Smart Battery Concept: A Battery that Can Breathe

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***Abstract*— Lithium-ion batteries are used in a wide range of applications such as electric vehicles and energy storage systems. However, the aging of the battery cell is inevitable. Especially for battery packs with hundreds of battery cells connected in series/parallel, the aging process will be aggravated due to the difference between battery cells, leading to a limited lifetime and reliability issues. This paper introduces the concept of Smart Battery that combines advanced power electronics and artificial intelligence (AI) intending to develop a new generation of battery solutions for transportation and grid storage. The key feature for controlling the lifetime is the bypass device, a half-bridge that can control individual cell-level load management without affecting the load. An advanced AI-based lifetime controller is trained to recognize the signs of stressed battery cells and decide to insert rest time, resulting in a pulsed current operation. Finally, the following features are expected to be achieved: increased safety and reliability by fault-tolerant operation, user-controlled lifetime, and software reconfiguration for 2nd life applications. The early experimental results are promising, showing cycle lifetime extension over 50%.**

Keywords*— *Smart Battery, artificial intelligence, pulse current, lifetime extension, second-life applications.

I. INTRODUCTION

Thanks to their high power (up to 1500 W/kg) and energy density (up to 250 Wh/kg), high energy efficiency (more than 95%), and also relatively long cycle life (more than 3000 cycles), Lithium-ion (Li-ion) batteries are promising solutions for both enhancing the flexibility of clean energy and powering EVs [1]. Over the past three decades, Li-ion batteries have become an integral part of daily routines, and nowadays, they show the highest growth and the major proportion of investments in the battery market in a world still dominated by lead-acid batteries. Li-ion batteries are used widely from powering portable electronic devices to more advanced applications (e.g., electric vehicles, grid storage, and satellites) [2].

Battery packs are composed of string of ceries and parallel connected cells to meet the voltage and current requirements of the applications [3]. However, primarily caused by manufacturing tolerances and enhanced by the operating conditions of the battery system, the inconsistency in voltage and capacity of the battery cells will increase over their life [4]. As a result, the differences in battery cells' performance and degradation behavior would be aggravated by those differences in battery state.. Therefore, it is essential to employ strategies to extend the battery lifetime, ensure fault tolerance operation to subsequently assure reliable operation of the battery pack and increase the driving range of the EV. This paper introduces the concept of Smart Battery aiming at increasing the performance and extending the lifetime of the battery using power electronics and artificial intelligence (AI).

II. THE SMART BATTERY

Smart Battery (SB) [5] is a new concept that combines advanced power electronics, wireless communication, and AI with the goal to develop the new generation of battery solutions for transportation and grid storage where the following new features are achieved: increased safety and reliability by fault-tolerant operation, user-controlled lifetime and software reconfiguration for 2nd life applications. The structure of SB is shown in Fig. 1 and consists of a battery cell, a switching device, and a slave controller. The cell is not directly connected to the battery string but through the switching device which is implemented by a simple half-bridge MOSFET circuit and allows two operation modes: inserted or bypassed, as shown in Fig. 2. Thus cell-level load management is achieved. The slave controller can monitor the voltage (V), current (I), and temperature (T) of the cell and also estimate the state of charge (SOC) of the cell. All slaves are communicating wirelessly with a Master controller that is performing higher (package) level functions such as (i) state of health (SOH) estimation and remaining useful life (RUL) prediction using AI, (ii) SOC & SOH balancing and (iii) lifetime control. The balancing process is done by bypassing one cell at a time and thus not affecting the load current. In contrast to other active balancing methods, this balancing method is not requiring the use of DC/DC converters and is, therefore, an ultra-low energy balancing technique. The switching device is also used to permanently bypass faulted cells and thus adding fault-tolerant operation mode, increasing the safety and reliability at the system level.

