percentage increase in voltage). This can be done by computing first the derivative of F_r with respect to discharge rate c by finding eta from $\frac{dF_r}{dc} = 0$. As our aim is to compute *maxima*, we add the condition that $\frac{d^2F_r}{dc^2} < 0$. Of course, utilization of this method is dependent on information about how recovery efficiency is affected by discharge rate c, discharge time t_d, and recovery time t_r.

2.7 Battery Tradeoffs

Battery tradeoffs are interesting and challenging phenomena that offer challenges and opportunities in intelligent systems. A very simple example can be derived from the previously discussed recovery and rate discharge effects: in a parallel pack of batteries, the rate discharge effect would want all cells to be connected in parallel (to minimize individual current), while the recovery effect demands the cells to be rested (at least to an optimal rest time).

The rate discharge effect, which is applicable for the process of charging as well, itself presents a dilemma of power versus output energy. If we deliver high power (to meet higher load demand or to charge the battery quickly), the stored energy will be reduced. On the contrary, if we charge (or discharge) for optimal energy efficiency, it will require a long time. Either of these conditions might be true depending on the condition. As discussed earlier, the discharge rate (current) affects the longevity of the battery by reducing the cycle count. The tradeoff means we can provide more but we will lose some of the stored energy in the battery (SoC). Similarly, charging at a very high rate reduces the cycle count. Here we face the dilemma of either charging very slowly (without

Table 1. Description of Battery Tradeoffs

Battery Tradeoff	Detail
Discharge rate against battery charge	Higher discharge rate means total energy output will be decreased (than at a lower rate). Explained in Section 2.5.
Discharge rate against battery life	At higher discharge rate, battery life (cycle count) will be reduced. Details in Section 2.4
Charge rate against battery life	Fast charging (at higher current) implies battery's life will be reduced. For details, see Section 2.4.

affecting battery life) or charging quickly but at the cost of reduced battery life. As summarized in [3], the battery tradeoffs are shown in Table 1.

3 HARDWARE TOPOLOGIES OF RECONFIGURABLE BATTERIES

First of all, the overall system architecture of reconfigurable batteries is explicated. Next, we present the commonly used architectures' realization of reconfigurable battery systems. From a practical perspective, it may not be feasible to have a large-scale fully reconfigurable battery, i.e., ability to control every individual battery. That is why it is a common practice in large batteries to monitor and reconfigure *modules* instead of batteries. A module may be a collection of batteries in series, referred to as a series-connected module (SCM). Alternatively, we might consider a module as a group of batteries connected in parallel, known as PCM. In the following discussion of architectures, we discuss (and draw) a typical battery as the smallest unit; practically, it may be a module (composed of multiple batteries) instead of a single battery.

3.1 System Architecture of Reconfigurable Batteries

One example of a reconfigurable battery pack is shown in Figure 6. We can see that in addition to batteries, a reconfiguration hardware (composed of switches) is employed for provision of configuration flexibility; we will have a detailed discussion about designs of reconfiguration hardwares in subsequent parts. In a typical reconfigurable battery pack, in addition to batteries, a reconfiguration hardware (composed of switches) is employed for provision of configuration flexibility; we will have a detailed discussion about designs of reconfiguration hardwares in subsequent parts. In some reconfiguration switching designs, the placement of batteries does not matter: all batteries have complete flexibility to be connected in series or parallel, or to be disconnected altogether. On the contrary, some architectures require the preliminary step of designing a pack: maximum cells that can be connected in series and parallel.

Because of the limited safety operation window of Li-Ion batteries, with respect to temperature and voltage, the battery management system (BMS) is a necessary part of any practical battery pack [77]. Details of the BMS, including some famous designs, have been shown in Section 4.1. Typical performance-tracking functions of the BMS include SoC estimation, SoH calculation, and fault detection [77, 110]. Sensing becomes even more significant and critical in large-scale systems, where the problem becomes challenging due to uncertainties of using more hardware components [55]. In addition to monitoring, the BMS is also responsible for intelligently controlling the battery and, in this case, for adaptively reconfiguring the battery to optimize overall system performance. Reconfiguration of battery connections depends on several factors (discussed in detail later), including the requirement to provide desired output to load, ensuring balanced charge among batteries, and scheduling of rest. So overall, the BMS requires hardware (e.g., sensors and switches) as well as software methods such as performance tracking and control of battery topology using high-level algorithms.

The traditional approach of BMS design incorporates a central controller, which monitors and controls all batteries in the system. In [54], a hierarchical approach of BMS design is proposed, where a global BMS communicates with several local BMSs. To achieve a scalable and reliable reconfigurable system, it is proposed in [20, 111] to have a completely distributed BMS in which computation (and decision making) is decentralized. Such a system can leverage the recent rise of smart cells [110], which include monitoring and communication devices, to achieve robust distributed control in the battery network.

4 BATTERY PACKS: FIXED ARCHITECTURE

It is impossible to build a single battery of desired size because of process and production limitations [97]. That is why for heavy loads, battery packs containing thousands of batteries are developed. For example, the battery pack of the Tesla Roadster has 6,800 batteries connected in a pack, where every battery is a standard 18650 rechargeable one [8]. As discussed earlier, every battery has complex, nonlinear processes that are difficult to model and predict. The problem becomes even more complex when we are dealing with battery packs. The network of batteries, connected together in a particular configuration, gives rise to many challenges.

A key issue in battery pack design is safety. Thermal design requires special attention to ensure that heat is properly dissipated and batteries remain safe [31, 107]. Additionally, the safety operational voltage range of batteries (specially Li-Ion) is very small, resulting in a very limited temperature-voltage operation range that is safe (referred to as the safety window) [31]. As discussed earlier, utilization of batteries at overcharge and undercharge conditions also leads to degradation of capacity and, in the worst case, to a safety hazard.

While usage of batteries is currently increasing, it is expected to increase at a higher rate in the future. Small applications, such as cell phones, smart watches, and personal digital tablets, require a single battery. But even moderate loads, in addition to heavy ones, require a battery pack. For example, batteries of laptops and notebooks generally have six to 12 individual cells. On higher loads, most of the practical applications of energy storage employ battery packs. The established applications of battery packs include electric and hybrid electric vehicles [8, 11, 91, 104], grids and micro-grids [10, 30, 98, 122], storing wind energy [76], and uninterruptible power supply (UPS), which is now being adopted by Google, Microsoft, and Facebook for data centers [34].

4.1 Battery Management System

Perhaps the most significant component of the battery pack is the BMS. The BMS monitors voltage, SoC, SoH, and temperature of every battery during charging and discharging. The two main types of BMSs are flat and modular BMSs from the perspective of design structure. A flat BMS is most suited for small-scale applications. This is because, in a large-scale system, a huge amount of wiring can become complex, which is unsuitable for a flat BMS design [1]. Modular BMSs or modularized battery management systems are more appropriate for a large-scale battery system design. The reason is extendability, which caters to hardware of various sizes [66]. Functions like monitoring, protection, SOC and SOH estimation, cell balancing, and charge/discharge control should be incorporated into the BMS [1].

The measurement block acquires voltages, current values of battery cells, and ambient temperature across battery packs [119]. Some methods also monitor internal impedance [65]. Safety features and thermal management are important to prevent the battery pack from operating at conditions that may be harmful to the user or system [79]. The work in [90] describes that the recovery effect can be utilized to extend lifetime. If a battery is not in a safe region (in any respect), the BMS can disconnect the cell from the pack. In the literature, many elegant solutions have been proposed to address the problem of BMS design and deal with practical considerations

[9, 24, 72, 80, 94–96, 101, 112, 114, 121]. A comprehensive review of the BMS and related problems is presented in [77].

4.2 Challenges

4.2.1 Cell Imbalance. Differences in the SoC of individual cells are a commonly occurring phenomenon because of material variance. This problem arises only when batteries are connected in series; cells in parallel naturally *balance* one another. Many solutions for the problem of imbalance have been proposed. Some earlier approaches did the balancing on the basis of voltage; however, most modern approaches utilize SoC information for cell balancing. *Passive balancing* (also known as resistive bleeding) dissipates the energy from cells with higher SoC and repeats it until all cells have a similar SoC. Passive balancing techniques require a long balancing time because of the low rate of charge tranfer between cells [78]. An innovative technique is presented in [85] in which optimal cell-to-cell balancing is achieved for serially connected Li-Ion cells by adding individual cell equalizers. *Active balancing* is an energy-efficient scheme that uses cells with a higher SoC to charge the weaker cells. This transfer (in contrast to loss in passive approaches) saves energy and that is the reason for its widespread adaptation in practical systems. In most active balancing techniques, low-charged cells forcefully extract the charge from cells with a high SOC, which ensures higher energy efficiency but with higher hardware cost and difficult management [86, 92].

