INTELLIGENT MANAGEMENT TECHNIQUES FOR RECONFIGURABLE BATTERY SYSTEMS

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Intelligent Management Techniques for Reconfigurable Battery Systems

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CERTIFICATE OF ORIGINALITY

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Abstract

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 which 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 of high performance and long lasting batteries is on the rise. This novel field requires new understanding, principles and evaluation metrics of proposed schemes.

Traditionally used methods, in battery management system for measuring State of Charge (SoC) of a battery cell are Coulomb counting and Extended Kalman Filter (EKF) which suffer from the accumulation of noise and common phenomenon of biased noise, respectively. The noise in sensor readings makes the estimation even more challenging, especially in battery-operated systems where the supply voltage of sensor keeps changing. The traditional approach of dealing with ever-increasing demand for accuracy is to develop more complicated and sophisticated solutions which generally require special models. A key challenge in the adoption of such systems is the inherent requirement of specialized knowledge and hit-and-trial based tuning. In this study, we explore a new dimension from the perspective of a self-tuning algorithm which can provide accurate SoC estimation without error accumulation by creating a negative feedback loop and enhancing its strength to penalize the estimation error. Specifically, we propose a novel method which uses battery model and a conservative filter with a strong feedback which guarantees that worst-case amplification of noise is minimized. We capitalize on battery model for data fusion of current and voltage signals for SoC estimation. To compute the best parameters, we formulate the Linear Matrix Inequality (LMI) conditions which are optimally solved using open-source tools. This approach also features a low computational expense during estimation which can be used in real-time applications. Thorough mathematical proofs, as well as detailed experimental results, are provided which highlight the advantages of the proposed method over traditional techniques.

Charging a battery pack with variable power supply e.g. solar panels or air driven generators can cause voltage mismatch which may result in damage to the battery pack. Conventionally, DC-DC converters are used to solve this problem but these converters can cause charging inefficiency. In this work, instead of DC-DC converters, battery pack with reconfigurable architecture is used to solve this voltage mismatch problem. We develop algorithms to dynamically decide the battery connections of reconfigurable battery pack, to both minimize the voltage mismatch and maintain SoC balancing among difference batteries. Moreover, we develop techniques to integrate the solar panel into the reconfigurable circuit of the batteries to further improve the charging efficiency when the power output condition of different panels are different (e.g., when some of the panels are shaded).

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1 Introduction

Renewable energy, such as wind, solar, hydroelectric etc., provides substantial benefits for our climate, our health, and our economy. The production of electricity from renewable energy sources, such as solar, wind, and hydro power, is highly unstable as they strongly depend on environment conditions. Therefore, the energy generated usually needs to be stored in batteries before being delivered to the consumers. When charging batteries using these unstable energy sources, a significant problem is the mismatch between the voltages of the power supply and the batteries[65]. This mismatch leads to low charging efficiency and may damage the health of battery cells. A common solution in practice is to use converters between the power supply and the battery. However, extra converters not only increase the cost, but also incur considerable energy losses[63].

In addition to providing variable output, traditional solar systems also suffer from shade. If shade covers even a small area of the panel in an array, the output of the whole array suffers drastically. In this study, the problem of voltage mismatch when charging with variable power supply is solved using reconfigurable batteries. Reconfigurable battery pack can not only improves the charging efficiency but also the health of the batteries. Cells in reconfigurable battery pack are connected with switches which can be turned on or off depending on the desired configuration and topologies, which provides control over scalability of voltage output. Therefore, the problem of mismatch can be resolved by dynamically configuring the switches while charging so that the battery pack is able to keep up with the varying charging voltage. Developing an algorithm to efficiently reconfigure large-scale battery packs at runtime is a challenge. The problem of configuring the switches to match an expected output voltage is in general NP-hard [77].

Apart from the charging efficiency, another important issue in battery system is the state of charge (SoC) balancing. State of charge (SoC) is the measure of charge with respect to the total storage of a battery cell. Charging or discharging can highly suffer if there is a significant deviation among the SoC of battery cells in a battery pack. This may also result in decreased health of the cells if it is overdrawn which ultimately leads to decreased lifetime of the battery pack. SoC balancing is taken into consideration which adds an extra dimension of complexity to reconfiguration algorithms.

In order to acquire accurate estimate of SoC, we propose a novel method which uses battery model and a conservative filter with a strong feedback which guarantees that worst-case amplification of noise is minimized. We capitalize on battery model for data fusion of current and voltage signals for SoC estimation. To compute the best parameters, we formulate the LMI conditions which are optimally solved using open-source tools. This approach also features a low computational expense during estimation which can be used in real-time applications.

The above mentioned challenges are addressed by developing algorithms for reconfigurable battery pack. The objective of these algorithms is to match the voltage of reconfigurable battery pack appropriately with the target voltage while balancing the SoC of battery pack cells simultaneously. More specifically, there are two major contributions:

First, a framework to model the problem of switch configuration is developed as an optimization problem to do two things; 1) match the target voltage and 2)maintain SoC balance. This approach can be expanded to tackle more complex application scenarios as well by including corresponding constraints. Generality is the strength of this approach. However, it may be difficult to be implemented because of high computational effort may be required to solve the optimization problem . The second contribution is an efficient heuristic algorithm that is developed to quickly find high-quality suboptimal configuration solutions. This is done by locally adjusting the connection between neighboring battery cells. Moreover, we develop techniques to integrate the solar panel into the reconfigurable circuit of the batteries to further improve the charging efficiency when the power output condition of different panels are different (e.g., when some of the panels are shaded).

In order to evaluate our approach, we build a reconfigurable battery prototype and use solar panels as a power source. Different aspects of our techniques are evaluated by conducting empirical simulation experiments. Experimental results show considerably improved charging efficiency in batteries with reconfiguration that using reconfiguration batteries can significantly improve the charging efficiency. We also discuss the trade-off between the optimality and efficiency of our two methods.

We integrate solar panels with reconfigurable battery pack which provides an ability to reconfigure solar panels in series parallel combinations depending on the load requirement. The benefit of this integration is that a shaded solar panel can be simply bypassed allowing rest of the solar panels to provide maximum power. This is different from conventional systems where shade over single solar panel has drastic impact over output of the whole string. We compare the output of traditional solar panel systems and solar panels integrated with reconfigurable battery pack with the use of our algorithms. The latter shows improved output when there is shade over panels.

2 Background

A variety of techniques have been proposed to measure or monitor the SoC of a cell or battery, each having its relative merits [32]. Charge counting or current integration is, at present, the most commonly used technique, requiring dynamic measurement of the cell/battery current, the time integral of which is considered to provide a direct indication of SoC [33]. SOH (state of Health) is a quantifying estimation that reflects the general condition of a battery and its ability to deliver the specified performance compared with a fresh battery. Battery capacity (i.e., the energy storage capacity) has long been the target of researchers as the definitive battery SOH indicator [35]. In general, a lithium battery is deemed to fail when its capacity fades by 20 % of the rated value [36].

Due to complexity of electrochemical processes in batteries and noise in sensors, many sophisticated algorithms have been proposed for efficient battery monitoring,such as estimation of SoC [34]. An earlier work which uses voltage as the basis of So Cestimation was presented in [37]. Though this work dealt with complexities such as hysteresis, it was concluded that it is difficult to estimate SoC for some battery types such as Nickel-metal hydrid. A fuzzy logic approach for SoC estimation was presented in [38] which required training data which is challenging because of changing properties in different conditions. A complex neural network based approach was presented in [39], but it is restricted to lead acid batteries and requires complex network design and computations.

A hybrid neural network and genetic algorithm based approach of SoC estimation of series connected modules (battery cells) was discussed in [40]. Despite the promising result, the proposed method is relatively complex and has high computational cost.In [41], a complicated mathematical model has been devised,specifically for lead acid batteries, which can predict the SoC and remaining operation time with up to 10% error. A nonlinear estimation method based on the sliding mode observer is presented in [42]. This paper also discusses the parameters of the battery model through different tests. A clever algorithm was presented in [43], it combines the weighted sum of(previously discussed) complex voltage based methods and Coulomb counting techniques. An earlier method based on Kalman filter was presented in [44–47]. In addition to a few similar methods, a famous estimation algorithm based on Extended Kalman Filter (EKF) is proposed in [48–53] have shown promising results. The method proposed in [54] can robustly estimate SoC by using simple but accurate battery model and employing a conservative filtering technique. The H_∞ filter is solved optimally by formulating it as an LMI problem. The separation of computation (calculation of gain once and iterative implementation of estimator) enables the proposed method to be implemented on embedded controllers without compromising real-time operation requirements. One of the problems for electric vehicle (EV) designers is that energy and power density need to be carefully balanced. In an EV, small batteries increase the vehicle's range and light batteries increase the power-to-weight ratio, enabling the EV to achieve better acceleration. More batteries, however, increase the cost of the vehicle design. EVs do have quick acceleration, due to the high torque of the electric motor.

Currently nickel metal hydride (NiMH) and Lithium (Lithium Ion or Lithium polymer) are the common, although research continues into new battery chemistries, such as nano-phosphate cathodes, to allow for high discharge rates, for higher performance. The discharge rate for batteries not only contributes to acceleration rates, but also how quickly the batteries will be charged. The higher the rate, the more energy is lost through heat. Capacitors, are available as alternative components. They have high charge and discharge rates, resulting in lower losses but these benefits can be outweighed by their low energy density [55].

The charging management concepts can also be divided into centralized and decentralized approaches [83]. The decentralized approaches let the EVs optimize its charging behavior based on, for example, a price signal broadcast. The drawback of this approach is that the EV needs to collect and store the trip history. If the EVs should coordinate their charging, for example to include distribution grid constraints, the need for EV-to-EV communication is high.

The centralized approaches focus on a centralized unit that directly controls the charging of the EVs. Additional studies on forecasting and managing EV charging can be found in [57, 58]. A novel method for optimization was presented by [59] which describes the method for planing the charging of electric vehicles with electric grid constraints including voltage and power. This method provides an individual charging plan for each vehicle and which helps in avoiding the congestion on distribution grids.

2.1 Battery Management System

Perhaps the most significant component of battery pack is BMS. BMS monitors voltage, SoC, SoH and temperature of every battery during charging and discharging. The two main types of BMSs are flat and modular BMS from the perspective of design structure. Flat BMS is most suited for small scale applications. This is because, in a large scale system, huge amount of wiring can become complex which is unsuitable for flat BMS design [87]. Modular BMS or modularized battery management systems is more appropriate for a large scale battery system design. The reason is extend-ability which caters for hardware of various sizes [152]. Functions like monitoring, protection, SOC and SOH estimation, cell balancing, and charge/discharge control should be Incorporated in BMS [87].