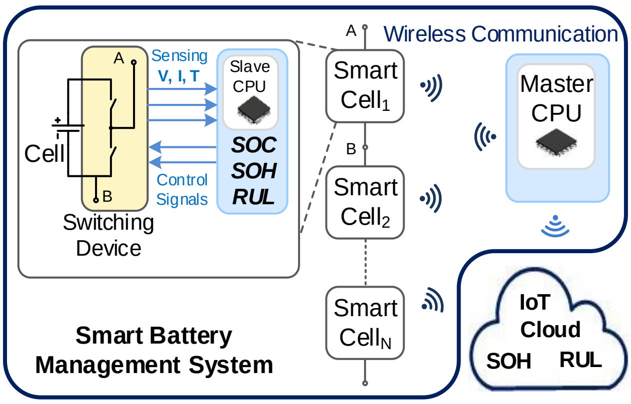
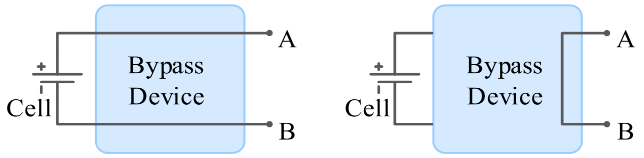


Fig. 1. Smart Battery structure.



(a) (b)

Fig. 2. The operation mode of the switching device: a) inserted, b) bypassed.

A. *Lifetime Extension with Pulse Current*

1) Pulse Current

Pulse current (PC) charging has been proposed to improve the performance and lifetime of Lithium-ion batteries, in previous studies. According to the current profile, the PC can be categorized into Negative Pulse Current (NPC) and Positive Pulse Current (PPC). The NPC consists of a positive pulse current, a negative pulse current, and a relaxation time during a period. The NPC can eliminate the concentration polarization and increase the power transfer rate, thereby reducing the charging time by removing the constant voltage (CV) charging in the traditional charging method. Moreover, the negative pulse and the relaxation time can improve the active material utilization to extend the battery lifetime. The PPC is the constant current charging followed by a relaxation period, as shown in Fig. 3. The amplitude and the duration of the positive pulse are A_p and t_p, respectively. The relaxation time is t_r. The period of the PPC is T. Then, the frequency f and the duty cycle D of the PPC can be determined as follows:

$$f = \frac{1}{T} \tag{1}$$

$$D = \frac{t_p}{T} \tag{2}$$

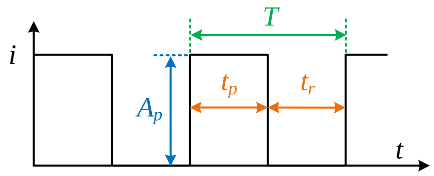


Fig. 3. Positive pulse current (PPC).

2) Implementation with Bypass Device

The bypass device, i.e., a half-bridge circuit, is used to implement the PC for each cell. In a battery pack, N cells are connected in series, and each of them is not directly connected to the pack but through the half-bridge circuit. The function of the bypass device is to connect or disconnected the battery cell according to the SOC and SOH of all cells in the battery pack. Fig. 4 is the schematic of the implementation method for the PC in a battery pack. To maintain the continuous current of the battery pack, at least one cell should be inserted in the battery pack. For example, Cell#1 and Cell#2 are conducted complementary in the first period, ensuring continuous current through the entire battery pack, as shown in Fig. 4. In fact, to maintain the pack voltage-operated in a stable range, a specific number of the battery cells should be set to connect to the battery pack at the same time.