Problems of design and control of active balancing have been addressed in the literature. Some of the proposed methods include equalizing converters for charging [45], control formulation [14, 15, 49, 71], DC-DC converters [67, 68], switched capacitors [88], ultra capacitors [118], flyback converters [32, 105], and hierarchical balancing [4, 18]. Since this is a well-studied area, interested readers can refer to the comprehensive survey presented in [13, 82]. One case study of mitigating cell imbalance in battery packs using system reconfiguration was presented in [40], which introduces an algorithm named CSR, a Cell Skipping-assisted Reconfiguration algorithm that can help with identifying system configuration in order to deliver near-optimal capacity of the battery pack.

4.2.2 Energy Management. Energy management is a challenging and fruitful domain in battery packs. Two common scenarios that signify the importance of energy management include cell failures and the possibility to increase the operational time of the system. The advantage of the intelligent scheduling algorithm in increasing the operation time of portable electronic devices is shown in [99]. A nonlinear optimization approach for similar applications is presented in [7]. A comparison of several simple and complex scheduling algorithms and their optimality has been discussed in [51]. Energy management and battery optimization have also been achieved using the method of quadratic programming in several cases, especially in hybrid and electric vehicles [23, 28, 29, 37].

4.2.3 Fault Tolerance. Large-scale reconfigurable battery systems are expected to last for a long time. In order to have high system reliability, it is imperative to have a fault-tolerant design. In [75], large-scale battery systems were evaluated for reliability. A fault-tolerant system allows the use of different circuit elements with a broader range of quality. A well-designed fault-tolerant system can help in lowering the maintenance cost as well. Fault diagnosis tools can detect various types of faults such as single stuck-at fault (SSF), open fault, bridging fault, and so forth [46, 89].

4.3 Two Switches (Series-Connected Modules)

An SCM architecture for reconfigurable batteries has been used in [58, 60, 63, 69]. The simplicity of the architecture (because batteries can only be connected in series) leads to a simple design of the

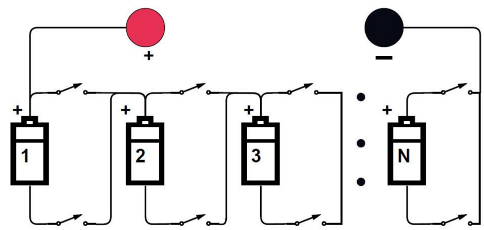

Fig. 3. A series-connected module (SCM) reconfigurable architecture as used in [58, 60, 63, 69].

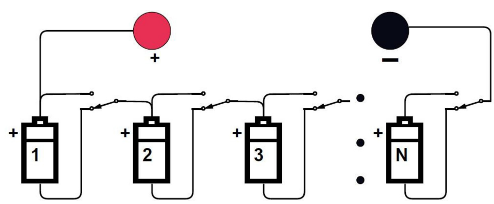

Fig. 4. A series-connected module (SCM) reconfigurable system using a two-way switch, proposed in [5].

architecture. SCM reconfigurable architectures require only two switches per battery, i.e., typical on-off (single-pole, single-throw) switches.

An SCM reconfigurable architecture from [63] is shown in Figure 3. If two-way switches are used (single pole, double throw), only one switch is required for every battery. Such an architecture has been proposed in [5]. The hardware topology of a two-way switch is shown in Figure 4. Though a PCM-based reconfigurable architecture has not been presented in the literature, it is straightforward to see that such a system can also be designed using two (on-off) switches per cell.

4.4 Nearly 1 Switch

An interesting architecture uses a clever tradeoff: its flexibility is limited but it can include or disconnect switches. Such an architecture has been used in [59, 62, 61]. The hardware topology with this configuration is shown in Figure 5. We see that now the restriction is that we can have a maximum of n batteries in parallel and a maximum of m in series. These maximum connections can be at the same time as well: a configuration of n parallel strings, each having m cells in series, is possible. The advantage of such a restriction is that it requires only a small number of switches; precisely, it requires $mn + m$ switches for a complete system, i.e., one switch per battery and one switch for every PCM. As we will soon see, this reduces the number of switches considerably.

4.5 Three Switches and DESA

Usage of three switches for every battery to have a reconfigurable system is very common in the proposed designs. The architecture from [113] (which is perhaps the first work in reconfigurable batteries) is shown in Figure 7. DESA (dependable, efficient, scalable architecture), proposed in [54], uses three switches and is used commonly. Both architectures (DESA in Figure 6 and Figure 7) use three switches per cell and are functionally the same: any cell can be configured in series, parallel, or disconnected altogether. A similar design with the same number of switches is presented in [42, 69, 117].

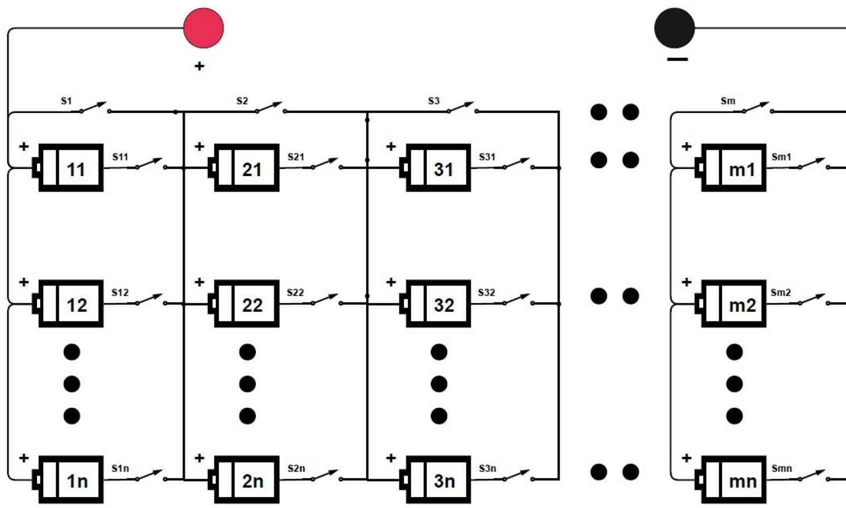

Fig. 5. A hybrid reconfigurable architecture using nearly ibe switch per battery, used in [59, 61, 62].

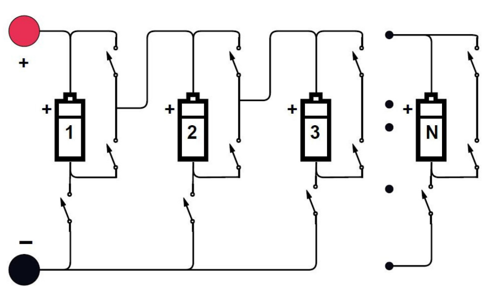

Fig. 6. DESA architecture presented in [54].

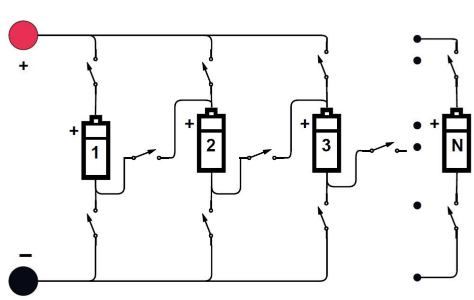

Fig. 7. A flexible architecture requiring three switches for every battery, as used in [38, 113].

Remark. Functionally, the simplified three-switch architecture and DESA are similar: they can reconfigure battery connections. However, as we will see in the detailed analysis (in Section 5.3), DESA has fewer power losses as compared to a simple three-switch architecture.

4.6 Five Switches

A topology using five switches is also frequently used. The architecture of a reconfigurable system with five switches is shown in Figure 8. This architecture has been used in [26, 27]. The authors

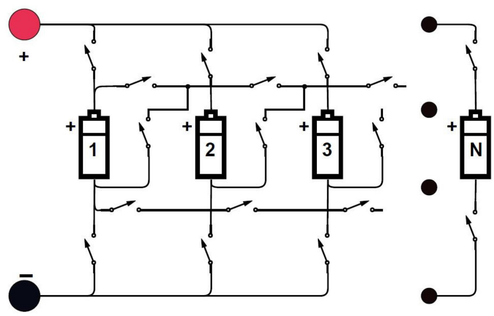

Fig. 8. Reconfigurable architecture using five switches for every battery, utilized in [26, 27].