The measurement block acquires voltages, currents values of battery cells and ambient temperature across battery pack [205]. Some methods also monitor internal impedance [151]. Safety features and thermal management are important to prevent battery pack from operating at conditions that may be harmful to user or system [165]. The work in [176] describes that recovery effect can be utilized to extend lifetime. If a battery is not in safe region (in any respect), 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 [158], [110], [95], [198], [180–182], [187], [200], [207], [166]. A comprehensive review of BMS and related problems is presented in [163].

2.2 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 [160] which covers battery chemistries and their specific properties in detail.

2.2.1 Modeling

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

A kinetic battery model, which used a controlled voltage source, is presented in [167]. This work has been extended later on in to a hybrid model in [143]. The proposed hybrid model has been used in some reconfigurable battery systems, such as [149]. The work in [186] 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 co-design, such as [206]. The model in [206] is equivalent to commonly used Rakhmatov-Vrudhula-Wallach model which can be used for scheduling and policy development in cyber part of the system. Capacity fading over time and temperature effects have been considered in the model presented in [119]. 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 [122].

2.2.2 Second Order Model

A commonly used second order electric model (having two resistor-capacitor pairs) is presented in [107]. Unlike other methods, this model has one resistor-capacitor pair for short-term instantaneous response while other for 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.

2.2.3 Simplified Nonlinear Model

An alternative battery model is presented in [201] 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 the paper discusses models of other types of batteries, we restrict the scope to Li-Ion batteries. Interested readers are referred to [201], [143] for equations about other battery types. The charge model of Li-Ion battery is given in (1).

$$V_{battery} = V_{OC} - R \cdot i - K \frac{C}{it - 0.1 \cdot C} \cdot i^* - K \frac{C}{C - it} \cdot it + A \cdot exp(-B \cdot it), \quad (1)$$

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 exponential zone (volts) and B is the time constant inverse ($(ampere - hours)^{-1}$).

The discharge model of Li-Ion battery is shown in (2):

$$V_{battery} = V_{OC} - R \cdot i - K \frac{C}{C - it} \cdot (it + i^*) + A \cdot exp(-B \cdot it), \quad (2)$$

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 discharge model is shown in fig. 1.

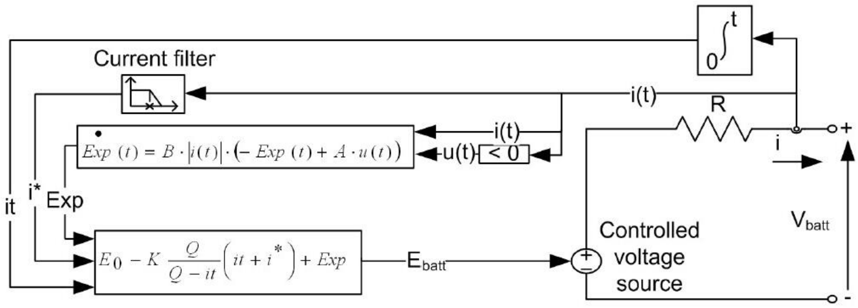


Figure 1: Battery model implementation in Simulink [201].

We can see that the battery voltage is determined by the expression shown in (2), 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 Fig. 1, and the only difference is the calculation of battery voltage (E_{batt}): now it is calculated according to (2).

2.2.4 State-of-Charge

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

$$SoC = SoC_i - \frac{1}{3600C} \int_0^t i(\tau)d\tau, \tag{3}$$

where SoC_i is the initial storage capacity of the battery and i is the current (amperes). General convention is to consider current as *positive* when battery is being charged and *negative* while discharging. Note that we need to know the initial SoC, as shown in (3).

SoC estimation is a challenging problem due to several reasons: initial SoC may not be known, noise in sensors and degradation of total capacity C of battery. 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, specially in low temperatures). All these factors give rise to the problem of SoC estimation.

There are two basic physical quantities which can be used (individually or combined) to estimate the SoC: current (i) and voltage (V). The method relying solely on current is referred as *Coulomb Counting* and can be mathematically written as (3). This method is based on current and voltage of a cell is fully ignored. The disadvantage of this method is that error accumulates over time and becomes significantly large. This is specially because the integrative nature of this method. An estimation method based on Coulomb counting is presented in [179]. Voltage based method for SoC estimation was presented in [202]. This work dealt with complexities such as hysteresis (difference in voltage levels at same SoC while charging and discharging). it was also discussed that SoC for few of the battery types such as Nickel-metal hydrid can be difficult to estimate. A closed form analytical expression for SoC estimation based on both current and voltage was presented in [188]. A fuzzy logic approach for SoC was presented in [192] which required a training data which is challenging to replicate because of changing properties depend on various conditions. An approach based on complex neural network restricted to lead acid batteries was presented in [103]; it also has complex network design and computations. SoC estimation technique based on genetic algorithm and hybrid neural network for series connected modules (battery cells) was introduced in [156]. This complex method has promising results but the method has high computational cost. In [173], A mathematical model that can predict the SoC and remaining operation time for lead acid batteries is presented in [173] but it suffers from low accuracy. Parameters of battery have been put through different tests in a study presented in [142]. An algorithm introduced in [130] combines the weighted sum of common voltage based SoC estimation techniques and Coulomb counting. A Kalman filter based technique for SoC estimation was was discussed in [180]. Extended Kalman Filter (EKF) based estimation method is presented in [108]. The paper provides the design of estimation technique along with detailed simulations and experimental results. However, determination of actual SoC and its comparison with estimated SoC is not shown.

2.2.5 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 unit-less quantity and generally it 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 actual capacity of a battery. A review of impedance-based measurement methods for SoH is presented in [134].

SOH can help in creating effective for the substitution of weak battery cells. Generally SOH is acquired by comparing fully charged capacity with the rated nominal capacity. Other methods, involving using internal resistance/impedance, ability to accept a charge, rate of self-discharge , charge-discharge cycles, etc., have been adopted. Because of nature of 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 [170]and [129].

2.2.6 Battery Life

Capacity fading is a commonly occurring phenomenon which causes reduction in storage capacity of battery i.e. reduced SoH. Several factors contribute to reduction in fading, including lithium deposition during overcharge, decomposition of electrolyte and film formation on electrode [88]. These side processes have been studied and modeled but generally they are dependent on type and chemistry of battery. As discussed earlier, SoH is a measure of remaining capacity of battery. However, we need to quantify the *longevity of battery* as well. *Cycle count* is a common method of specifying the process of capacity fading during life cycle of a battery. A cycle is defined to be complete process of charging and discharging the battery. To assess the longevity of battery, a common way is to measure (and predict for future) the remaining capacity after particular cycle count.

Among many usage conditions causing capacity fade (such as overcharge and undercharge), we feel the need to specify a common cause which is relevant to subsequent discussion. According to work in [88] and [188], the capacity fading is mainly due to film growth on 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 rate (current) of reaction [188]. 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.

2.3 Rate Discharge Effect

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 battery will decrease. This is counterintuitive because law of conservation of energy states otherwise. However this occurs due to limitations of internal electrochemical reactions of battery. Peukert's law is expressed as [160]:

$$C_p = i^k t, \tag{4}$$

where i is current (amperes), C_p is the rated storage storage capacity (ampere-hours) and t is the operation time (hours). Ideally, in absence of such effect, operation time should have been $t = \frac{C_p}{I}$ which is represented $k = 1$ in (4). But in reality, all batteries have $k > 1$ so $t < \frac{C_p}{I}$.

This law dictates an important objective for algorithms: minimize current of individual battery. Rate discharge effect has been studied for fixed architecture systems in [92] where internal loss of energy is evaluated. Work in [160] and [102] investigated the effect of higher discharge rate on battery storage capacity and temperature rise, respectively. This phenomenon has been leveraged reconfigurable systems to enhance performance, such as [203], [139], [138] and [124]. This property gives an important goal for algorithms: minimize current of batteries to increase operation time.

2.3.1 Recovery Effect

After discharge, when a battery is rested, the electrochemical processes lead to voltage recovery of battery [160]. So the voltage of 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 higher discharge rate because during rest period, the battery has possibility to recover from polarization effects which have higher impact when the load is heavy [160]. Other than increased voltage, such rests (sometimes referred as the process of intermittent discharging) also increase the service life of battery.

A mathematical method to model recovery effect is proposed in [138]. 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 $F_r : c \times t_d \times t_r \rightarrow V_{out}$, 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 percentage increase in voltage). This can be done by computing first 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 that how recovery efficiency is affected by discharge rate c, discharge time t_d and recovery time t_r.

2.3.2 Battery Trade-offs

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

Rate discharge effect, which is applicable for 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 long time. Either of this condition might be true, depending on the condition. As discussed earlier, discharge rate (current) affects the longevity of battery by reducing the cycle count. The trade-off means we can provide more more but we will lose some of stored energy in battery (SoC). Similarly, charging at very high rate reduces the cycle count. Here we face the dilemma of either to charge very slow (without affecting battery life) or to charge quickly but at cost of reduced battery life.

2.4 Hardware topologies of Reconfigurable Batteries

First of all, overall system architecture of reconfigurable batteries is explicated. Next, we present the commonly used architectures realization of reconfigurable battery systems. From practical perspective, it may not be feasible to have 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 as 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) typical battery as the smallest unit; practically it may be a module (comprised of multiple batteries) instead of a single battery.

2.5 System Architecture of Reconfigurable Batteries

In a typical reconfigurable battery pack, in addition to batteries, a reconfiguration hardware (comprised of switches) is employed for provision of configuration flexibility; we will have 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 limited safety operation window of Li-Ion batteries, with respect to temperature and voltage, BMS is a necessary part of any practical battery pack [163]. Details of BMS, including some famous designs, have been shown in section 2.1. Typical performance tracking functions of BMS include SoC estimation, SoH calculation and fault detection[196], [163]. Sensing becomes even more significant and critical in large scale system where problem becomes challenging due to uncertainties of using more hardware components [141]. In addition to monitoring, BMS is also responsible to intelligently control the battery, and in this case, to adaptively reconfigure the battery to optimize overall system performance. Reconfiguration of battery connections depends on several factors (discussed in detail later) including requirement to provide desired output to load, ensuring balanced charge among batteries and scheduling of rest. So overall, 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.

Traditional approach of BMS design incorporates a central controller which monitors and controls all batteries in system. In [140], a hierarchical approach of BMS design is proposed where a global BMS communicates with several local BMS. To achieve a scalable and reliable reconfigurable system, it is proposed in [197], [106] to have a completely distributed BMS in which computation (and decision making) is decentralized. Such system can leverage the recent rise of smart cells [196] which include monitoring and communication devices to achieve robust distributed control in the battery network.