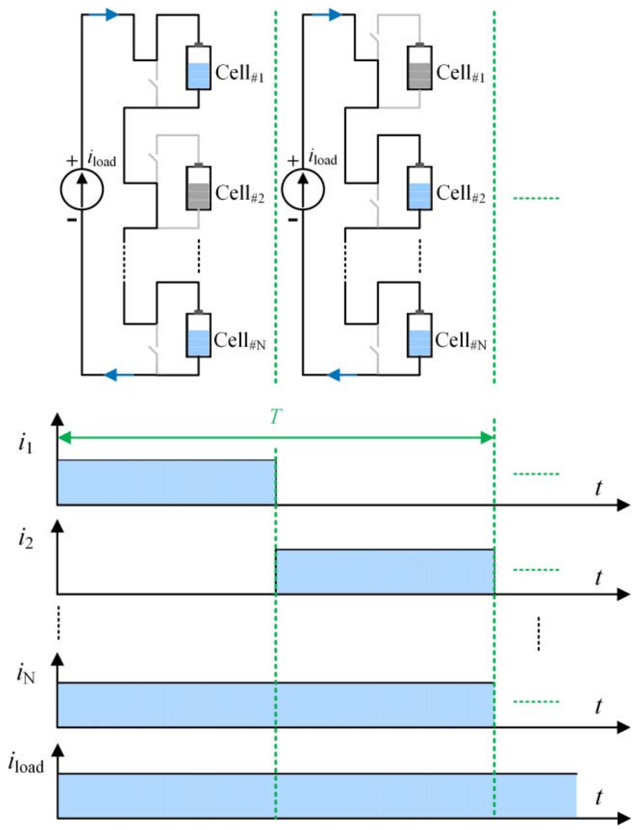


Fig. 4. The schematic of PC generation.

2) Lifetime Extension Results

Fig. 5 summarizes the existing studies on the lifetime effect of the PC charging on the Li-ion batteries. It was concluded in [6] that the NPC charging can extend the battery lifetime by 128 cycles compared to the traditional constant current-constant voltage (CC-CV) charging. In [7], the NPC charging at 0.046 Hz and 0.023 Hz can extend the battery lifetime by 17% compared to the CC-CV charging. However, the charging rate is lower than the constant current by around 10% due to the existence of discharging current during the charging process [8]. [9] showed that the PPC charging with optimal parameters, i.e., 50% duty cycle, 12 kHz frequency, and 25 °C ambient temperature can extend the battery lifetime by 100 cycles compared to the CC-CV charging. Meanwhile, [10] demonstrated that the lifetime of the battery using the Positive Pulse Current-Constant Voltage (PPC-CV) charging can be improved by around 0.3% compared to the CC-CV charging. In [11], the PPC-CV charging at 1 kHz shows a similar rate of the capacity fade with the CC-CV charging. However, it was found that PPC-CV charging at 50 Hz and 100 Hz accelerated the degradation of the battery. As a result, the capacity fade was increased by 7.6% and 12%, respectively.

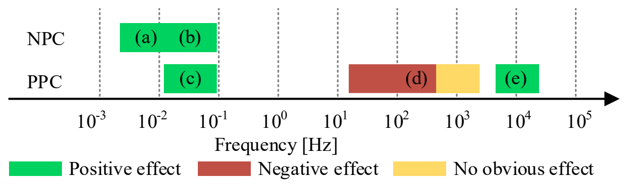


Fig. 5. Lifetime effect of pulse current charging at different frequencies: (a) [7], (b) [8], (c) [10], (d) [11], and (e) [9].

According to the above analysis, it can be concluded that PPC charging helps to extend the battery lifetime. However, it still needs to study the effect of the current parameters (i.e., the frequency, duty cycle, and amplitude) on the lifetime extension. In our latest research work, the effect of the PPC on the lifetime of NMC-based Li-ion batteries at five frequencies between 0,05 Hz and 2 kHz, considering a 50% duty cycle was investigated. To accelerate the degradation of the battery cell, the cycling aging tests were performed at 35 °C. The capacity of the batteries was measured before starting the aging tests and after 100 full equivalent cycles, in order to analyze the effect of the frequency of the PC on the battery degradation and lifetime, At 25 °C ambient temperature, the battery cells were fully charged by applying a 1C CC-CV pattern; then, they were discharged by applying a 1C current after one-hour relaxation. The obtained discharged capacity is regarded as the capacity at the current aging state.

Since we are discarding the NPC, the PPC will be only considered from now on, which will be called PC for simplicity. Fig. 6 shows the results of the capacity fade of the battery cells that were cycled with the CC and PC charging conditions. It can be observed that the battery cell under CC charging reached its End of Life (EOL), i.e., a 20% capacity fade, after 500 cycles. In contrast, under the PC charging at 0.05 Hz, the battery cell reached its EOL after 900 cycles. The results show that PC charging can extend the battery lifetime by around 80% compared to standard CC charging. It can also be seen from Fig. 6 that the degradation of the battery cell is manifested as a two-stage variation. The first stage of the degradation is mainly dominated by the Loss of Lithium Inventory (LLI), while in the second stage, both the LLI and Loss of Active Material (LAM) occur to accelerate the capacity fade of the battery. By observing the rate of the capacity fade, the PC charging can slow down the degradation by inhibiting the LLI and LAM.