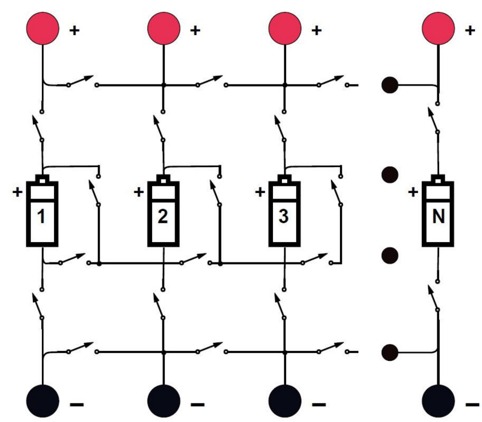

Fig. 9. Topology of reconfigurable system that requires six switches for every battery, used in [50, 52, 53].

in [27] claim the architecture to use six switches, but it is generally observed that the topology requires only five switches for every battery. A simple version of this architecture (with four switches per battery) was used in perhaps the earliest work of reconfigurable batteries, in [113].

4.6.1 Architecture Having Six Switches. A general and more flexible architecture requiring six switches for every battery has been used in several works. The configuration of the six-switch architecture is shown in Figure 9. This topology has been used in [50, 52, 53, 78].

4.7 Multiple Outputs

An interesting concept has been proposed in architecture that capitalizes on the rate discharge effect. The architecture proposed in [50, 52, 53] proposes the capability to deal with multiple loads with only one battery pack. The key novelty in this topology is the ability to serve different loads with a separate set of batteries. So the architecture (shown in Figure 9) has multiple *output terminal pairs* to deal with more than one load, as opposed to the traditional single-output terminal pair (one for positive and the other for ground). Of course, the provision of multiple outputs comes at a cost: the required number of switches is highest (six switches per battery), which increases the requirements and complexity in any reasonably large system.

Utilization of multiple loads and a near-optimal solution of finding an optimal configuration based on such system (with multiple loads) is presented in [38]. Though this works discusses

Table 2. A Functional Comparison of Existing Reconfiguration Architectures

Architecture	No. of Batteries	Total No. of Switches	Max. Series Cells	Max. Parallel Cells	Multiple Isolated Loads
SCM [58, 60, 63, 69]	N	2N	N	Zero	No
Nearly one switch [59, 61, 62]	n×m	mn+m	m	n	No
Three switch [38]	N	3N	N	N	No
DESA [54]	N	3N	N	N	No
Five switch [26, 27]	N	5N	N	N	No
Six switch [50, 52, 53]	N	6N	N	N	Yes

multiple loads, the configuration showed requires three switches per battery (as shown in Figure 7), and the additional hardware (switches) required for flexible output terminal is not discussed.

4.8 Reconfigurable Battery Charging

Recently, dedicated hardware as well as software techniques have been proposed for efficient charging of reconfigurable batteries [41, 42]. The reconfiguration architecture considered in these methods is the one that requires three switches for every cell (Figure 7) with some additional hardware. In software control, the standard scheme of charging Li-Ion batteries is used.

Charging a reconfigurable battery pack with a variable power source, e.g., solar panels, is presented in [83]. Charging is started with cells having a lower SoC, and any cell with a higher SoC is added in as the SoC of a charging group rises to its value. This process of adding cells continues until all cells have been fully charged. Charging solar panels affected by shade can also be handled by reconfiguration as discussed in [73]. A detailed method of classification of groups as well as charging every category based on the graph model is presented in [41, 42].

5 ANALYSIS OF ARCHITECTURES

Though many architectures have been proposed to achieve reconfiguration capability, the advantages (and drawbacks) of existing methods have not been investigated. A summary of these architectures is presented in [25]. While new architectures have been proposed on the basis of novelty and benefits, adoption of existing architectures in recent works has been haphazard. Keeping this in mind, the architectures have been categorized with respect to the number of switches in this article, in Section 3. Now we analyze the flexibility, losses, and additional capabilities of these architectures in a systematic way.

5.1 Flexibility

Since a reconfigurable battery can be considered as a graph, measures of connectivity in the graph can be used to quantify the flexibility of different architectures. Out-degree connectivity can be a formal way of analyzing the flexibility of any particular architecture. The graph model has only been proposed for a three-switch architecture (shown in Figure 7), and even for that system, out-degree connectivity has not been discussed. As discussed, it is difficult to specify out-degree connectivity and perhaps it can be realized with the help of software constraints on the graph.

5.2 Functional Comparison

While specification of out-degree remains an open research problem, we analyze the flexibility of the architecture in terms of practical aspects. Table 2 compares different architectures with respect to the required number of switches and maximum cells that can be connected in parallel and series.

Table 3. Comparison of Losses in Different Architectures

Architecture	Resistance in Series	Resistance in Parallel
SCM [58, 60, 63, 69]	$2R_{on}$	N/A
Nearly one switch [59, 61, 62]	$2R_{on}$	$2R_{on}$
Three switch [38]	$3R_{on}$	$4R_{on}$
DESA [54]	$2R_{on}$	$3R_{on}$
Five switch [26, 27]	$3R_{on}$	$4R_{on}$
Six switch [50, 52, 53]	$4R_{on}$	$6R_{on}$

Two batteries are considered to be connected in series or parallel and they are powering up a single load. The on-resistance (R_{on}) of every switch is assumed to be same.

As discussed earlier, in terms of configuration flexibility, there is no apparent advantage of having architecture with a higher number of switches. On the contrary, topology having more switches increases cost, size, and reliability overhead. However, one key advantage of a six-switch architecture is also highlighted: the ability to serve multiple loads separately, which can be leveraged to enhance operation time.

5.3 Losses

The overall number of switches is a good indication of reconfiguration overhead in terms of size, cost, complexity, and digital input/output (I/O) requirements. However, in any particular configuration (with some cells in series and some in parallel), not all the switches are being used. This leads to an important observation: losses in any particular topology do not entirely depend on the architecture; it also depends on the configuration. A comparative analysis of losses of all architectures is presented in Table 3. The scenario considered includes a battery having two cells and losses (in terms of resistance) and is presented in the table. The on-resistance of every switch is considered to be uniform, i.e., R_{on}. Once we know total resistance in either case (series or parallel), the power losses can be calculated as $P_{loss} = I^2R$, where I represents current and R is the total resistance.

An important observation from Table 3 is the superiority of DESA [54] over other three-switch architectures. Though three-switch architecture (Figure 7) seems functionally similar to DESA (Figure 6), the resistance in DESA architecture is less than other architectures. This asserts the superiority of the DESA architecture, despite the apparent complexity in structure in contrast to the simpler three-switch architecture.

5.4 Future Work: Added Flexibility

The six-switch architecture is the only one that proposes utilization of more switches than others and also explicitly mentions the advantage of this additional overhead: the ability to deal with multiple loads separately, which extends operational time. This line of thinking poses the open question: with additional flexibility of a complex system (five and six switch), is there any additional benefit offered that is not available in simple architectures (three switch, DESA, or nearly one switch)? A formal investigation will either explore the added benefit or render these extra switches as surplus and future researchers can adopt simple architectures.

6 MODELING AND SOFTWARE METHODS

In this section, we investigate modeling and software methods that have been used in reconfigurable battery systems to enhance performance.

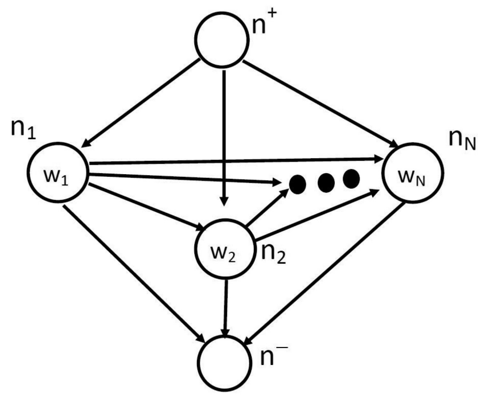

Fig. 10. Graph modeling of a reconfigurable battery system.

6.1 Modeling of Reconfigurable Architectures

Reconfigurable battery systems can be modeled as a directed graph. This approach has been proposed and used by several papers such as [38, 41, 42].

The graph model of a typical reconfigurable battery is shown in Figure 10. In this approach, we have a graph $G = (V, E, W)$, where V is a set of vertices, E is a set of edges, and W is a set of weights of every node. Physically, W_i shows the voltage of node V_i. Here, V is defined as the set of all vertices, and every battery in the network is a vertex. Additionally, we have two more vertices n^+ and n_-, which represent the positive and negative output terminals:

$$V = \{n_1, n_2, \ldots, n_N, n_+, n_-\}, \tag{9}$$

where N is the total number of batteries in the network. E is straightforward: it contains all the edges of the network. The direction of the conventional current is followed in this directed graph, i.e., from positive to negative. Weights W are defined as

$$W = \{w_1, w_2, \ldots, w_N, w_{n_+}, w_{n_-}\}, \tag{10}$$

where w_i represents the voltage of battery i. Also, $w_{n_+} = w_{n_-} = 0$.