2.6 Battery Packs: Fixed Architecture

It is impossible to build a single battery of desired size because of process and production limitations [183]. That is why for heavy loads, battery packs of thousands of batteries are developed. For example, battery pack of Tesla Roadster has 6800 batteries connected in a pack, where every battery is a standard 18650 rechargeable one [94]. As discussed earlier, every battery has complex, nonlinear processes which are difficult to model and predict. The problem becomes even more complex when we are dealing with battery packs. 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 [193], [117]. Additionally, 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 as safety window) [117]. As discussed earlier, utilization of batteries at over-charge and under-charge conditions also leads to degradation of capacity and, in worst case, to a safety hazard.

While usage of batteries is currently increasing, it is expected to increase at a higher rate in 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 6 to 12 individual cells. On higher loads, most of practical applications of energy storage employ battery packs. The established applications of battery packs include electric and hybrid electric vehicles [94], [190], [177], [97], grid and micro-grids [184], [208], [96], [116], storing wind energy [162] and Un-interruptible power supply (UPS) which is now being adopted by Google, Microsoft and Facebook for data centers [120].

2.7 Challenges

2.7.1 Cell Imbalance

Difference in SoC of individual cells is 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 approached 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 similar SoC. Passive balancing techniques require long balancing time because of low rate of charge tranfer between cells [164]. An innovative technique is presented in [171] 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 higher SoC to charge the weaker cells. This transfer (in contrast to loss in passive approaches) saves energy and that is the reason of its widespread adaptation in practical systems. In most active balancing techniques, low charged cells forcefully extract the charge from cells with high SOC which ensures higher energy efficiency but with higher hardware cost and difficult management [172, 178].

Problems of design and control of active balancing have been addressed in literature. Some of the proposed methods include equalizing converters for charging [131], control formulation [135], [157], [100], [101], DC-DC converters [154], [153], switched capacitor [174], ultra capacitors [204], flyback converter [191], [118], and hierarchical balancing [90],[104]. Since this is a well-studied area, interested readers can refer to the comprehensive survey presented in [168] and [99]. One case study of mitigating cell imbalance in battery packs using system reconfiguration was presented in [126] which introduces an algorithm named CSR, a Cell Skipping-assisted Reconfiguration algorithm which can help with identifying system configuration in order to deliver near optimal capacity of the battery pack.

2.7.2 Energy Management

Energy management is a challenging and fruitful domain in battery packs. Two common scenarios which signify the importance of energy management include cell failures and possibility to increase operational time of system. Advantage of intelligent scheduling algorithm to increase operation time of portable electronic device is shown in [185]. A nonlinear optimization approach for similar applications is presented in [93]. A comparison of several simple and complex scheduling algorithms and their optimality has been discussed in [137]. Energy management and battery optimization have also been achieved using the method of quadratic programming in several cases specially in hybrid and electric vehicles .

2.7.3 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 fault tolerance design . In [161], large scale battery systems have been 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) and open fault and bridging fault etc. [132, 175].

2.8 Two Switches (Series Connected Modules)

SCM architecture for reconfigurable batteries has been used in [144], [146], [149] and [155]. The simplicity of architecture (because batteries can only be connected in series) leads to a simple design of 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 [149] is shown in Fig. 2a. If two-way switches are used (single pole, double throw), only one switch is required for every battery. Such architecture has been proposed in [91]. Hardware topology of a two-way switch is shown in Fig. 2b. Though PCM based reconfigurable architecture has not been presented in literature, it is straightforward to see that such system can also be designed using two (on-off) switches per cell.

2.9 Nearly 1 Switch

An interesting architecture uses a clever trade-off: its flexibility is limited but it can include or disconnect switches. Such architecture has been used in [145], [148] and [147]. The

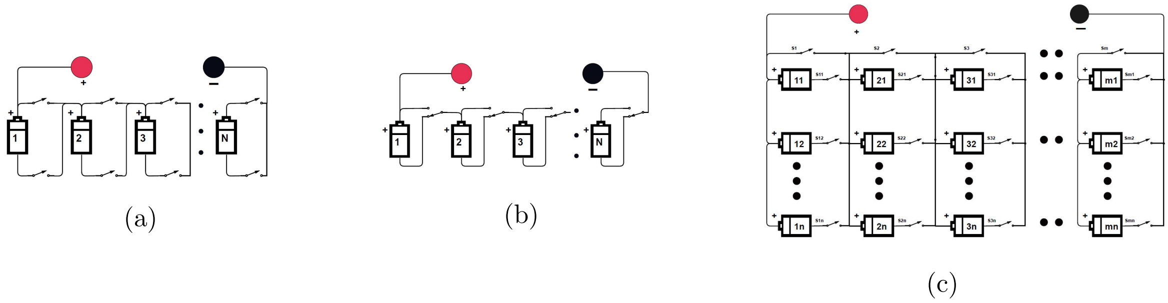


Figure 2: (a): A series connected module (SCM) reconfigurable architecture as used in [144], [146], [149] and [155] , (b): A series connected module (SCM) reconfigurable system using a two-way switch, proposed in [91], (c): A hybrid reconfigurable architecture using nearly 1 switch per battery, used in [145], [148] and [147](c).

Figure 3: (a): DESA architecture presented in [140], (b): A flexible architecture requiring 3 switches for every battery, as used in [199], [124].

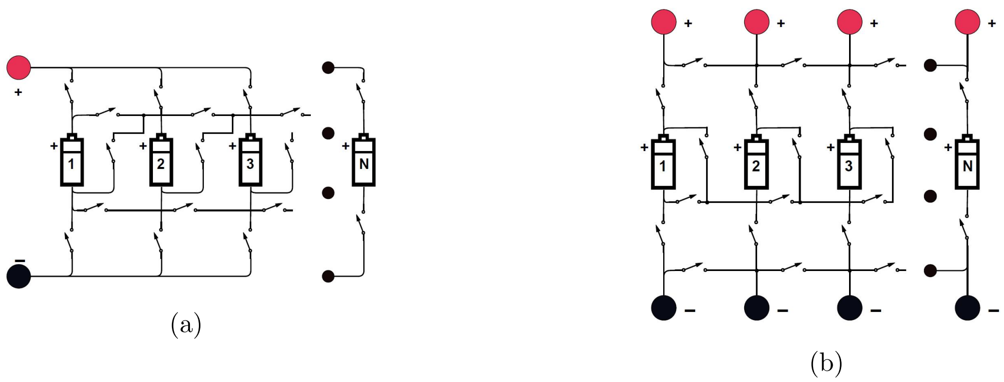


Figure 4: (a): Reconfigurable architecture using five switches for every battery, utilized in [112] and [113], (b): Topology of reconfigurable system which requires six switches for every battery [139], [138] and [136].

hardware topology with this configuration is shown in Fig. 2c. We see that now restriction is that we can have maximum of n batteries in parallel and maximum of m in series. These maximum connections can be at the same time as well: configuration of n parallel strings, each having m cells in series is possible. Advantage of such restriction is that is requires only a small number of switches, precisely it requires $mn + m$ switches for complete system i.e. one switch per battery and 1 switch for every PCM. As we will soon see, this reduces number of switches considerably.

2.10 Three Switches and DESA

Usage of 3 switches for every battery to have a reconfigurable system is very common in the proposed designs. The architecture from [199] (which is perhaps the first work in reconfigurable batteries) is shown in Fig. 3b. DESA (dependable, efficient, scalable architecture), proposed in [140] uses 3 switches and is used commonly. Both architectures (DESA in Fig. 3a and Fig. 3b) use 3 switches per cell, and are functionally the same: any cell can be configured in series, parallel or disconnected altogether. A similar design with same number of switches is presented in [203], [155], and [128].

Functionally, the simplified three-switch architecture and DESA are similar: they can reconfigure battery connections. However, as we will see in detailed analysis (in section 3.3), DESA has less power losses as compared to simple three-switch architecture.

2.11 Five switches

Topology using five switches is also frequently used. Architecture of reconfigurable system with five switches is shown in Fig. 4a. This architecture has been used in [112] and [113]. The authors in [113] 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 [199].

2.11.1 Architecture having 6 switches

A general and more flexible architecture requiring 6 switches for every battery has been used in several works. The configuration of 6 switch architecture is shown in Fig. 4b. This topology has been used in [139], [138], [164] and [136].

2.12 Multiple Outputs

An interesting concept has been proposed in architecture which capitalizes on rate discharge effect. The architecture proposed in [139], [138] and [136] proposes the capability to deal with multiple loads by only one battery pack. The key novelty in this topology is the ability to serve different loads with separate set of batteries. So the architecture (shown in Fig. 4b) has multiple *output terminal pairs*, to deal with more than one loads, as opposed to the traditional single output terminal pair (one for positive and other for ground). Of course the provision of multiple outputs comes at a cost: the required number of switches is highest (6 switches per battery) which increase requirements and complexity in any reasonably large system.

Utilization of multiple loads and near-optimal solution of finding optimal configuration based on such system (with multiple loads) is presented in [124]. Though this works discusses multiple loads, the configuration showed requries three switches per battery (as shown in Fig. 3b) and the additional hardware (switches) required for flexible output terminal is not discussed.

2.13 Reconfigurable Battery Charging

Recently, dedicated hardware as well as software techniques have been proposed for efficient charging of reconfigurable batteries [128], [127]. The reconfiguration architecture considered in these methods is the one which requires three switches for every cell (Fig. 3b) with some additional hardware. In software control, the standard scheme of charging Li-Ion batteries is used.

Charging reconfigurable battery pack with variable power source e.g. solar panels is presented in [169]. Charging is started with cells having lower SoC, and any cell with 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. Detailed method of classification of groups as well as charging every category based on the graph model is presented in [128], [127].

3 Analysis of Architectures

Though many architectures have been proposed to achieve reconfiguration capability, advantages (and drawbacks) of existing methods have not been investigated. A summary of these architectures is presented in [111]. 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 number of switches in this paper, in Section 2.4. Now we analyze flexibility, losses and additional capabilities of these architectures in a systematic way.

3.1 Flexibility

Since reconfigurable battery can be considered as a graph, measures of connectivity in graph can be used to quantify flexibility of different architectures. Out-degree connectivity can be a formal way of analyzing flexibility of any particular architecture. Graph model has only been proposed for a 3-switch architecture (shown in Fig. 3b), 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 help of software constraints on the graph.

Table 1: A functional comparison of existing reconfiguration architectures

Architecture	No. of batteries	Total no. of switches	Max. ser--ies cells	Max. par--allel cells	Multiple iso--lated loads
SCM [144], [146], [155], [149]	N	2N	N	Zero	No
Nearly 1 switch [145], [148], [147]	n×m	mn+m	m	n	No
Three switch [124]	N	3N	N	N	No
DESA [140]	N	3N	N	N	No
Five switch [112], [113]	N	5N	N	N	No
Six Switch [139], [138], [136]	N	6N	N	N	Yes

3.2 Functional Comparison

While specification of out-degree remains an open research problem, we analyze flexibility of architecture in terms of practical aspects. A comprehensive table, shown in Table 1, compares different architectures with respect to required number of switches and maximum cells that can be connected in parallel and series.