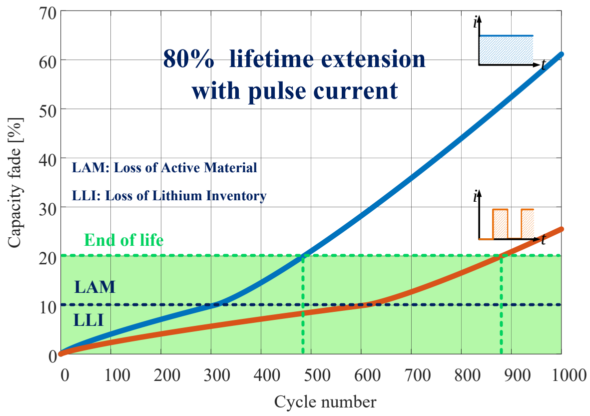


Fig. 6. Capacity fade of the tested battery cells using the CC and PPC charging after 1000 cycles.

B. *Lifetime Control Using AI*

Uncertainties related to the battery lifetime are a bottleneck for the large-scale acceptance and adoption of batteries. From the moment they exit the production line, batteries are subjected to degradation, which results in the gradual reduction of their lifetime. Furthermore, during the real-life operation, Lithium-ion batteries are exposed to a wide range of operating conditions combining periods of idling (standby) and cycling (charging or discharging), which most of the time are non-deterministic and difficult to predict in advance. All these make the battery lifetime modeling and prediction a challenging process.

Traditionally, Lithium-ion battery lifetime modeling is based on data obtained from laboratory accelerated lifetime tests, which use either synthetic profiles (see Fig. 7) [12] or realistic driving cycles (see Fig. 8) [13]. Then, the parametrization of the lifetime model is performed using various techniques ranging from linear regression to neural networks. However, these models tend to lose accuracy predicting the battery lifetime in real-life applications subjected to realistic driving patterns and environmental conditions, and/or when applied in the long-term run [14].

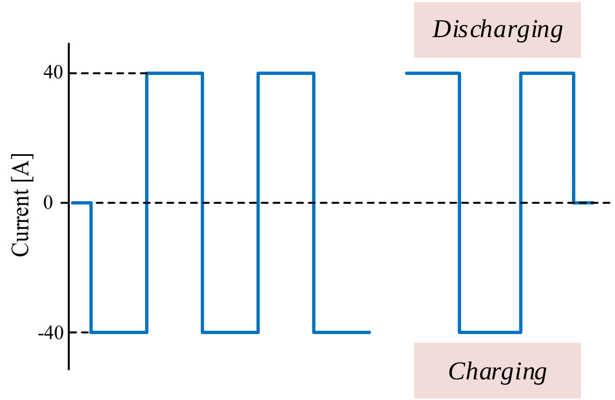


Fig. 7. Synthetic charging-discharging profile; the values of the current are for orientation purposes only.

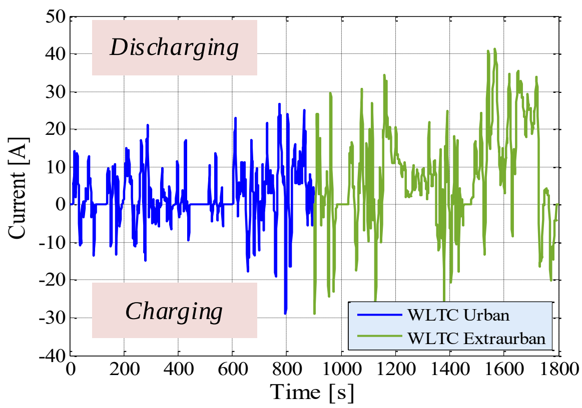


Fig. 8. Standardized WLTC driving cycle profile; the values of the current are for orientation purposes only.

The SB concept is alleviating this challenge by continuous online retraining of the lifetime model. The initial lifetime model is also trained based on laboratory accelerated lifetime tests. Nevertheless, the model is continuously retrained using field battery data, which are harvested from the real-life battery operation and stored io the Cloud. This will allow on one hand a more accurate lifetime prediction and at the same time optimization of the battery operation, by avoiding scenarios, which are accelerating the battery degradation.