The abstract graph modeling effectively decomposes the problem of network configuration in two tasks. First, on the graph level, a *high-level* configuration of the system can be found, according to the objective of maximizing operation time. In this stage, only the graph model and edge connectivity are used to find the optimal configuration (i.e., which cells to configure in series or parallel). Once this (difficult) problem has been solved, a straightforward second phase is to find *switch states*: for a known connection scheme, which switches to turn on and others to be turned off.

6.1.1 Comments on Graph Modeling. Graph representation of a reconfigurable battery is a challenging task. Since the connections among batteries can be changed, this *switching topology* makes it difficult to capture the edge connectivity. The problem is further complicated due to a simplification in the proposed method: representation of a two-terminal battery with a simple node. Though this simplification helps in decomposing the problem in two parts (solving for configuration and finding states of switches), it creates a problem as well.

The key challenge here is to determine the out-degree connectivity of the graph. The most conservative case will be to have out-degree connectivity of 2, implying that a battery is only connected to its spatial neighbors. The other extreme is to consider an all-to-all connection topology.

The paper that proposed graph modeling shows an all-to-all configuration of the graph, but in evaluations, they consider out-degree connectivity from 1 to 5 [38].

As an example, two farthest batteries in a network, n_1 and n_N, can be connected. However, this does not guarantee all-to-all connectivity. The scenario in which battery n_i is connected to n_j, battery n_k, such that $i < k < j$, cannot be connected to any other battery n_l, such that $l < i$ or $l > j$. This clearly prohibits the connection from n_1 to n_N, which could be possible in some scenario (other batteries in between are disconnected).

Remark. In our opinion, the problem of graph connectivity is an open area and it can be investigated by researchers in the future. Perhaps the solution lies in having an all-to-all connectivity with additional constraints that incorporate the physical limitations of a particular topology. Developing a set of constraints for every architecture will be helpful in terms of functionality as well to analyze their flexibility.

6.2 Scheduling

Scheduling has been a powerful tool to improve the operation time of reconfigurable battery systems. Configuration flexibility and the ability to implement software algorithms enable the utilization of scheduling algorithms. These techniques can be used to intelligently *schedule the energy* to maintain desired states of the system.

The work in [52] explores the problem of energy scheduling in detail. They consider the battery properties of both the rate discharge effect and recovery effect and evaluated the performance of several scheduling algorithms. The authors proposed a weighted-k round-robin (kRR) scheduling algorithm that varies from 1-RR to nRR according to load demand and remaining energy in the batteries. In addition to extending the operation time as compared to the baseline system, the results show the ability of fault tolerance.

6.3 Battery Policies

A recent work presented in [3] investigates the interesting problem of dealing with battery tradeoffs. Battery tradeoffs, as summarized in Table 1, pose challenging questions of whether to go for instantaneous benefit or long-term advantage. The work in [3] proposes utilization of application programming interfaces (APIs), which control the charge or discharge speed according to high-level information. In increasing devices, such as smart watches and personal electronic tablets, it is possible to know the requirement (and routine) of the user, which can be used through APIs to leverage battery tradeoffs for optimal results. The architecture in [3] proposes utilization of a switch-mode regulator for discharging and a reverse buck regulator for charging, hence the capability to *control* the rate of charging or discharging.

6.4 Optimization Techniques

In [38], optimization problems and their solutions have been formally posed based on the graph modeling. Since this paper also considers multiple loads, they formulate separate problems for single and multiple loads. It is shown that both problems are NP-hard and a polynomial solution cannot be guaranteed. For a single load change, it is proposed that a set of all feasible paths is found by a depth-first search (DFS) algorithm with pruning. To decrease current, the problem can then be considered as finding the largest set of disjoint paths. This problem has been formulated as an integer program (IP), which can be used by commercial solvers. Since the problem of multiple loads is more challenging and there are additional constraints because of conflicts in paths, a greedy algorithm is proposed for this scenario. First, load selection is prioritized according to the current requirement: the load that demands more current is dealt with earlier. Second, for every selected load, the path selection is done on the basis on minimal conflict. The path that has the fewest conflicts with other paths (hence the possibility of adding more paths) is selected first. In [103], lithium-ion battery pack diagnostics were improved by optimizing the internal allocation for demand current for identifying different parameters. Another optimization problem is formulated as the Lagrangian relaxation problem and a dynamic programming solution is proposed in [27, 72].

Remark. It is proposed that the objective function is to minimize the current of individual batteries, which increases operation time, according to the rate discharge effect. The requirement of meeting load demand is ensured by formulating it as a constraint of the optimization problem.

6.5 Utilization of Different Battery Types

The work in [3] also proposes a novel method to integrate batteries of different chemistries. Traditionally, a system only has a single type of battery because of fixed connection topology. In this work, it is proposed that since the charge and discharge rate of batteries can be controlled independently, it enables the designers to have different types of batteries in a single system. To understand the benefit of this ability, consider the possibilities of combining a battery with higher power capability (but low storage, such as LiFePO4 cathode Li-Ion) with a battery that has more storage capacity but can provide limited power (such as CoO2 cathode Li-Ion).

6.6 Dynamic Reconfiguration

The problem of dynamic reconfiguration, based on load demand and the SoC of cells, has been studied by many researchers in detail. Authors in [26] proposed a model that formulates series and parallel connections separately and uses them according to load demand. The problem of reconfiguration is broken into two steps of meeting load requirement and recovering from cell failure in [53]. A dynamic reconfiguration based on mosfets is presented in [35]. A switch configuration algorithm and DESA architecture were presented in [54]. An optimal switching algorithm based on the current SoC of batteries is presented in [59, 62].

Traditionally, reconfiguration is done on the basis of the SoC of batteries. However, a recent work [39] proposes reconfiguration on the basis of the SoH of cells.

7 APPLICATIONS AND OPPORTUNITIES

First, we review the existing and potential applications of the reconfigurable batteries, followed by a discussion on challenges and research opportunities.

7.1 Applications

Suitable applications for reconfigurable batteries include large-scale systems, such as UPS and data centers, hybrid and electric vehicles, micro-grids, and renewable energy storage systems [64]. Dynamic changes in load requirement and higher demand for reliability and system performance make these application areas suitable for reconfigurable battery packs. Interestingly though, researchers have already shown the benefit of this technology for improved performance in consumer electronics, including laptops and electronic tablets. A review of the existing and potential applications of reconfigurable batteries is presented in [25]. Mostly, existing work on reconfigurable batteries has been evaluated in laboratory settings. But there are already some examples that have shown improved performance of reconfigurable battery systems.

7.1.1 Light Loads. In [117], two applications were considered: a customer reference board (CRB) by Intel (Napa platform) and a laptop. In this work, they modified the original system having switches (for charging and discharging) and added more switches for reconfiguration. Based on dynamic reconfiguration, they showed an improvement of up to 15 minutes of operation time. Twelve light bulbs (3.6 watts each) were used in [38] to demonstrate the superiority of the reconfigurable system. In [3], a smart watch and a two-in-one (tablet with a detachable keyboard) were considered. In this exciting work, the authors showed superiority of software techniques by leveraging battery tradeoffs to enhance the operation time of widely used gadgets.

A programmable electric load has been used as load by many researchers [39, 58–60, 62].

7.1.2 Heavy Loads. An exciting new field that requires flexible energy storage has been termed as energy internet with the help of energy routers [12, 47]. Perhaps the work in [5] is the only existing one that has successfully applied a reconfigurable battery system to an electric vehicle. A module switch for reconfiguration is proposed for electric vehicle application. The designed system was implemented on hardware and it was tested for currents as high as 160 amperes. Thermal aspects were considered in the design and results also show the stability in high powered application.

7.2 Opportunities and Challenges

7.2.1 Modeling and Simulation. Though an abstract graph model of the reconfigurable battery system has been proposed, it has some limitations. As discussed earlier, connectivity remains an open issue because it is not straightforward to determine the out-degree connectivity of such systems. The right solution perhaps lies between extremes of conservative connectivity with spatial neighbors and all-to-all connectivity. Formulation of accurate constraints that depict the connectivity of different architectures will increase our understanding and also provide insight into the benefits of more flexible systems.

So far, there is no unified framework for simulation of reconfigurable battery systems. With growing research interest in this field, it is a need of the time to develop such a system that can be readily used by others. Currently all researchers develop their own simulation environment by using a model of a single battery and building everything manually. This difficulty leads to increased time requirements and a lack of a common framework for ease of collaboration and comparison.