As discussed earlier, in terms of configuration flexibility, there is no apparent advantage of having architecture with more number of switches. On the contrary, topology having more switches increases cost, size and reliability overhead. However one key advantage of 6-switch architecture is also highlighted: ability to serve multiple loads separately, which can be leveraged to enhance operation time.

3.3 Losses

Overall number of switches are a good indication of reconfiguration overhead in terms of size, cost, complexity and digital input/output (I/O) requirement. 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 2. The scenario considered includes a battery having two cells and losses (in terms of resistance) are 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 2 is the superiority of DESA [140], over other three

Table 2: Comparison of losses in different architectures. Two batteries are considered to be connected in series or parallel and they are powering up a single load. On-resistance (R_{on}) of every switch is assumed to be same

Architecture	Resistance in series	Resistance in parallel
SCM [144], [149], [146], [155]	$2R_{on}$	N/A
Nearly 1 switch [145], [148], [147]	$2R_{on}$	$2R_{on}$
Three switch [124]	$3R_{on}$	$4R_{on}$
DESA [140]	$2R_{on}$	$3R_{on}$
Five switch [112], [113]	$3R_{on}$	$4R_{on}$
Six Switch [139], [138], [136]	$4R_{on}$	$6R_{on}$

switch architecture. Though three switch architecture (Fig. 3b) seems functionally similar to DESA (Fig. 3a), the resistance in DESA architecture is less than other architecture. This asserts the superiority of DESA architecture, despite apparent complexity in structure in contrast to the simpler three-switch architecture.

3.4 Future Work: Added Flexibility

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

4 Modeling and Software Methods

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

4.1 Modeling of Reconfigurable Architectures

Reconfigurable battery systems can be modeled as a directed graph [124, 127, 128].

The graph model of typical reconfigurable battery is shown in Fig. 5. In this approach, we have a graph $G = (V, E, W)$ where V is set of vertices, E is set of edges and W is set of weights of every node. Physically, W_i shows the voltage of node V_i. Here, V is defined as 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.

$$V = \{n_1, n_2, ..., n_N, n_+, n_-\}, \quad (5)$$

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 conventional current is followed in this directed graph i.e. from positive to negative. Weights W are defined as:

$$W = \{w_1, w_2, ..., w_N, w_{n_+}, w_{n_-}\}, \quad (6)$$

where w_i represents 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 graph level a *high level* configuration of the system can be found, according to objective of maximizing operation time. In this stage, only graph model and edge connectivity is 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.

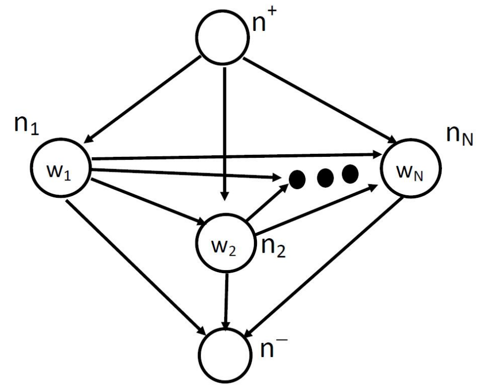


Figure 5: Graph modeling of a reconfigurable battery system.

4.1.1 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 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 graph, but in evaluations, they consider out-degree connectivity from 1 to 5 [124].

As an example, two farthest batteries in network, n_1 and n_N can be connected. However, this does not warrant 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).

In our opinion, the problem of graph connectivity is an open area and it can be investigated by researchers in 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 set of constraints for every architecture will be helpful in terms of functionality as well to analyze their flexibility.

4.2 Scheduling

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

The work in [138] explores the problem of energy scheduling in details. They consider both battery properties of rate discharge effect and recovery effect and evaluated performance of several scheduling algorithms. The authors proposed a weighted-k Round Robin (kRR) scheduling algorithm which 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 baseline system, the results also show ability of fault tolerance.

4.3 Battery Policies

A recent work presented in [89] investigates the interesting problem of dealing with battery trade-offs. Battery trade-offs pose challenging questions of whether to go for instantaneous benefit or long-term advantage. The work in [89] 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 trade-offs for optimal results.The architecture in [89] proposes utilization of switch-mode regulator for discharging and reverse buck regulator for charging; hence the capability to *control* the rate of charging or discharging.

4.4 Optimization Techniques

In [124], 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 polynomial solution cannot be guaranteed. For a single load change, it is proposed that 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 largest set of disjoint paths. This problem has been formulated as an integer program (IP) which can be used by commercial solvers. Since 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 the demands more current is dealt with earlier. Secondly, for every selected load, the path selection is done on basis on minimal conflict. The path that has least conflicts with other paths (hence possibility of adding more paths) is selected first. In [189], 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 Lagrangian relaxation problem and a dynamic programming solution is proposed in [113] and [158]. It is proposed that the objective function is to minimize the current of individual batteries which increases operation time, according to rate discharge effect. Requirement of meeting load demand is ensured by formulating it as constraint of optimization problem.

4.5 Utilization of Different Battery Types

The work in [89] 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 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 battery with higher power capability (but low storage, as LiFePO4 cathode Li-Ion) with a battery that has more storage capacity but can provide limited power (as CoO2 cathode Li-Ion).

4.6 Dynamic Reconfiguration

The problem of dynamic reconfiguration, based on load demand and SoC of cells, has been studied by many researchers in detail. Authors in [112] proposed a model that formulates series and parallel connections separately and uses them according to load demand. Problem of reconfiguration is broken to two steps of meeting load requirement and recovering from cell failure in [139].A dynamic reconfiguration based on mosfets is presented in [121]. A switch configuration algorithm (and DESA architecture) were presented in [140]. An optimal switching algorithm based on current SoC of batteries is presented in [145] and [148].

Traditionally, reconfiguration is done on the basis of SoC os batteries. However a recent work [125] proposes reconfiguration on the basis of SoH of cells.

5 Applications and Opportunities

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

5.1 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. Dynamic change in load requirement and higher demand of reliability and systems performance make these application areas suitable for reconfigurable battery packs. Interestingly though, researchers have already shown 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 battery is presented in [111]. Mostly existing work on reconfigurable batteries has been evaluated in laboratory settings. But there are already some examples which have shown improved performance of reconfigurable battery systems.

5.1.1 Light Loads

In [203], 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 watt each) were used in [124] to demonstrate the superiority of reconfigurable system. In [89], a smart watch and a 2-in-1 (tablet with a detachable keyboard) was considered. In this exciting work, the authors showed superiority of software techniques by leveraging battery trade-offs to enhance operation of time of widely used gadgets.

A programmable electric load has been used as load by many researchers [144], [146], [145], [148], and [125].

5.1.2 Heavy Loads

An exciting new field that requires flexible energy storage has been termed as energy internet with help of energy routers [133], [98]. Perhaps the work in [91] is the only existing one that has successfully applied 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 a currents as high as 160 amperes. Thermal aspects were considered in the design and results also show the stability in

5.2 Opportunities and Challenges

5.2.1 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 system. The right solution perhaps lies between extremes of conservative connectivity with spatial neighbors and all-to-all connectivity. Formulation of accurate constraints which depict the connectivity of different architectures will increase our understanding and also provide insight to 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 system which can be readily used by others. Currently all researchers develop their own simulation environment by using model of a single battery and building everything manually. This difficulty leads to increased time requirement and a lack of common framework for ease of collaboration and comparison.

5.2.2 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 number of switches from six at the cost of sacrificing some loads. For most practical applications, 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 large number of batteries a modular and reconfigurable battery system is presented in [105]. One case study in [194] shows that 8 percent of the total weight of entire system is accounted for by switches and related elements.This value can increase with the degree of reconfigurability required.

5.2.3 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 module (fixed configuration) and how much should be reconfiguration flexibility? 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?

5.2.4 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 large number of switches and significance of reliability of system from practical perspective. A detailed study about types of failures in switches, their detection and prediction and their impact on system integrity are key areas to be explored.

5.2.5 Intelligent Algorithms

Other than large-scale systems, there is a lot of room for improvement in small applications such as smart phones, tablets, smart watches etc. By having flexible batteries and employing *high level* policies, we can leverage the battery trade-offs 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 cost of reduced battery life) is suitable in 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 it will be explored in future.

5.2.6 Distributed Reconfigurable Battery Systems

As explained in [197], an interesting future direction is reconfigurable battery systems which 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 which are capable of tracking performance as well as communication to achieve distributed control framework [196], [195]. Existing designs of smart cells capable of distributed control are limited to fixed topology. It is 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.

6 State of Charge Estimation

6.1 Problem Formulation

In this section, battery model and its representation are briefly discussed, followed by the formulation of filtering problem for estimation of SoC.

6.1.1 Battery Model

Because of the nonlinear properties of batteries, specially Lithium-Ion (Li-Ion), a detailed battery model is required for estimation of SoC. However, modeling problem has been extensively investigated in literature. We consider the second order battery model.

Many techniques, such as usage of pulses presented in [85], have been rigorously used to identify the parameters of battery model. Let us define the state vector as $[v_1 \quad v_2 \quad SOC]^T$.

Current drawn from the battery, i, is considered as input for the model.

$$\begin{bmatrix} \dot{v}_1 \\ \dot{v}_2 \\ S\dot{o}C \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{R_1C_1} & 0 & 0 \\ 0 & -\dfrac{1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ SoC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ -\dfrac{1}{3600 \cdot Cap} \end{bmatrix} \cdot i + E \cdot v_n. \tag{7}$$

Here Cap is the total storage capacity of the battery in Ampere-hours. Also, v_1 and v_2 represent the voltage drop across C_1 and C_2 respectively. Vector v_n represents the noise which 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.