AI technologies, due to their flexibility, are suitable for the parametrization of the battery lifetime model. Specifically, according to the data, the relationship between features (i.e., the health indicators that contain the aging information, such as *V*, *I*, *T*, and their statistics) and battery cells' cycle life can be offline established. The artificial neural network (ANN) is one of the most popular AI algorithms for various applications, such as pattern recognition, optimization, and prediction. ANNs have the capacity to learn the degradation behavior of the battery because they use the activation function to introduce the nonlinear properties to the network, making thus ANNs universal function approximators. Deep Learning (DL) is suitable for modeling nonlinear data with a large number of inputs through the cooperation between neurons in multiple layered networks. With the development of big data and cloud computation, the DL algorithms such as deep neural network (DNN) [15], convolutional neural network (CNN) [16], and recurrent neural network (RNN) [17] are promising because they can extract the battery aging information from the measurement automatically. Especially, RNNs (see Fig. 9) are suitable algorithms because of their intrinsic characteristic of modelling time-dependent parameters, such as the lifetime. The performance comparison of current advanced ANNs and DLs is summarized in Table I.

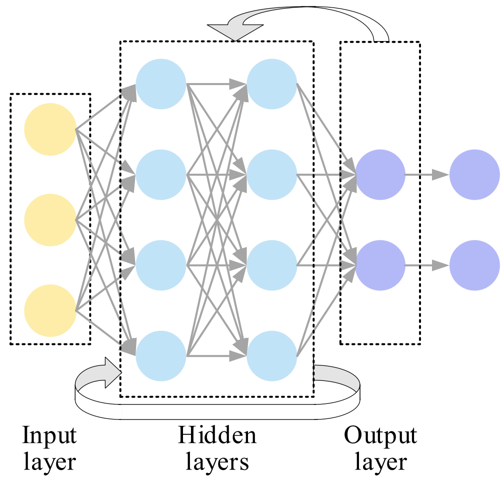


Fig. 9. The basic structure for RNN.

TABLE I. ADVANTAGES AND DISADVANTAGES OF VARIOUS ANN METHODS.

Method	Advantages	Disadvantages
Single layer ANNs	▪ Fast learning speed ▪ Good generalization performance ▪ Less computational complexity	Compared to RNN ▪ Cannot capture the sequential information Compared to DL ▪ Less estimation accuracy
DL (Multiple layers ANNs)	Generally for DL ▪ Good to model with nonlinear data with a large number of inputs ▪ Work well with a large dataset ▪ Easy for extracting global features from raw data	Generally for DL ▪ Relay on a large training dataset ▪ Overfitting
	Particularly for RNN ▪ Capturing the long-term historical information	Particularly for RNN ▪ Gradient vanishing Gradient exploding

AI is increasingly used for state estimation in batteries (e.g., SOC, SOH, and/or state of temperature) [18], RUL prediction [19], and balancing control [20]. AI-based lifetime controller (see Fig. 10) can be designed based on the battery aging data and learning and optimization theory, thereby avoiding the complex battery modeling processes.

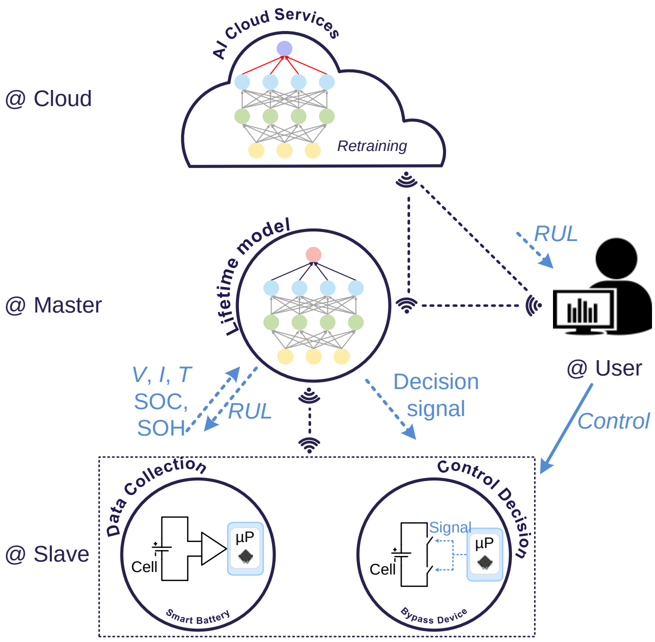


Fig. 10. Diagram of AI-based lifetime controller.