7.2.2 Hardware Design. There is still room for hardware development because of a clear gap. On one hand, we have systems that can only deal with a single load (generally requiring three switches per cell), and on the other hand, we have a system that can deal with as many loads as batteries (and requires six switches per cell). It is possible to reduce the number of switches from six at the cost of sacrificing some loads. For most practical applications, the number of loads is always limited. For example, for an electrical vehicle, other than its drive motor, the only load is secondary appliances, which generally operate at low voltage (usually 12 volts). To deal with a large number of batteries, a modular and reconfigurable battery system is presented in [19]. One case study in [108] shows that 8% of the total weight of the entire system is accounted for by switches and related elements. This value can increase with the degree of reconfigurability required.

7.2.3 Granularity. Granularity of reconfiguration remains an unexplored area so far. In small-scale systems, it is possible to reconfigure every battery. But for large systems, it is impossible to have so many switches. So reconfiguration should be done on modules and not batteries where a module itself is a fixed-connection combination of batteries. This leads us to the challenging questions: what should be the size of the module (fixed configuration) and how much reconfiguration flexibility should there be? This research area must be investigated before industrial adoption of this technology. A secondary question arises about module design, whether it should be SCM, PCM, or hybrid.

7.2.4 Hardware Overhead. Another issue linked with granularity is the assessment of hardware overhead. While there are efficient switches (MOSFETs) that have been reported to have less than 1% losses, there are other practical aspects that need to be analyzed. Overall losses in different (generally adopted) configurations, size of the control circuit, and cost remain important issues because these switches require dedicated effort and resources. An equally important issue is the effect of switches on overall system reliability. Though it has been shown that reconfigurable systems can deal with cell failure, what will happen in case of *switch failure*? This is important to analyze because of the large number of switches and the significance of the reliability of the system from a practical perspective. A detailed study about the types of failures in switches, their detection and prediction, and their impact on system integrity are key areas to be explored.

7.2.5 Intelligent Algorithms. Other than large-scale systems, there is a lot of room for improvement in small applications such as smartphones, tablets, smart watches, and so forth. By having flexible batteries and employing *high-level* policies, we can leverage the battery tradeoffs for improved operation time. Since these gadgets already come with advanced features such as motion tracking and personal scheduling, such information can be used to automatically set the best policy for the user. For example, the information of a user's routine and the next activity can help an intelligent algorithm to choose whether a fast charge (at the cost of reduced battery life) is suitable in the current situation. The possibility of using high-level information (which is becoming increasingly more accessible) to enhance battery performance is exciting and promising and hopefully will be explored in the future.

7.2.6 Distributed Reconfigurable Battery Systems. As explained in [111], an interesting future direction is reconfigurable battery systems that are fully distributed. Existing practical reconfigurable designs are all centralized, which causes a bottleneck in real-time control of large-scale systems. Recently we have seen the rise of smart cells that are capable of tracking performance as well as communication to achieve a distributed control framework [109, 110]. Existing designs of smart cells capable of distributed control are limited to fixed topology. It is a promising and exciting new avenue to test the potential of such smart cells in a system capable of reconfiguration in connections of batteries to optimize the overall performance.

8 CONCLUSION

We have incrementally developed the details of reconfigurable battery systems. We started with single battery, its modeling, and basic properties that can be leveraged for optimal performance. We discussed all hardware topologies in detail and compared their functionality and losses. A discussion on software techniques was followed by some approaches that specifically used optimization techniques for improved performance. Importantly, we summarized the opportunities and challenges in reconfigurable batteries.

We note that there are several hardware topologies that have been tested by researchers. Though there is room for more novel topologies, there are existing ones that can be readily used by any interested researcher. In modeling, as well as simulation, of reconfigurable batteries, there is a lot of room for improvement and contribution from the community. A formal analysis of connectivity and flexibility of existing architectures will provide useful insight. From a practical perspective, investigation is required to analyze the suitable level of granularity for optimal results. Hardware overhead other than losses (size, cost, reliability) also need to be formally studied for widespread adoption of this technology. We hope future research in these directions will accelerate the development of solutions with reconfigurable batteries.

REFERENCES

[1] Adnan H. Anbuky, Zifang Ma, and David Sanders. 2000. Distributed VRLA battery management organisation with provision for embedded Internet interface. In *22nd International Telecommunications Energy Conference, 2000 (INTELEC'00).* IEEE, 713–720.

[2] Pankaj Arora, Ralph E. White, and Marc Doyle. 1998. Capacity fade mechanisms and side reactions in lithium-ion batteries. *Journal of the Electrochemical Society* 145, 10 (1998), 3647–3667.

[3] Anirudh Badam, Ranveer Chandra, Jon Dutra, Anthony Ferrese, Steve Hodges, Pan Hu, Julia Meinershagen, Thomas Moscibroda, Bodhi Priyantha, and Evangelia Skiani. 2015. Software defined batteries. In *Proceedings of the 25th Symposium on Operating Systems Principles (SOSP'15).* ACM, 215–229.

[4] Federico Baronti, Gabriele Fantechi, Emanuele Leonardi, Roberto Roncella, and Roberto Saletti. 2011. Hierarchical platform for monitoring, managing and charge balancing of LiPo batteries. In *2011 IEEE Vehicle Power and Propulsion Conference (VPPC'11).* IEEE, 1–6.

[5] Federico Baronti, Gabriele Fantechi, Roberto Roncella, and Roberto Saletti. 2012. Design of a module switch for battery pack reconfiguration in high-power applications. In *IEEE International Symposium on Industrial Electronics (ISIE'12).* IEEE, 1330–1335.

[6] Luca Benini, Davide Bruni, A. Mach, Enrico Macii, and Massimo Poncino. 2003. Discharge current steering for battery lifetime optimization. *IEEE Transactions on Computers* 52, 8 (2003), 985–995.

[7] Luca Benini, Davide Bruni, A. Mach, Enrico Macii, and Massimo Poncino. 2003. Discharge current steering for battery lifetime optimization. *IEEE Transactions on Computers* 52, 8 (2003), 985–995.

[8] Gene Berdichevsky, Kurt Kelty, J. B. Straubel, and Erik Toomre. 2006. The Tesla Roadster battery system. *Tesla Motors*, 1–5.

[9] Henk Jan Bergveld, Wanda S. Kruijt, and Peter H. L. Notten. 2002. *Battery Management Systems.* Springer.

[10] Michael Bragard, Nils Soltau, Stephan Thomas, and Rik W. De Doncker. 2010. The balance of renewable sources and user demands in grids: Power electronics for modular battery energy storage systems. *IEEE Transactions on Power Electronics* 25, 12 (2010), 3049–3056.

[11] Mamadou Baïo Camara, Hamid Gualous, Frederic Gustin, Alain Berthon, and Brayima Dakyo. 2010. DC/DC converter design for supercapacitor and battery power management in hybrid vehicle applications—Polynomial control strategy. *IEEE Transactions on Industrial Electronics* 57, 2 (2010), 587–597.

[12] Junwei Cao, Meng Kun, and Wang Jiye. 2014. Energy internet and energy router. *China Science Information Sciences* 44, 6 (2014), 714–727.

[13] Jian Cao, Nigel Schofield, and Ali Emadi. 2008. Battery balancing methods: A comprehensive review. In *IEEE Vehicle Power and Propulsion Conference, 2008 (VPPC'08).* IEEE, 1–6.

[14] Pablo A. Cassani and Sheldon S. Williamson. 2009. Feasibility analysis of a novel cell equalizer topology for plug-in hybrid electric vehicle energy-storage systems. *IEEE Transactions on Vehicular Technology* 58, 8 (2009), 3938–3946.

[15] Pablo A. Cassani and Sheldon S. Williamson. 2010. Design, testing, and validation of a simplified control scheme for a novel plug-in hybrid electric vehicle battery cell equalizer. *IEEE Transactions on Industrial Electronics* 57, 12 (2010), 3956–3962.

[16] Giuliano Castelli, Alberto Macii, Enrico Macii, and Massimo Poncino. 2001. Current-controlled policies for battery-driven dynamic power management. In *The 8th IEEE International Conference on Electronics, Circuits and Systems (ICECS'01)*, Vol. 2. IEEE, 959–962.

[17] Chingchuen Chan, LO Wai-chau Edward, and Shen Weixiang. 2000. The available capacity computation model based on artificial neural network for lead–acid batteries in electric vehicles. *Journal of Power Sources* 87, 1 (2000), 201–204.

[18] Efstratios Chatzinikolaou and Daniel J. Rogers. 2018. Hierarchical distributed balancing control for large scale reconfigurable AC battery packs. *IEEE Transactions on Power Electronics* 33, 7 (2018), 5592–5602.