Generally, the terminal voltage is considered the system output; however, there is a complication in it. It is widely known that the relationship between open circuit voltage v_{OC} and SoC is nonlinear. Battery voltage can be represented as a nonlinear function of SoC as shown in (8). This relationship can be determined experimentally:

$$v_{oc} = f(SoC). \tag{8}$$

The output voltage can be written as

$$y = f(SoC) + v_1 + v_2 + R_{series} \cdot i. \tag{9}$$

Linearized output equation can be derived by using Taylor series and ignoring higher-order terms, as shown in (10):

$$y = \begin{bmatrix} 1 & 1 & \dfrac{\partial f(SoC)}{\partial SOC} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ SoC \end{bmatrix} + R_{series} \cdot i + F \cdot v_n. \tag{10}$$

Here F relates the noise vector to the observed output. Matrices A, B, C and D can be taken from (7) and (10).
For the purpose of estimation, we consider the output to be estimated state z given by:

$$z = Gx + Bu + Jv_n. \tag{11}$$

6.1.2 Estimation Problem

Considering independently, there are two methods of estimation of SoC: relying on current (coulomb counting) or by measuring voltage. Coulomb counting is the obvious choice, but it suffers from the accumulation of noise over time and hence a drift from actual value is added. Voltage based methods are limited because of the nonlinear relation of SoC with voltage. Additionally, Li-Ion batteries have a flat voltage-SoC curve i.e. there is a very small change in voltage for a considerable change in SoC. This is the reason why estimation is used to combine both voltage and current values to get the best result. A typical estimation problem can be formed as (12) - (13). Here $\hat{x}$ and $\hat{y}$ represent the estimated state and output, respectively. Determining gain, K, is the main objective of filter design. As discussed in subsequent sections, both EKF and H_∞ filter employ different methods to calculate K but they have same structure as shown in (12) - (14):

$$\dot{\hat{x}} = A\hat{x} + K(y - \hat{y}) \tag{12}$$

$$\hat{y} = C\hat{x} \tag{13}$$

$$\hat{z} = G\hat{x} + Bu. \tag{14}$$

The proposed method can robustly estimate SoC by using simple but accurate battery model and employing a conservative filtering technique. The H_∞ filter is solved optimally by formulating it as an LMI problem. The separation of computation (calculation of gain once and iterative implementation of estimator) enables the proposed method to be implemented on embedded controllers without compromising real-time operation requirements. Note that superiority of the proposed algorithm has been demonstrated on standard battery model, specialized or complex modeling is not required(published work [54]).

6.2 Evaluation

The proposed method has been rigorously evaluated for robustness in both simulations and experimental tests. It is important to note that in all evaluations, we have used the nonlinear system model; the linearized version is used only for the purpose of filtering. This makes all our evaluations realistic by inducing the errors due to linearization as well modeling errors. Such errors are generally ignored by works that are limited to simulations only. In simulations and experiments, we first investigate the case of unbiased noise, where all estimation methods work well. Then we evaluate these techniques in the presence of biased noise: this shows the advantage of the proposed method over others.

6.3 Baseline for Comparison

Before we evaluate the performance of proposed H_∞ filter, let us first have a look at the baseline of the methods we will be comparing with. We compare the performance of our filter with two commonly used methods for SoC estimation which are Coulomb counting and EKF filter.

The reason for selecting Coulomb counting is straightforward: it is simplest and the most commonly used method. EKF method has been included in the comparison because it has been rigorously studied and experimental results, though with limited noise types, are available in the literature, such as in [108].

6.3.1 Coulomb Counting

Coulomb counting is a simple method of estimating SoC which relies solely on current measurement. It can be represented as

$$SoC = SoC_i - \frac{1}{3600 \cdot Cap} \cdot \int_0^t i(t)dt, \tag{15}$$

where SoC_i is the initial SoC, Cap is the battery storage capacity (Ah) and i is the current (A). Because of noise in current measurements, there is some error in SoC estimation. Since Coulomb counting, presented in (15), is an integrative process, the error keeps accumulating over time and grows large for longer operating time. The other alternative is to use voltage measurement for SoC estimation. As discussed before, the SoC-voltage relationship is highly nonlinear and even worse is the fact that SoC-voltage curve of Li-Ion batteries is flat i.e. for a large change in SoC, there is only a small difference in voltage.

6.3.2 EKF Estimation

Let us have a brief look at the design of EKF filter for the system defined in (7) and (10). Prior state estimation is given by:

$$\dot{\hat{x}}^- = Ax + Bu.$$

Output estimation is

$$\hat{y} = C\hat{x}^- + Du.$$

The prior covariance matrix P^- can be calculated using

$$P^- = APA^T + Q,$$

where Q is the process noise and P is the covariance matrix calculated previously. The Kalman gain L can be computed by

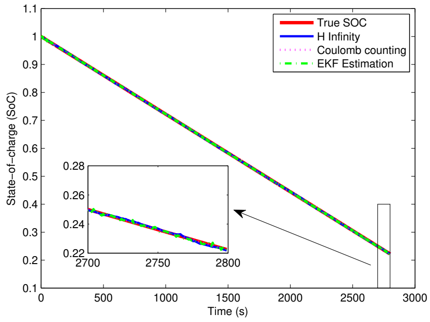
$$L = P^- C^T [CP^- C^T + R]^{-1},$$

where R is measurement noise. After measurement update y, the final state estimate is

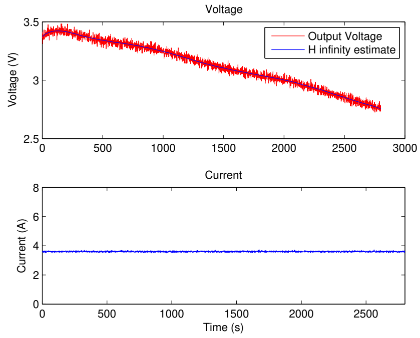
$$\hat{x} = \hat{x}^- + L[y - \hat{y}],$$

and covariance matrix P is updated by

$$P = (I - LC)P^-.$$



(a) State-of-charge over time.



(b) Current and voltage signals over time (actual current is 3.6 A).

Figure 6: Simulation result of State-of-charge estimation with minimal noise.

6.4 Filter Gains

For H_∞ filter, the matrices E and F, as explained in (7) and (10), are used as tuning parameters. The values used for these matrices are:

$$E = 10^{-3} \begin{bmatrix} 0.2 & 0 & 0 & 0 \\ 0 & 0.2 & 0 & 0 \\ 0 & 0 & 0.07 & 0 \end{bmatrix},$$
$$F = \begin{bmatrix} 0 & 0 & 0 & 100 \end{bmatrix}.$$

For EKF, we need a process noise matrix Q and a measurement noise matrix R. The matrices used for EKF are:

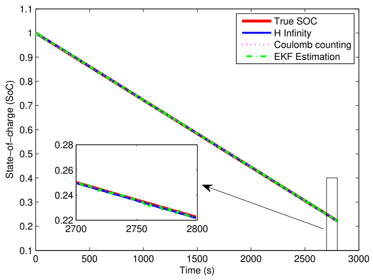
$$Q = 10^{-3} \begin{bmatrix} 0.2 & 0 & 0 \\ 0 & 0.2 & 0 \\ 0 & 0 & 0.07 \end{bmatrix}, R = 100.$$

As shown in simulation and experimental results, the EKF filter outperforms other methods in the presence of Gaussian noise; this shows the correct tuning of filter parameters.

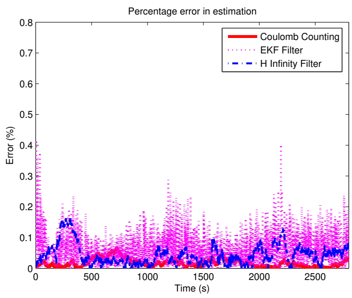
6.5 Simulations

We analyzed the results of an ideal case where there is little noise in current and voltage. The SoC estimation result is shown in Fig. 6a and the current and voltage signals used for this simulation are given in Fig. 6b.

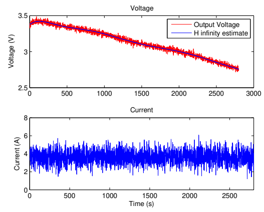
Next, let us analyze the effect of unbiased (zero mean) noise on the performance of all estimation methods. The current and voltage signals for this evaluation are shown in Fig. 7c; variance of noise in current is $0.5A^2$. The resulting SoC estimation is shown in Fig. 7a and the error in estimation is shown in Fig. 7b. The interesting inference from this test is



(a) Simulation result of State-of-charge with unbiased noise.

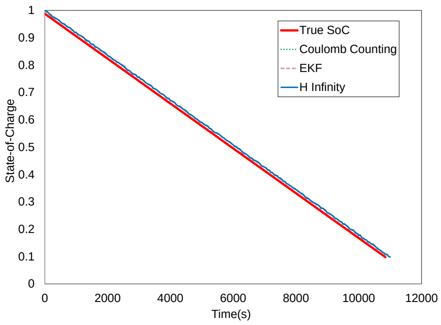


(b) Error in SoC estimation.

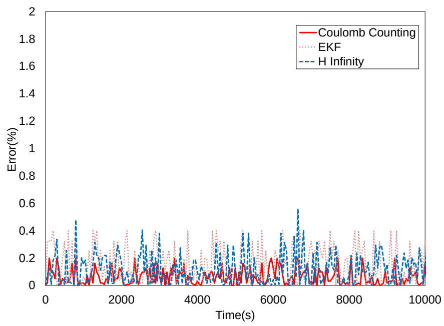


(c) Current and voltage signals with unbiased noise (actual current is 3.6 A).

Figure 7: Estimation result with unbiased noise.



(a) Experimental result of State-of-charge estimation (the noise has zero mean).



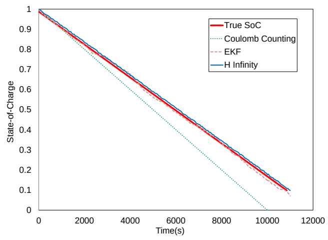
(b) Error in State-of-charge estimation.

Figure 8: Experimental result with unbiased noise.

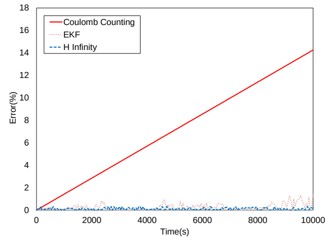
the robustness of all methods, including the Coulomb counting which performs well when the noise has zero mean.

Let us initially consider the case where noise is unbiased. The result of this experiment is shown in Fig. 8a and error in estimation is shown in Fig. 8b. The variance of current noise was almost $0.2A^2$. Because of small load (motor), the experiment took longer to be completed. We see that in this near-perfect scenario, both H_∞ and Coulomb counting perform well.

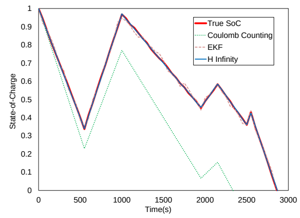
However, if we have noise with bias in it, the situation is completely different. The next experiment has a $0.2A$ bias in current reading. The resulting estimation is shown in Fig. 9a and error is plotted in Fig. 9b. We see that now H_∞ is still robust but Coulomb counting has accumulated large noise. Moreover, the algorithm has been tested for extreme conditions. In this experiment we negate all the safety guidelines for Li-Ion battery and discharge current as well as charge at very high and erratic rate. This is done in order to



(a) Experimental result of State-of-charge estimation with biased noise.