As shown in Fig. 10, the local Slave board has two functions, i.e., data collection and control decision. The collected *V*, *I*, and *T* of the cell and the estimated SOC and SOH in the Slave are transmitted to the Master controller through wireless communication, so that the RUL prediction can be realized. At the same time, the decision signal can also be generated from the AI-based controller embedded in the Master. Then the predicted RUL can be sent to the user. Based on this information, the user can make control decisions such as adjusting the SB operation to increase performance and/or extend lifetime. Meanwhile, the decision signal will be sent back to the local Slave board to realize bypass balancing and PC for lifetime extension. In addition, information interaction can be realized between the Master and the Cloud. Relying on the powerful computing capabilities of the cloud services, the AI-based controller can be combined with online learning algorithms and the field data to re-train the lifetime model and update its parameters in real-time. It should be noted that the data stored in the cloud servers can come from local measurement data and/or data sharing between users.

C. *Hardware Implementation of AI Lifetime Controller*

Cloud computing brings advantages such as global access, scalability, high computation power. The downside of cloud computing is that it is far from the actual system resulting in high latency. The computation stage between the actual system and the AI cloud improves operational efficiency and provides low latency in the system that has to make a decision relatively fast [21]. The AI on the edge computing using the AI-enabled embedded systems (edge devices) are apt in such cases. Such a system minimizes the impact due to the loss of the wireless network, which increases reliability and security. However, due to limited resources, the large computation on the edge device is not possible. Therefore, the demand between efficiency and precision has to be effectively balanced.

The edge devices mitigate adverse effects due to the loss of network connection to the cloud by directly working near the data source, as shown in Fig. 11. The edge device can then synchronize with the cloud services based on the availability of the network. The functioning of the edge-enabled device system is independent and collaborates with the cloud services when necessary. This computing architecture is referred to as dew computing [22], it takes full advantage of the local computation power and the cloud services. The growing use of the deep neural network (DNN) and machine learning (ML) in battery application increases the demand for frequent processing of information in real-time.

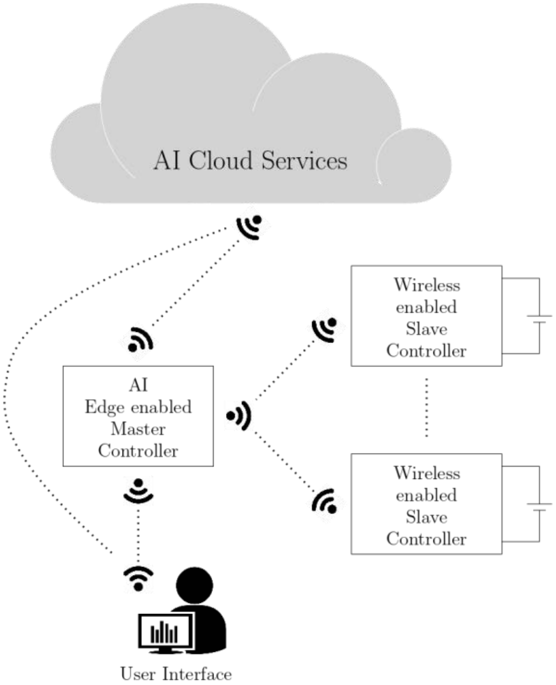


Fig. 11. Dew computing architecture for the implementation of ML/DNN models for battery life extension.

The NVIDIA Jetson Nano launched in 2019 focuses on the easy and efficient deployment of ML tasks. The Jetson Nano has a 128-core NVIDIA Maxwell™ architecture-based GPU, Quad-core ARM® A57. This powerful CUDA-X™ AI computer delivers 472 Giga floating-point operations per second (gflops) and only consumes roughly 5 W of power. This enables the implementation of the dew computing approach in a fast, powerful and affordable manner.