[19] Fa Chen, Wei Qiao, and Liyan Qu. 2017. A modular and reconfigurable battery system. In *2017 IEEE Applied Power Electronics Conference and Exposition (APEC'17).* IEEE, 2131–2135.

[20] Fa Chen, Wei Qiao, and Liyan Qu. 2017. A scalable and reconfigurable battery system. In *IEEE 8th International Symposium on Power Electronics for Distributed Generation Systems (PEDG'17).* IEEE, 1–6.

[21] Min Chen and Gabriel A. Rincón-Mora. 2006. Accurate electrical battery model capable of predicting runtime and IV performance. *IEEE Transactions on Energy Conversion,* 21, 2 (2006), 504–511.

[22] Zheng Chen, Yuhong Fu, and Chunting Chris Mi. 2013. State of charge estimation of lithium-ion batteries in electric drive vehicles using extended Kalman filtering. *IEEE Transactions on Vehicular Technology,* 62, 3 (2013), 1020–1030.

[23] Zheng Chen, Chris Chunting Mi, Rui Xiong, Jun Xu, and Chenwen You. 2014. Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming. *Journal of Power Sources* 248 (2014), 416–426.

[24] Carla-Fabiana Chiasserini and Ramesh R. Rao. 2001. Energy efficient battery management. *IEEE Journal on Selected Areas in Communications* 19, 7 (2001), 1235–1245.

[25] Song Ci, Ni Lin, and Dalei Wu. 2016. Reconfigurable battery techniques and systems: A survey. *IEEE Access* 4 (2016), 1175–1189.

[26] Song Ci, Jiucai Zhang, Hamid Sharif, and Mahmoud Alahmad. 2007. A novel design of adaptive reconfigurable multicell battery for power-aware embedded networked sensing systems. In *IEEE Global Telecommunications Conference, 2007 (GLOBECOM'07).* IEEE, 1043–1047.

[27] Song Ci, Jiucai Zhang, Hamid Sharif, and Mahmoud Alahmad. 2012. Dynamic reconfigurable multi-cell battery: A novel approach to improve battery performance. In *2012 27th Annual IEEE Applied Power Electronics Conference and Exposition (APEC'12).* IEEE, 439–442.

[28] Kristien Clement, Edwin Haesen, and Johan Driesen. 2009. Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids. In *IEEE/PES Power Systems Conference and Exposition, 2009 (PSCE'09).* IEEE, 1–7.

[29] Kristien Clement-Nyns, Edwin Haesen, and Johan Driesen. 2010. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems* 25, 1 (2010), 371–380.

[30] Jarno D. Dogger, Bart Roossien, and Frans D. J. Nieuwenhout. 2011. Characterization of Li-ion batteries for intelligent management of distributed grid-connected storage. *IEEE Transactions on Energy Conversion* 26, 1 (2011), 256–263.

[31] Dan Doughty and E. Peter Roth. 2012. A general discussion of Li ion battery safety. *Electrochemical Society Interface* 21, 2 (2012), 37–44.

[32] Markus Einhorn, Werner Roessler, and Juergen Fleig. 2011. Improved performance of serially connected Li-ion batteries with active cell balancing in electric vehicles. *IEEE Transactions on Vehicular Technology* 60, 6 (2011), 2448–2457.

[33] Ozan Erdinç, Bulent Vural, and Mehmet Uzunoğlu. 2009. A dynamic lithium-ion battery model considering the effects of temperature and capacity fading. In *2009 International Conference on Clean Electrical Power (ICCEP'09).* IEEE, 383–386.

[34] Sriram Govindan, Di Wang, Anand Sivasubramaniam, and Bhuvan Urgaonkar. 2013. Aggressive datacenter power provisioning with batteries. *ACM Transactions on Computer Systems (TOCS)* 31, 1 (2013), 2.

[35] Goksel Gunlu. 2017. Dynamically reconfigurable independent cellular switching circuits for managing battery modules. *IEEE Transactions on Energy Conversion* 32, 1 (2017), 194–201.

[36] Lin Guo, Manish Ramaswamy, Moinak Pyne, Benjamin J. Yurkovich, and Stephen Yurkovich. 2017. Modeling and experimental validation of series connected battery pack modules. In *IEEE Conference on Control Technology and Applications (CCTA'17).* IEEE, 859–865.

[37] Sekyung Han, Soohee Han, and Kaoru Sezaki. 2011. Optimal control of the plug-in electric vehicles for V2G frequency regulation using quadratic programming. In *2011 IEEE PES Innovative Smart Grid Technologies (ISGT'11).* IEEE, 1–6.

[38] Liang He, Lipeng Gu, Linghe Kong, Yu Gu, Cong Liu, and Tian He. 2013. Exploring adaptive reconfiguration to optimize energy efficiency in large-scale battery systems. In *2013 IEEE 34th Real-Time Systems Symposium (RTSS'13).* IEEE, 118–127.

[39] Liang He, Yu Gu, Ting Zhu, Cong Liu, and Kang G. Shin. 2015. SHARE: SoH-aware reconfiguration to enhance deliverable capacity of large-scale battery packs. In *Proceedings of the ACM/IEEE 6th International Conference on Cyber-Physical Systems (ICCPS'15).* ACM, 169–178.

[40] Liang He, Eugene Kim, and Kang G. Shin. 2017. A case study on improving capacity delivery of battery packs via reconfiguration. *ACM Transactions on Cyber-Physical Systems* 1, 2 (2017), 11.

[41] Liang He, Linghe Kong, Siyu Lin, Shaodong Ying, Yu Gu, Tian He, and Cong Liu. 2014. Reconfiguration-assisted charging in large-scale Lithium-ion battery systems. In *ACM/IEEE 5th International Conference on Cyber-Physical Systems (with CPS Week 2014) (ICCPS'14).* IEEE Computer Society, 60–71.

[42] Liang He, Linghe Kong, Siyu Lin, Shaodong Ying, Yu Gu, Tian He, and Cong Liu. 2014. RAC: Reconfiguration-assisted charging in large-scale lithium-ion battery systems. In *Proceedings of the ACM/IEEE 5th International Conference on Cyber-Physical Systems (with CPS Week 2014) (ICCPS'14).* IEEE Computer Society, 60–71.

[43] Liang He, Zhe Yang, Yu Gu, Cong Liu, Tian He, and Kang G. Shin. 2018. SoH-aware reconfiguration in battery packs. *IEEE Transactions on Smart Grid* 9, 4 (2018), 3727–3735.

[44] Y. He, W. Liu, and B. Koch. 2010. Battery algorithm verification and development using hardware-in-the-loop testing. *Journal of Power Sources* 195, 9 (2010), 2969–2974.

[45] Douglas C. Hopkins, C. R. Mosling, and S. T. Hung. 1991. The use of equalizing converters for serial charging of long battery strings. In *6th Annual Proceedings of the Applied Power Electronics Conference and Exposition, 1991 (APEC'91).* IEEE, 493–498.

[46] Camelia Hora, W. Beverloo, M. Lousberg, and R. Segers. 2001. On electrical fault diagnosis in full-scan circuits. In *International Workshop on Defect Based Testing*, 17–22.

[47] Alex Q. Huang, Mariesa L. Crow, Gerald Thomas Heydt, Jim P. Zheng, and Steiner J. Dale. 2011. The future renewable electric energy delivery and management (FREEDM) system: The energy internet. *Proceedings of the IEEE* 99, 1 (2011), 133–148.

[48] François R. Huet. 1998. A review of impedance measurements for determination of the state-of-charge or state-of-health of secondary batteries. *Journal of Power Sources* 70, 1 (1998), 59–69.

[49] Stephen T. Hung, Douglas C. Hopkins, and Charles R. Mosl. 1993. Extension of battery life via charge equalization control. *IEEE Transactions on Industrial Electronics* 40, 1 (1993), 96–104.

[50] Fangjian Jin and Kang G. Shin. 2012. Pack sizing and reconfiguration for management of large-scale batteries. In *IEEE/ACM 3rd International Conference on Cyber-Physical Systems (ICCPS'12)*. IEEE, 138–147.

[51] Marijn Jongerden, Boudewijn Haverkort, Henrik Bohnenkamp, and Joost-Pieter Katoen. 2009. Maximizing system lifetime by battery scheduling. In *IEEE/IFIP International Conference on Dependable Systems & Networks (DSN'09)*. IEEE, 63–72.

[52] Hahnsang Kim and Kang G. Shin. 2009. Scheduling of battery charge, discharge, and rest. In *30th IEEE Symposium on Real-Time Systems Symposium.* 13–22.