(b) Error in State-of-charge estimation.



(c) Experimental result of State-of-charge estimation with biased noise under extreme conditions.

Figure 9: The experiment result in the presence of biased noise.

achieve a relatively complex curve for SoC and test the performance of algorithm. It can be seen from fig 9c that coulomb counting accumulates much more error in this case but H_∞ is still robust and more accurate than EKF.

7 Efficient and Balanced Charging of Reconfigurable Battery by Solar Panels with Variable Power Supply

Safe charging only occurs when charging voltage is on an appropriate level relative to the nominal voltage level of the battery pack. In fixed battery pack, all the cells are treated homogeneously, so some of the cells may be over-charged while some may be under-charged. The over-charged cells may be damaged and the internal resistance will increase, which degrades the performance of the whole battery system. In contrast, the connections between battery cells in a reconfigurable battery pack are flexible. Any damaged or overcharged cells can be isolated or bypassed, while the remaining part of the battery pack continues to function. When the output of the power source changes, the reconfigurable battery system will dynamically change its configuration to match the charging voltage. This flexibility also allows to charge weaker cells with priority, bypass the fully charged cells to avoid overcharging and isolate the damaged cells. As shown in Figure 2, the reconfigurable battery pack consists of n cells and each cell is connected to three switches. These cells can be re-arranged for parallel, series or parallel-series combined connections. Based of the SoC of each cell and charging voltage, these cells will be selected and connected by the algorithms as presented in the following.

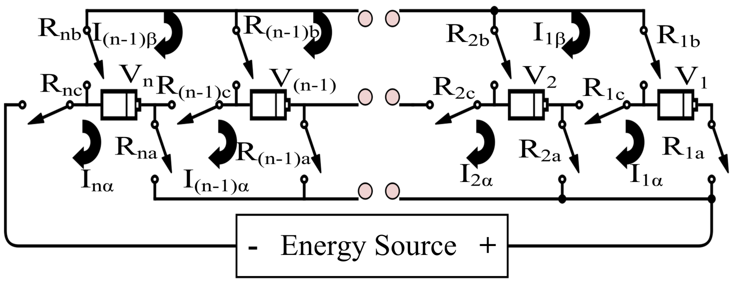


Figure 10: Reconfigurable battery pack.

7.1 system design

7.1.1 Overview

We use reconfigurable batteries to solve the voltage mismatch problem when charging with variable power supply, and improve the charging efficiency and the health of the batteries. In a reconfigurable battery pack, the connections between battery cells are equipped with switches, as shown in figure 1, and by configuring the on/off states of these switches, the battery cells are connected with different topologies, which results in different voltage of the overall battery pack. Therefore, we can dynamically reconfigure the switches during the charging procedure to let the battery pack voltage follow the varying charging voltage. However, the problem of configuring the switches to match an expected output voltage is in general NP-hard [77], and it is a challenging problem to develop efficient algorithms to reconfigure large-scale battery packs at runtime.

Apart from the charging efficiency, the SoC balancing is also an important issue in battery systems. A significant deviation among the SoC of different battery cells not only will lead to bottlenecks for energy charging/discharging, but may also hurt the health of the overdrawn cells and ultimately decrease the lifetime of the whole battery pack. The fluctuations of solar panel energy output caused by weather climate changes can be highly erratic. Variation of output voltage based on different weather is shown in Figure 1. The data has been gathered every 15 minutes under three different weather conditions. When the weather is sunny, the output is relatively smooth. In rainy or stormy days, the output of solar panel is highly variable which not only causes inefficiency during charging but is harmful for the battery as well.

Traditional systems consist of variable power source connected to a battery pack via DC-DC converters. As DC-DC converters' efficiency highly depend on the difference between the output and input voltage levels, high power losses can occur when the charging voltage is much higher than the nominal voltage of the battery. Another disadvantage of using the traditional system is cell imbalance in fixed battery pack caused by irregular charging or discharging. Cell imbalance can cause loss of capacity, lifetime and performance of the battery system.

In this work, we completely eliminate DC-DC converters hence improving the efficiency of charging a reconfigurable battery pack with solar panel. Our system design consists of a variable power source directly connected to a reconfigurable battery pack as shown in Figure 3. Reconfigurable battery pack consists of 3 switches connected to each battery cell. BMS (battery monitoring system) monitors the current and voltage across each cell while keeping track of SoC using the coulomb counting approach [80]. During the charging phase, the fully charged cells are isolated from the charging circuit.

Safe charging only occurs when charging voltage is on an appropriate level relative to the nominal voltage level of the battery pack. In fixed battery pack, all the cells are treated homogeneously, so some of the cells may be over-charged while some may be under-charged. The over-charged cells may be damaged and the internal resistance will increase, which degrades the performance of the whole battery system. In contrast, the connections between battery cells in a reconfigurable battery pack are flexible. Any damaged or overcharged cells can be isolated or bypassed, while the remaining part of the battery pack continues to function. When the output of the power source changes, the reconfigurable battery system will dynamically change its configuration to match the charging voltage. This flexibility also allows to charge weaker cells with priority, bypass the fully charged cells to avoid overcharging and isolate the damaged cells. As shown in Figure 2, the reconfigurable battery pack consists of n cells and each cell is connected to three switches. These cells can be re-arranged for parallel, series or parallel-series combined connections.

7.2 Optimization-based Approach

7.2.1 Notations

A battery is connected to three types of switches

- A switch of type a connects the positive pole of a battery cell to the positive pole of the energy source.
- A switch of type b connects the negative pole of a battery cell to the common bus connecting the negative poles of all the cells.
- A switch of type c connects the negative pole of a battery cell to the positive pole of the next cell. The only exception is the type-c switch of the last battery, which connects to the negative pole of the energy source.

We model switches as resistors which have either zero or infinity resistance depending on the whether it is on or off, and we use a variable R_{ia} to represent a switch of battery i of type a, and similarly for type b and c.

There are two types of loops in the circuit:

- The i^{th} α loops includes battery i, R_{ia}, R_{ic} and $R_{(i+1)a}$. The only exception if the n^{th} type-α loop, in which $R_{(i+1)a}$ is replaced by the energy source.
- The i^{th} β loops includes R_{ib}, R_{ic} and $R_{(i+1)b}$. There are only $n-1$ β loops.

We use variable I_{ia} (I_{ib})to represent the current of the i^{th} α (β) loop. The voltage of each cell i is a known constant V_i.

7.2.2 Constraints

According to the Kirchoff's Law, for the i^{th} α loop, $1 \leq i \leq n-1$, we have:

$$V_i = R_{ia}(I_{i\alpha} - I_{(i-1)\alpha}) + R_{(i+1)a}(I_{i\alpha} - I_{(i+1)\alpha}) + R_{ic}(I_{i\alpha} - I_{i\beta})$$

For the i^{th} β loop, $1 \leq i \leq n-1$, we have:

$$R_{ib}I_{i\beta} + R_{ic}(I_{i\beta} - I_{i\alpha}) + V_{i+1} + R_{(i+1)b}(I_{1\beta} - I_{(i+1)\beta}) = 0$$

For the n^{th} α loop, we have:

$$V_n = R_{na}(I_{n\alpha} - I_{(n-1)\alpha}) + R_T I_{n\alpha} + R_{nc}I_{n\alpha}$$

Finally, we have, by applying the Ohm's law to the energy source:

$$V_T = (\frac{V_n - R_{na}I_{(n-1)\alpha}}{\alpha_n})R_T$$

Note that there may exist short circuits with certain configurations of the switches. For example, if switches R_{1a}, R_{1c} and R_{2a} are all on, the positive and negative poles of battery 1 are directly wired, which leads to a short circuit. One may think we should add constraints to guarantee no short circuit will occur. However, as will be shown in the next subsection, the optimization target will automatically exclude short circuit from our solution. Since R_i are switches so they can only have values 0 or ∞ i.e.

$$R \in \{0.\infty\}$$

7.2.3 Objective Function

Let V_T^d be our target voltage. If we want to minimize the difference between the end-to-end voltage V_T of the battery pack and the target voltage V_T^d, the following objective function can be used:

$$min \quad ||V_T - V_T^d||^2$$

However, as mentioned above, the goal of our reconfiguration algorithm is to not only match the voltage, but also maintain good SoC balance among cells. Therefore, we will include a term to reflect the SoC balance in our optimization subject. To this end, we introduce the constant W_i for each cell i, and use the following objective function:

$$min \quad ||V_T - V_T^d||^2 + \sum_i W_i||I_{i\alpha} + I_{i\beta}||^2$$

where W is the weight of each cell based on its SoC. If there is a short circuit, some of $I_{i\alpha}$ or $I_{i\beta}$ will become infinite, and these solutions will automatically exclude due to our objective function.

7.3 Efficient Heuristics

The method in last section needs to solve the optimization problem, which is in general very expensive. Moreover, every time the configuration routine is called, this procedure will be do again from scratch, and the switch states may change largely even if the change in target voltage is very small (or even no change), which will lead to unnecessary wear of the switches.

In this section, we will present our second solution, a heuristic algorithm, that is more efficient in terms of computation time and incur much less unnecessary state change to the switches.

The main idea of our heuristic algorithm is to divide the cells into a number of groups. All the cells in the same group are connected in parallel, while different groups are connected in series, as shown in Figure 4. Then the switch configuration problem is reduced to the problem to decide the number of groups and the boundaries among these groups. When the boundary between two groups changes, only a small number of the switches related to outermost battery of each group need to be reconfigured. The total currency through each group is the same, and all the cells in the same group share this total currency. Therefore, the more cells in a group, the less energy will be charged to each of them. So to maintain a good SoC balance, our heuristic will try to let a weaker cell be in a group with fewer cells.

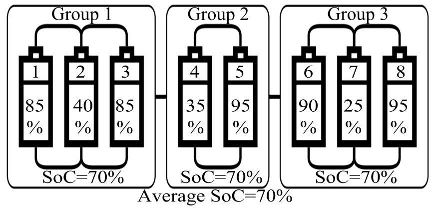


Figure 11: Illustration of the group-based topology.

For example, Lets consider a re-configurable battery pack of 8 cells each with 4 V as shown in Figure 4. It can be seen that cells have different SOCs. Based on SoC, first step is to prioritize the cells for charging. Cells will lower SoC become the candidate for priority charging. A threshold for low SoC can be set in order to set the priority. Based on the charging voltage and nominal voltage of each cell, we divide cells in groups. For the purpose of this example lets assume the that target voltage is 12 V. Based on target voltage and cell voltage, we need to create 3 groups of cells so that when we put these groups in series we can achieve the target voltage.Next step is to determine master cells that will be assigned to different groups. For 3 groups we choose 3 master cells. Master cells must be selected on the basis of weakest SOC. So we select Cell 2,4 and 7 as our master cells. Each of these cells will be assigned to their respective group. Cumulative SOC of each group should be the same. This is achieved by putting neighbouring cells in parallel to the master cells. So we put cell 1 and 3 parallel with master cell 2 in group 1, similarly, master cell 4 is paired with cell 5 in parallel in group 2 and finally in group 3 master cell 7 is in parallel with cell 6 and 8 in group 3 as shown in Figure 4. It can be seen that each group have the same voltage which is 4 V. All these groups in series provide us with the required target voltage.