The inference of the DNN and ML algorithms for the battery life extension can be easily implemented using a programing language such as python. The local DNN model directly acts on battery data in real-time. The DNN model can further be made up of several smaller DNN models that fit seamlessly depending on the type of battery cell technology and the available data. The complexity of the DNN model can increase or decrease based on the application, the required precision and efficiency, and the data that is made available to the model. In essence, the complete model is like a LEGO set, with each LEGO block representing the ML or DNN model.

Some of the DNN models in the edge device such as NVIDIA Jetson Nano will interact with the AI cloud service to repeatedly improve the model over time and customize it specifically to the battery pack it is acting on. In EV transportation, this approach over time will capture the impact of the user behavior on the battery pack in an EV. This is particularly advantageous in an SB pack as the continuous improvement in the ML or DNN models eases the need for complex models by predicting the lifetime of the battery pack with minimum data inputs and extend the lifetime by correcting the usage of the battery cells in the pack with the help of bypass device.

III. Applications of Smart Battery in PV and VSD

The SB has a bypass device, which allows the battery cells to either be included or excluded in the pack. The ability to selectively bypass or insert the cells in the pack can be exploited to vary the voltage across the smart battery pack. Furthermore, the use of a smart battery pack as a variable voltage source allows establishing a dc-link that can be regulated without the need for an additional power source. The advantages of the SB in applications of photovoltaics, EV, and grid-connected systems are discussed.

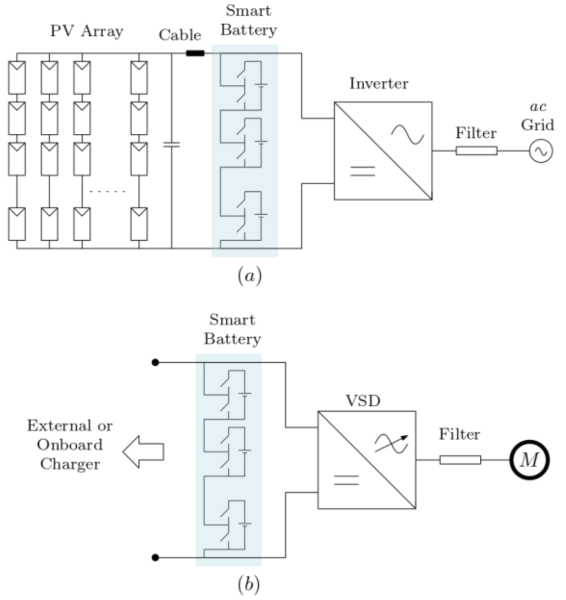


Fig. 12. Application of SB in (a) PV power plant with energy storage, (b) EV drain train.

Fig. 12(a) shows the application of the SB in a photovoltaic system. The use of the SB eliminates the need for an additional dc-dc converter to regulate the battery or PV array. The SB regulates the dc-link voltage to track the maximum power from the PV array. The inverter controls the power injected into the grid. The control of the inverter indirectly controls the power extracted or injected into the SB. The system allows full control of the power extracted from the PV array and the efficient use of the battery pack. Furthermore, the SB effectively manages the SOC of the battery cells. This eliminates the need for a sophisticated battery management system. The overall system eliminates the battery management system and the additional dc-dc converter. This not only reduces cost but also achieves higher efficiency in the range of 98% for the entire system.

In a single-phase system, the SB pack when connected to the grid through a separate inverter can be modulated differently. To generate a near sine wave output, the SB can be modulated to generate rectified sine wave, and the inverter switches at half the fundamental frequency to generate a sine wave at the output. This results in a nearly sinusoidal waveform at the output and reduces the filter requirement, shown in Fig. 13. Furthermore, since the inverter is switched at half the fundamental frequency resulting in negligible switching loss.