[53] Hahnsang Kim and Kang G. Shin. 2009. On dynamic reconfiguration of a large-scale battery system. In *15th IEEE Real-Time and Embedded Technology and Applications Symposium, 2009 (RTAS'09)*. IEEE, 87–96.

[54] Hahnsang Kim and Kang G. Shin. 2010. Dependable, efficient, scalable architecture for management of large-scale batteries. In *Proceedings of the 1st ACM/IEEE International Conference on Cyber-Physical Systems (ICCPS'10)*. ACM, 178–187.

[55] Hahnsang Kim and Kang G. Shin. 2011. Efficient sensing matters a lot for large-scale batteries. In *Proceedings of the 2011 IEEE/ACM Second International Conference on Cyber-Physical Systems*. IEEE Computer Society, 197–205.

[56] I. Kim. 2008. Nonlinear state of charge estimator for hybrid electric vehicle battery. *IEEE Transactions on Power Electronics* 23, 4 (2008), 2027–2034.

[57] Taesic Kim and AndWei Qiao. 2011. A hybrid battery model capable of capturing dynamic circuit characteristics and nonlinear capacity effects. *IEEE Transactions on Energy Conversion* 26, 4 (2011), 1172–1180.

[58] Taesic Kim, Wei Qiao, and Liyan Qu. 2010. Series-connected reconfigurable multicell battery: A novel design towards smart batteries. In *2010 IEEE Energy Conversion Congress and Exposition (ECCE'10)*. IEEE, 4257–4263.

[59] Taesic Kim, Wei Qiao, and Liyan Qu. 2011. Self-reconfigurable multicell batteries. In *2011 IEEE Energy Conversion Congress and Exposition (ECCE'11)*. IEEE, 3549–3555.

[60] Taesic Kim, Wei Qiao, and Liyan Qu. 2011. Series-connected self-reconfigurable multicell battery. In *2011 26th Annual IEEE Applied Power Electronics Conference and Exposition (APEC'11)*. IEEE, 1382–1387.

[61] Taesic Kim, Wei Qiao, and Liyan Qu. 2012. A multicell battery system design for electric and plug-in hybrid electric vehicles. In *2012 IEEE International Electric Vehicle Conference (IEVC'12)*. IEEE, 1–7.

[62] Taesic Kim, Wei Qiao, and Liyan Qu. 2012. Power electronics-enabled self-X multicell batteries: A design toward smart batteries. *IEEE Transactions on Power Electronics* 27, 11 (2012), 4723–4733.

[63] Taesic Kim, Wei Qiao, and Liyan Qu. 2012. A series-connected self-reconfigurable multicell battery capable of safe and effective charging/discharging and balancing operations. In *2012 27th Annual IEEE Applied Power Electronics Conference and Exposition (APEC'12)*. IEEE, 2259–2264.

[64] Younghyun Kim, Sangyoung Park, Yanzhi Wang, Qing Xie, Naehyuck Chang, Massimo Poncino, and Massoud Pedram. 2011. Balanced reconfiguration of storage banks in a hybrid electrical energy storage system. In *Proceedings of the International Conference on Computer-Aided Design (ICCAD'11)*. IEEE Press, 624–631.

[65] James D. Kozlowski. 2003. Electrochemical cell prognostics using online impedance measurements and model-based data fusion techniques. In *Proceedings of the 2003 IEEE Aerospace Conference (AEROCONF'03)*, Vol. 7. IEEE, 3257–3270.

[66] Nihal Kularatna. 2010. Rechargeable batteries and battery management systems design. In *36th Annual Conference on IEEE Industrial Electronics Society (IECON'10)*. IEEE, 1–2.

[67] Nasser H. Kutkut. 1998. A modular nondissipative current diverter for EV battery charge equalization. In *Conference Proceedings of the 13th Annual Applied Power Electronics Conference and Exposition, 1998 (APEC'98)*, Vol. 2. IEEE, 686–690.

[68] Nasser H. Kutkut and Deepak M. Divan. 1996. Dynamic equalization techniques for series battery stacks. In *18th International Telecommunications Energy Conference, 1996 (INTELEC'96)*. IEEE, 514–521.

[69] Barrie Lawson. 2012. A software configurable battery. In *EVS26 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium.*

[70] Yuang-Shung Lee, Wei-Yen Wang, and Tsung-Yuan Kuo. 2008. Soft computing for battery state-of-charge (BSOC) estimation in battery string systems. *IEEE Transactions on Industrial Electronics,* 55, 1 (2008), 229–239.

[71] Yuang-Shung Lee and Ming-Wang Cheng. 2005. Intelligent control battery equalization for series connected lithium-ion battery strings. *IEEE Transactions on Industrial Electronics* 52, 5 (2005), 1297–1307.

[72] Ni Lin and Song Ci. 2017. Toward dynamic programming-based management in reconfigurable battery packs. In *2017 IEEE Applied Power Electronics Conference and Exposition (APEC'17)*. IEEE, 2136–2140.
[73] Xue Lin, Yanzhi Wang, Siyu Yue, Donghwa Shin, Naehyuck Chang, and Massoud Pedram. 2012. Near-optimal, dynamic module reconfiguration in a photovoltaic system to combat partial shading effects. In *Proceedings of the 49th Annual Design Automation Conference (DAC'12)*. ACM, 516–521.
[74] T. B. Reddy. 2011. *Linden's Handbook of Batteries*. McGraw-Hill, New York.
[75] Mingjun Liu, Wenyuan Li, Caisheng Wang, Michael P. Polis, Le Yi Wang, and Jian Li. 2017. Reliability evaluation of large scale battery energy storage systems. *IEEE Transactions on Smart Grid* 8, 6 (2017), 2733–2743.
[76] Kuo-Yuan Lo, Yaw-Ming Chen, and Yung-Ruei Chang. 2011. MPPT battery charger for stand-alone wind power system. *IEEE Transactions on Power Electronics* 26, 6 (2011), 1631–1638.
[77] Languang Lu, Xuebing Han, Jianqiu Li, Jianfeng Hua, and Minggao Ouyang. 2013. A review on the key issues for lithium-ion battery management in electric vehicles. *Journal of Power Sources* 226 (2013), 272–288.
[78] Suman K. Mandal, Praveen S. Bhojwani, Saraju P. Mohanty, and Rabi N. Mahapatra. 2008. IntellBatt: Towards smarter battery design. In *45th ACM/IEEE Design Automation Conference, 2008 (DAC'08)*. IEEE, 872–877.
[79] Antonio Manenti, Andrea Abba, Alessandro Merati, Sergio M. Savaresi, and Angelo Geraci. 2011. A new BMS architecture based on cell redundancy. *IEEE Transactions on Industrial Electronics* 58, 9 (2011), 4314–4322.
[80] Antonio Manenti, Andrea Abba, Alessandro Merati, Sergio M. Savaresi, and Angelo Geraci. 2011. A new BMS architecture based on cell redundancy. *IEEE Transactions on Industrial Electronics* 58, 9 (2011), 4314–4322.
[81] James F. Manwell and Jon G. McGowan. 1994. Extension of the kinetic battery model for wind/hybrid power systems. In *Proceedings of European Wind Energy Association Conference and Exhibition (EWEC'94)*. 284–289.
[82] Stephen W. Moore and Peter J. Schneider. 2001. A review of cell equalization methods for lithium ion and lithium polymer battery systems. *SAE Publication* 2001010959.
[83] Shaheer Muhammad, Nan Guan, Shuai Li, Qixin Wang, and Zili Shao. 2017. Efficient and balanced charging of reconfigurable battery with variable power supply. In *IEEE 23rd International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA'17)*. IEEE, 1–6.
[84] Kong Soon Ng, Chin-Sien Moo, Yi-Ping Chen, and Yao-Ching Hsieh. 2009. Enhanced Coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries. *Applied Energy* 86, 9 (2009), 1506–1511.
[85] Quan Ouyang, Jian Chen, Jian Zheng, and Huazhen Fang. 2018. Optimal cell-to-cell balancing topology design for serially connected lithium-ion battery packs. *IEEE Transactions on Sustainable Energy* 9, 1 (2018), 350–360.
[86] Sang-Hyun Park, Ki-Bum Park, Hyoung-Suk Kim, Gun-Woo Moon, and Myung-Joong Youn. 2012. Single-magnetic cell-to-cell charge equalization converter with reduced number of transformer windings. *IEEE Transactions on Power Electronics* 27, 6 (2012), 2900–2911.
[87] Phillip Pascoe and Adnan Anbuky. 2004. VRLA battery discharge reserve time estimation. *IEEE Transactions on Power Electronics* 19, 6 (2004), 1515–1522.
[88] Cesar Pascual and Philip T. Krein. 1997. Switched capacitor system for automatic series battery equalization. In *Conference Proceedings of the 12th Annual Applied Power Electronics Conference and Exposition, 1997 (APEC'97)*, Vol. 2. IEEE, 848–854.
[89] Janak H. Patel. 1998. Stuck-at fault: A fault model for the next millennium. In *Proceedings of the International Test Conference (ITC'98)*. IEEE, 1166.
[90] B. Pattipati, B. Balasingam, G. V. Avvari, K. R. Pattipati, and Y. Bar-Shalom. 2014. Open circuit voltage characterization of lithium-ion batteries. *Journal of Power Sources* 269 (2014), 317–333.
[91] Scott B. Peterson, J. F. Whitacre, and Jay Apt. 2010. The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Journal of Power Sources* 195, 8 (2010), 2377–2384.
[92] Thanh Hai Phung, Jean Christophe Crebier, and Yves Lembeye. 2012. Voltage balancing converter network for series-connected battery stack. In *38th Annual Conference on IEEE Industrial Electronics Society (IECON'12)*. IEEE, 3007–3013.
[93] Sabine Piller, Marion Perrin, and Andreas Jossen. 2001. Methods for state-of-charge determination and their applications. *Journal of Power Sources* 96, 1 (2001), 113–120.
[94] Gregory Plett. 2004. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 1. Background. *Journal of Power Sources* 134, 2 (2004), 262–276.
[95] Gregory Plett. 2004. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification. *Journal of Power Sources* 134, 2 (2004), 262–276.
[96] Gregory Plett. 2004. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. *Journal of Power Sources* 134, 2 (2004), 277–292.
[97] Gregory L. Plett and Martin J. Klein. 2009. Simulating battery packs comprising parallel cell modules and series cell modules. In *Proceedings of Electric Vehicle Symposium and Exhibition (EVS'09)*, 1–17.
[98] Hao Qian, Jianhui Zhang, Jih-Sheng Lai, and Wensong Yu. 2011. A high-efficiency grid-tie battery energy storage system. *IEEE Transactions on Power Electronics* 26, 3 (2011), 886–896.