More specifically, our heuristic algorithm works in the following steps:

1. Compute the average SoC of all cells, denoted by $\overline{S}$.

Algorithm 7.1 Heuristic Pseudocode

```
n ← total number of cells
C ← Each Cell
for i = 1 : n do
    get SoC of C(i)
end for
for i = 1 : n do
    prioritize m(i) = index(min(c))
end for
S ← number of sessions
S=target voltage/voltage of cell
for i = 1 : S do
    S(i) = m(i)
end for
g = 1
Sort(S)
for i = 1 : length(S) do
    for k = g : n do
        put C(k) in parallel connection
        if K == S(i) then
            if SoC of session==threshold then
                k = g
                make series connection
            else
                if K == S(i + 1) then
                    k = g
                    make a series connection
                else
                    put C(k) in parallel connection
                end if
            end if
        end if
    end for
end for
```

2. Compute the number of groups g by $g = \lceil V_T^d / V_{cell} \rceil$, where V_T^d is the target voltage and V_{cell} is the nominal voltage of each cell.

3. Select the g weakest cell (with the lowest SoC). We call them *master* cells, each of which be assigned to a different group.

4. Decide the boundary among different groups. We assume all the batteries are placed in a line and we scan them from left to right. First, all the batteries on the left side of the first master cell are assigned to the first group. Then we decide the boundary between the first and second group. This is done by adding more batteries into group one until the average SoC of all the cells currently in it for the first time falls into the range $[\overline{S} - \delta, \overline{S} + \delta]$ where S is the average SoC of all cells and δ is a pre-defined constant. All the cells between this point and the second master cell are added to the second group. This procedure repeats until the boundary of all the groups are decided.

The complexity of our algorithm depends on the method we use to select the g weakest cells and all the other operations can be done in linear time. In our experiments, we use the quickselect algorithm [62] which has worst-case time complexity of $O(n^2)$ but on average can finish between $O(n)$ and $O(logn)$ time. Therefore, the overall complexity of our algorithm is $O(n^2)$.

7.4 Integrated solar panels with Re-configurable battery pack

Shade over a single cell of a solar panel can block the flow of electricity from the entire panel which can greatly affect its electrical output. This phenomenon can cause overheating which can also result in the permanent damage to the panel. Nature of electrical characteristics of solar cells is such that maximum power losses magnify nonlinearly in presence of shade [82]. Shade on a solar panel array can cause many undesired effects such as damage to the solar panel and increase in loss of load probability [83].

Traditionally, solar panels are connected in series to make strings which are then connected in parallel to each other. Number of solar panel in the string and number of strings depend on power requirement. Figure 6 shows a basic schematic of a traditional system. As we know that shade falling on one part of a string can impact the output for that entire string. Figure 7 shows the difference between the outputs of shaded and unshaded strings of three BP Solar 1.01W Polycrystalline Photo-voltaic Solar Panels connected in series. It is clear that the output of the entire string will be reduced to virtually zero for as long as there is shade on the solar panel.

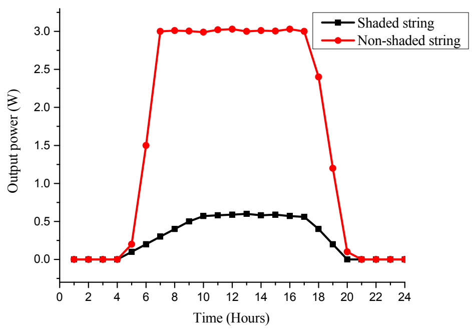


Figure 12: Difference between the outputs of shaded solar panel string and un-shaded solar panel string

In this work, we integrate the solar panels with re-configurable battery pack as shown in figure 5. By integrating solar panels with re-configurable architecture we not only can bypass the shaded solar panel to improve the output of solar panels but can also match the power requirement of batteries for efficient and balanced charging. To verify this, we compare the output of the traditional system as shown in figure 6 with solar panels integrated with re-configurable architecture.

By integrating solar panels with re-configurable architecture, it will be possible to charge specific battery cells with low SoC by bypassing fully charged cells. This ensures that fully charged cells will not get overcharged. Tanking advantage of reconfigurablility and by the integration of solar panels we can group cells with low SoC with solar panels in parallel and to balance th SoC we can even put cells wth high SoC in the group as well. In this way, not only will the transfer of SoC occur in between cells ultimately achieving cell balancing but also each group will be charged simultaneously. The goal is to achieve balanced SoC for the whole battery pack. We divide the cells in in groups with same cumulative SoC. Number of groups should be equal to the number of unshaded solar panels available. Lets take an example of reconfigurable battery pack of 8 cells and 4 solar panels. If all the cells have equal SoCs then cells will be divided into 4 groups and one solar panel will be assigned to each group. If two of the solar panels are in the shade and are not active, these solar panels are disconnected from the battery pack and in this case there will be 2 groups of cells with same cumulative SoC and 2 remaining solar panels will be assigned to each group.

According to the Kirchoff's Law, for the i^{th} α loop, $1 \le i \le n-1$, we have:

$$V_i = S_{ia}(I_{i\alpha} - I_{(i-1)\alpha}) + S_{(i+1)a}(I_{i\alpha} - I_{(i+1)\alpha}) + S_{ic}(I_{i\alpha} - I_{i\beta})$$

For the i^{th} β loop, $1 \le i \le n-1$, we have:

$$S_{ib}I_{i\beta} + S_{ic}(I_{i\beta} - I_{i\alpha}) + PV_i + S_{(i+1)b}(I_{1\beta} - I_{(i+1)\beta}) = 0$$

For the n^{th} α loop, we have:

$$PV_n = S_{na}(I_{n\alpha} - I_{(n-1)\alpha}) + S_{nc}I_{n\alpha}$$

In a traditional system, all the battery cells will be charged uniformly without considering the need of individual cell which may cause imbalance and lead to damage and power loss. In our system, we set a priority of each cell based on the SoC. Cells with lowest SoC get the highest priority to be recharged. So available solar panels can b grouped together to charge cells with low SoC until cell balancing is achieved. On the other hand, if there is shaded on some of the panels, this can be easily rectified by isolating the affected panels and keep using the functioning panels. As an example. lets consider reconfigurable battery pack of 8 cells with different SoC integrated with 8 solar PV panels with 5 of the panel under shade. In this scenario, only 3 panels are functional. now we will prioritize individual cells according to SoC. Lets consider that cell 2,4 and 7 have the lowest of SoC and call them master cells. We will group the neighbouring cells of master cells in parallel with them and make 3 groups. Now we assign each group a functioning solar panel. This will ensure that all cells are being charged and cells will be in more balanced state at the end of charging phase.

Algorithm 7.2 Pseudocode for reconfigurable battery pack with solar panels

$P \leftarrow$ total number of solar panels
$Pshaded \leftarrow$ total number of solar panels in shade or inactive
disconnect $Pshaded$
$Pactive = P - Pshaded$
$n \leftarrow$ total number of cells
$C \leftarrow$ Each Cell
for $i = 1 : n$ **do**
  $SoC \leftarrow$get SoC of $C(i)$
end for
for $i = 1 : n$ **do**
  $m(i) = index(min(c))$
end for
Sort $m(i)$
$G \leftarrow$ number of groups
$G = Pactive$
for $i = 1 : G$ **do**
  $G(i) = m(i)$
end for
$g = 1$
for $i = 1 : length(G)$ **do**
  for $k = g : n$ **do**
    put $C(k)$ in parallel connection
    if SoC of $C(k)$==SoC **then**
      $k = g$
    end if
  end for
  make parallel connection
end for

7.5 Evaluation

7.5.1 prototype

We have prototyped part of BMS i.e. reconfiguration and cell balancing. Although the switching frequency of electromechanical relays is relatively low, we use them because they have negligible internal resistance.

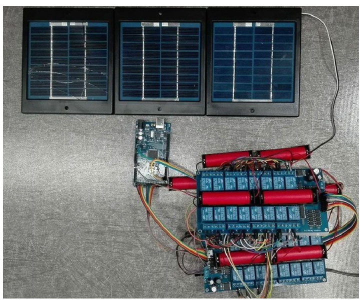


Figure 13: Hardware Prototype

Monitoring system consists of INA219 sensors which measure current and voltage of each cell. Each sensor can sense up to 3A of current and measure the voltage up to 30 V. An Arduino Mega 2560 Microcontroller is used to control switching matrix to acquire the desired configuration. SoC measurement of each cell is done on-line using coulomb counting.

7.5.2 Simulator

Since the scale of our hardware prototype is limited, it is difficult to evaluate our techniques for large scale battery systems. To compensate this limitation, we also use software simulator for empirical experiences with larger scales. In particular, we develop a simulator in *Simulink*. We use our hardware prototype to validate the accuracy of the simulator. The results show that the error between simulation results and the experiment results with the hardware prototype is ignorable.

7.6 Results

7.6.1 Voltage Matching

We first conduct experiments on our hardware prototype with 8 battery cells on a cloudy day. We evaluate how the voltage of the battery pack follows the changing output voltage of the solar panels with both methods. The reconfiguration is invoked every one minute.

In Figure 8a, OPT represents our first method by solving the optimization problem, and HEU represents the heuristic algorithm. We can see that both methods can follow the change of the solar panel output very well, and the performance of OPT is slightly better than HEU.

Then we do experiments with the same setting with the simulator, using the output voltage trace logged in the above experiment. As shown in Figure 8b, the results obtained from the hardware implementation and from the simulator are very close to each other.