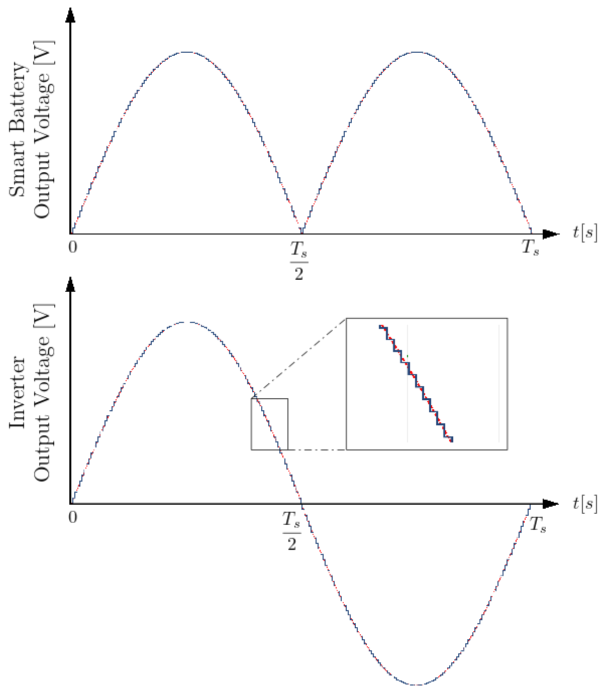


Fig. 13. The SB and the inverter output voltage for a single-phase system.

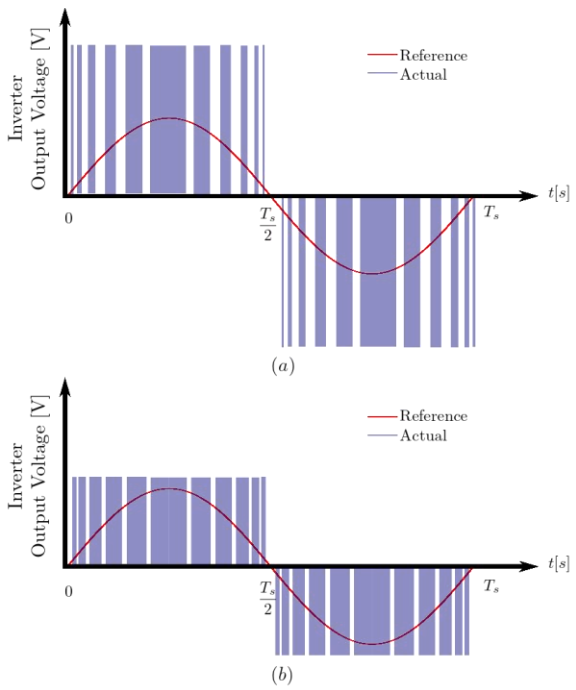


Fig. 14. The inverter output voltage in the EV drive train (a) maintaining constant dc-link voltage,the modulation index is M=0.5, (b) variable dc-link voltage, the modulation index M = 0.8. In both of these cases, the same reference voltage is generated.

Fig. 12(b) shows the application of the SB in the EV drive train. In the case of a single-phase EV drive train, the advantages are similar to the one discussed for the single-phase PV-SB storage systems. It should be noted that based on control strategy different modulation schemes can be applied for SB and the inverters.

One such scheme can be during the low torque operation, wherein the dc-link voltage can be reduced and the modulation index of the inverter can be maintained at its nominal in order to increase the overall efficiency, reduce the torque ripple, and mitigate the EMI. Such an operation is illustrated in Fig. 14. In a traditional EV drive train, the dc-link voltage is maintained at a constant value and the inverter modulation index is varied, shown in Fig. 14(a). In the case of the SB, the dc-link voltage is variable, and the inverter can operate at a higher modulation index as shown in Fig. 14(b). Depending on the control strategy, these two methods can be used at different operating conditions with the main objective of extending the lifetime of the battery cells.

IV. Discussion

SB is a new concept that allows the cells to relax or breathe using the bypass device, without affecting the load current. This relaxation time is capable of significantly extend the lifetime of cells by up to 100%. In order to optimize the time and duration of the relaxation time insertion, AI is used to learn the user patterns and continuously improve the performance of the lifetime model and lifetime prediction. SB structure allows online data collection and cloud communication for periodical retraining. The SB concept is capable of controlling the terminal voltage by controlling the number of bypassed cells. This feature can be used in EVs to minimize the losses by adapting the dc bus voltage to the loading conditions and in PV+ESS applications for achieving MPPT without the need of dc-dc converter or minimizing the grid filter requirements.

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