[99] Ravishankar Rao, Sarma Vrudhula, and Daler Rakhmatov. 2003. Analysis of discharge techniques for multiple battery systems. In *Proceedings of the 2003 International Symposium on Low Power Electronics and Design (ISLPED'03)*. IEEE, 44–47.

[100] Venkat Rao, Gaurav Singhal, Anshul Kumar, and Nicolas Navet. 2005. Battery model for embedded systems. In *18th International Conference on VLSI Design (VLSID'05)*. IEEE, 105–110.

[101] Werner Roessler. 2008. *Lithium-Ion Battery Management Integrating Active Load Balancing*. Technical Report. SAE Technical Paper.

[102] Peng Rong and Massoud Pedram. 2006. An analytical model for predicting the remaining battery capacity of lithium-ion batteries. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems* 14, 5 (2006), 441–451.

[103] Michael J. Rothenberger, Jariullah Safi, Ji Liu, Joel Anstrom, Sean Brennan, and Hosam K. Fathy. 2017. Improving lithium-ion battery pack diagnostics by optimizing the internal allocation of demand current for parameter identifiability. *Journal of Dynamic Systems, Measurement, and Control* 139, 8 (2017), 081001.

[104] Jesús Sallán, Juan L. Villa, Andrés Llombart, and José Fco Sanz. 2009. Optimal design of ICPT systems applied to electric vehicle battery charge. *IEEE Transactions on Industrial Electronics* 56, 6 (2009), 2140–2149.

[105] Jong-Won Shin, Gab-Su Seo, Chang-Yoon Chun, and Bo-Hyung Cho. 2010. Selective flyback balancing circuit with improved balancing speed for series connected lithium-ion batteries. In *2010 International Power Electronics Conference (IPEC'10)*. IEEE, 1180–1184.

[106] Pritpal Singh, Craig Fennie, De Reisner, and Alvin J. Salkind. 1998. A fuzzy logic approach to state-of-charge determination in high performance batteries with applications to electric vehicles. In *15th Electric Vehicle Symposium (EVS'98)*. 30–35.

[107] Kandler Smith and Chao-Yang Wang. 2006. Power and thermal characterization of a lithium-ion battery pack for hybrid-electric vehicles. *Journal of Power Sources* 160, 1 (2006), 662–673.

[108] Ci Song. 2015. Energy informatization and internet-based management and its applications in distributed energy storage system. *Proceedings of the Chinese Society of Electrical Engineering (CSEE'15)*. 3643–3648.

[109] Sebastian Steinhorst, Matthias Kauer, Arne Meeuw, Swaminathan Narayanaswamy, Martin Lukasiewycz, and Samarjit Chakraborty. 2016. Cyber-physical co-simulation framework for smart cells in scalable battery packs. *ACM Transactions on Design Automation of Electronic Systems* 21, 4, Article 62 (June 2016), 26 pages. Retrieved from DOI:https://doi.org/10.1145/2891407

[110] Sebastian Steinhorst, Martin Lukasiewycz, Swaminathan Narayanaswamy, Matthias Kauer, and Samarjit Chakraborty. 2014. Smart cells for embedded battery management. In *IEEE International Conference on Cyber-Physical Systems, Networks, and Applications (CPSNA'14)*. IEEE, 59–64.

[111] Sebastian Steinhorst, Zili Shao, Samarjit Chakraborty, Matthias Kauer, Shuai Li, Martin Lukasiewycz, Swaminathan Narayanaswamy, Muhammad Usman Rafique, and Qixin Wang. 2016. Distributed reconfigurable battery system management architectures. In *2016 21st Asia and South Pacific Design Automation Conference (ASP-DAC'16)*. IEEE, 429–434.

[112] Thomas Stuart, Fang Fang, Xiaopeng Wang, Cyrus Ashtiani, and Ahmad Pesaran. 2002. A modular battery management system for HEVs. In *Future Car Congress*. Citeseer.

[113] Vinesh Sukumar, Mahmoud Alahmad, Kevin Buck, Herbert Hess, Harry Li, Dave Cox, Fadi Nessir Zghoul, Jeremy Jackson, Stephen Terry, Ben Blalock, and M. M. Mojarradi. 2004. Switch array system for thin film lithium microbatteries. *Journal of Power Sources* 136, 2 (2004), 401–407.

[114] Antoni Szumanowski and Yuhua Chang. 2008. Battery management system based on battery nonlinear dynamics modeling. *IEEE Transactions on Vehicular Technology* 57, 3 (2008), 1425–1432.

[115] Olivier Tremblay and Louis-A Dessaint. 2009. Experimental validation of a battery dynamic model for EV applications. *World Electric Vehicle Journal* 3, 1 (2009), 1–10.

[116] Mark Verbrugge and Edward Tate. 2004. Adaptive state of charge algorithm for nickel metal hydride batteries including hysteresis phenomena. *Journal of Power Sources* 126, 1 (2004), 236–249.

[117] Horacio Visairo and Pavan Kumar. 2008. A reconfigurable battery pack for improving power conversion efficiency in portable devices. In *7th International Caribbean Conference on Devices, Circuits and Systems (ICCDCS'08)*. IEEE, 1–6.

[118] Aiguo Xu, Shaojun Xie, and Xiaobao Liu. 2009. Dynamic voltage equalization for series-connected ultracapacitors in EV/HEV applications. *IEEE Transactions on Vehicular Technology* 58, 8 (2009), 3981–3987.

[119] Dongping Xu, Lifang Wang, and Jian Yang. 2010. Research on li-ion battery management system. In *International Conference on Electrical and Control Engineering (ICECE'10)*. IEEE, 4106–4109.

[120] Fumin Zhang, Zhenwu Shi, and Wayne Wolf. 2009. A dynamic battery model for co-design in cyber-physical systems. In *29th IEEE International Conference on Distributed Computing Systems Workshops, 2009 (ICDCS Workshops' 09)*. IEEE, 51–56.

[121] Minxin Zheng, Bojin Qi, and Hongjie Wu. 2008. A Li-ion battery management system based on CAN-bus for electric vehicle. In *3rd IEEE Conference on Industrial Electronics and Applications (ICIEA'08)*. IEEE, 1180–1184.
[122] Haihua Zhou, Tuhin Bhattacharya, Duong Tran, Tuck Sing Terence Siew, and Ashwin M. Khambadkone. 2011. Composite energy storage system involving battery and ultracapacitor with dynamic energy management in microgrid applications. *IEEE Transactions on Power Electronics* 26, 3 (2011), 923–930.

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