7.6.2 Cell Balancing

We evaluate the effectiveness of our methods for cell balancing by using simulation. From the results shown in Figure 9a, we can see that by our methods the cells become very balanced at the end of the experiment, but not the case for fixed battery packs. Our first method OPT performs better than HEU, but the difference is very small. We further compare our two methods OPT and HEU with different battery pack scales, using the deviation metric Δ defined as follows

$$\Delta = \frac{\sum_{i=1\cdots n}(S_i - \overline{S})^2}{n}$$

where n is the number of cells, S_i is the final SoC of battery cell i and $\overline{S}$ is the average of the final SoC of all cells. The results are shown in Figure 9c, from which we can see that

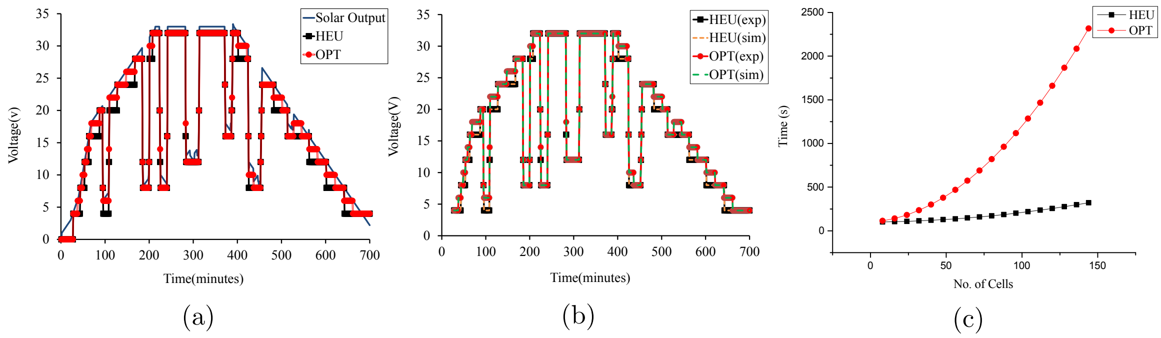


Figure 14: Comparison of HEU and OPT for voltage matching(a), Comparison of results by hardware-based experiments and simulations(b), Comparison of results by hardware-based experiments and simulations(c)

the gap between OPT and HEU becomes larger as the scale of the battery pack increases.

7.6.3 Charging Efficiency

In the following we evaluate the charging efficiency of different methods under different battery pack scales. The experiments are conducted using simulators. We compare the ratio between the energy actually transferred into the battery pack and the total amount of energy generated by the solar panel, the results of which are shown in Figure 9b. We can see that the charging efficiency of our methods using reconfigurable batteries are very high: it consistently maintains a ratio above 90%, even when the battery system is of fairly large scales. On the other hand, the charging efficiency using fixed batteries is only around 60% and a significant portion of energy has been wasted. Finally, the charging efficiency of OPT in most cases is slightly better than HEU.

7.6.4 Time Overhead

We compare the time overhead of our two methods. Recall that in Figure 11 we observe that the performance, in terms of the capability for cell balancing, of OPT becomes more superior to HEU for larger battery packs. However, the benefit of OPT comes at the price of a much higher time overhead, as shown in Figure 8c.

7.6.5 Re-configurable Solar Panel

Finally we compare the output of the traditional system as shown in Figure 6 with solar panels integrated with reconfigurable architecture as shown in Figure 5. For this experiment, in a sunny day, a shaded area was introduced to one of the panels in both traditional system as well as re-configurable solar panel. As expected, in traditional system, the string with a shaded solar panel produced very low output as shown in Figure 11a. Although, the other string produced maximum power, the total power produced was only the 60 percent of what

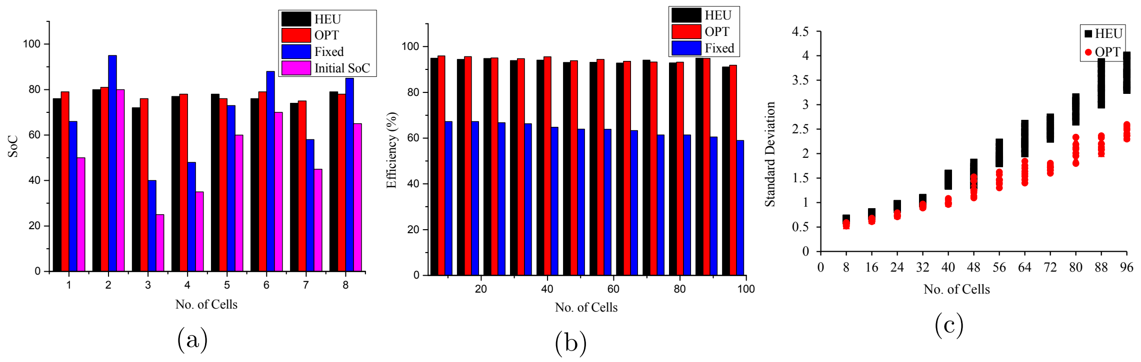
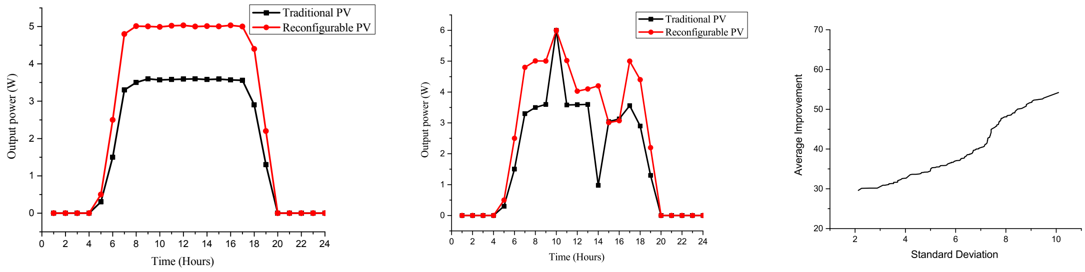


Figure 15: SoC balancing comparison among our two methods and using fixed batteries(a), Efficiency comparison of our methods and using fixed battery pack(b), SoC balancing comparison between our two methods with different battery pack scales(c)

re-configurable solar panel produced. Individual solar panels connected to re-configurable architecture produced more power than traditional system because the shaded panel was simply bypassed.

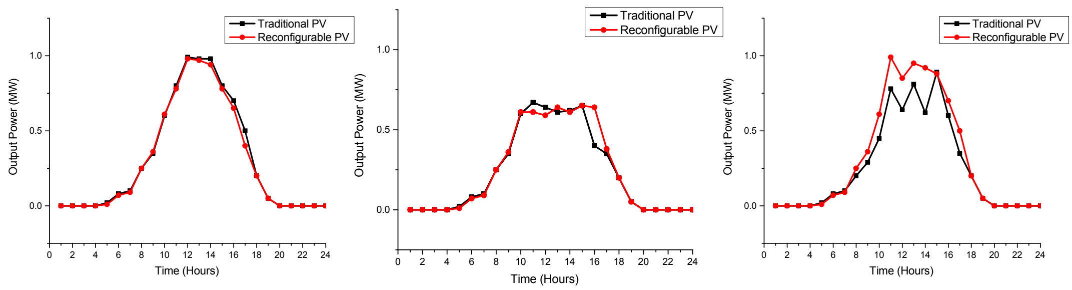
Evaluation under variable or moving shade has also been done. It can be seen in Figure 11b that the voltage of both traditional and re-configurable system fluctuate when the shade is moving. Both systems provide maximum power when there is no shade. If there is a shade on one solar panel then re-configurable battery pack performs better because, in traditional system, whole array containing shaded panel goes down. When there is a shade covering more than one solar panel then re-configurable architecture will provide the power out of the remaining active solar panels. In case of traditional system, if shaded solar panels are in same array we get the out put from only one array. We get the same output from re-configurable solar panel and traditional system if 3 solar panel of same array are in shade. The voltage of traditional system goes to approximately zero when both arrays have shaded panels.

In figure 12, the results of a large scale traditional solar farm with solar panels divided into arrays and reconfigurable solar panel are shown. It can be seen in figure 12a and 12b that during the sunny day or the cloudy day the output of both systems is almost the same because during full sunny day or full cloudy day the solar irradiance is is uniform. The difference can be seen in figure 12c when it is partially cloudy. On a large scale, it is possible that some solar panels get more light than the others, in this situation, reconfigurability is an advantage because in traditional system, whole array can be compromised and deliver negligible power but in reconfigurable architecture it is possible to acquire power from individual solar panels. Figure 11c shows the average percentage improvement of re-configurable architecture over traditional system during partially cloudy or variable shadow conditions. In most recorded cases, 25 to 40 percent of improvement can be observed.



(a) (b) (c)

Figure 16: Comparison between the outputs of traditional system and reconfigurable solar panel in the presence of shade(a), Comparison between the outputs of traditional system and reconfigurable solar panel in the presence of variable or moving shade(b), Average percentage improvement vs standard deviation(c)



(a) (b) (c)

Figure 17: Comparison between the outputs of large scale traditional system and reconfigurable solar panel on full sunny day(a), Comparison between the outputs of large scale traditional system and reconfigurable solar panel on a cloudy day(b), Comparison between the outputs of large scale traditional system and reconfigurable solar panel a partially sunny/cloudy day(c)

8 Conclusion

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

We note that there are several hardware topologies which 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 of improvement and contribution from the community. A formal analysis of connectivity and flexibility of existing architectures will provide useful insight. From 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 wide-spread adoption of this technology. We hope future research in these directions will accelerate the development of solutions with reconfigurable batteries. We have also shown a method that can robustly estimate SoC by using simple but accurate battery model and employing a conservative filtering technique. The H_∞ filter is solved optimally by formulating it as an LMI problem. The separation of computation (calculation of gain once and iterative implementation of estimator) enables the proposed method to be implemented on embedded controllers without compromising real-time operation requirements. Note that superiority of the proposed algorithm has been demonstrated on standard battery model, specialized or complex modeling is not required.

We extend the robustness of current methods by using data fusion techniques. Our detailed results confirm the improved performance over both Coulomb counting and Kalman filtering. Since H_∞ filter makes no such assumption of noise type, it can deal with biased noise as well. It is important to note that perhaps the simplest method of Coulomb counting also performs well in the presence of unbiased noise and it is immune to noise in voltage sensing. A performance comparison of filters under different conditions for Li-Ion battery is presented in Table I. It is important to see that Coulomb counting outperforms other techniques in the presence of unbiased noise because both H_∞ and EKF have modeling and linearization errors. Performance of filters under different and extreme conditions have been observed in different batteries. The comparison of error in estimation methods in Lead-Acid battery is presented in Table II.

We have also talked about the problem of charging a reconfigurable battery pack with a variable power source such as solar panel is discussed. We first consider the case where only the battery pack is reconfigurable. In this case, two methods are proposed for the reconfiguration of battery pack in order to achieve efficient voltage matching for safe charging. The first method is optimization based. It is more accurate but requires higher time overhead processing. The second method is heuristic algorithm which provides the results close to the optimization based method and requires much less time to compute a solution as compared to the first method. Both methods perform adequate cell balancing for reconfigurable battery pack as compared to a fixed battery pack. Then we integrate the solar panel into the reconfiguration circuit of the battery pack so that the connections among solar panels and batteries are co-reconfigured, to achieve higher charging efficiency when the output voltage of individual solar panels are different.

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