Second Life Battery Pack as Stationary Energy Storage for Smart Grid

Shijie Tong, Matthew P. Klein, and Jae Wan Park
University of California Davis

Abstract

This paper presents the use of a second life battery pack in a smart grid-tied photovoltaic battery energy system. The system was developed for a single family household integrating a PV array, second life battery pack, grid back feeding, and plug-in hybrid electric vehicle charging station. The battery pack was assembled using retired vehicle traction batteries. The pack is configured with 9 cells in each parallel bank, 15 banks in series featuring 48V nominal and a 12kWh nominal capacity. Limited by the weakest bank in the pack, the second life battery pack has an accessible capacity of 10kWh, or 58% of its original condition. A battery management was developed to handle the bank-to-bank imbalance and ensure the safe operation of the battery pack. An energy management algorithm was established to optimize the energy harvest from PV while minimizing the grid dependence. An information network was constructed to acquire data from the battery, PV, major appliances, and major inverters using Zigbee and wireless qualified devices. The system presented here achieved utilization of used vehicle traction batteries for second round of application, optimization of solar energy harvest and supported electric vehicle charging.

Introduction

Second life batteries are batteries retired from their first application either plug-in hybrid electric vehicles (PHEV) or electric vehicles (EV) and seek their second round of application. According to the US Advanced Battery Consortium (USABC) standard for EV batteries, a battery has reached its end of life when the present cell capacity has dropped below 80% of the rated capacity or the present power density becomes less than 80% of the rated power density at 80% depth of discharge (DoD) [1]. For PHEVs the impact of battery pack performance degradation is less significant since the performance degradation due to aging can be compensated by the internal combustion engine (ICE). As a result, a PHEV battery may degrade more than the USABC standard specifies while still being able to provide value in an automotive application. Consequently, it is expected that batteries with less than 80% of the rated capacity will be retired from PHEV/EV applications and become available to the second life market [2]. As PHEVs and EVs gain popularity the number of aged vehicle batteries will increase, posing recycling issues and making second life applications more attractive [3]. Second use of lithium-ion traction batteries is a potentially viable approach to extend the useful life of a battery, which aids in conserving resources and reducing environmental impacts, and is expected to have significant market potential as lithium-ion battery packs are beginning mass production for transportation use [2]. A second life battery pack, when properly sized, is able to deliver equivalent performance as a new battery pack but at a larger volume and lower cost. Another important feature of a second life battery pack is when cells of varying quantities of degradation are assembled together the performance of the whole pack is governed by the weakest bank in series. The increased likelihood of battery bank capacity imbalance in second life battery packs may potentially increase the risks of over voltage and/or over current within the pack, and therefore requires a well-integrated battery management system.

<table>
<thead>
<tr>
<th>Battery Types</th>
<th>Price kWh</th>
<th>Service Life</th>
<th>Issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead Acid Batteries</td>
<td>~600[4]</td>
<td>~2000 cycles**</td>
<td>Short life</td>
</tr>
<tr>
<td>2nd Life Lithium Batteries</td>
<td>~120***</td>
<td>~5 years****</td>
<td>Low power density;</td>
</tr>
</tbody>
</table>

*Test performed by Sandia National Lab on a LiFePO cell with 0.6C Utility PSOC cycle[5]
**Test performed by Sandia National Lab on AGM VRLA batteries with 1C Utility PSOC cycle. Note that carbon enhanced VRLA batteries have cycle life performance compatible to lithium battery at lower energy density[6]
***a discount of 80% is expected for second life battery price[2]
****Test performed in our lab on a second life LiFePO cell with 1C cycle resulting the cell degrading from original 80% capacity to 64% capacity [7]

As energy generation shifts from fossil fuels to alternatives, energy storage will become an important and necessary component for grid stability and peak shifting, due to the unmatched peak production of renewables versus grid demand[8-15]. Over the years, lithium ion batteries have gained popularity in energy storage systems of mobile electronics, automotive and aerospace applications [16-18]. Popular candidates for battery based stationary energy storage includes lithium batteries, lead acid batteries, flowing electrolyte batteries, or sodium-beta high temperature batteries[19]. The flowing electrolyte and sodium-beta high temperature batteries contain toxic or highly corrosive materials, requiring advanced infrastructure to provide thermal management, and are normally used in large-scale energy storage systems.
storage systems. For small-scale stationary energy storage, the prime battery storage candidates are compared in Table 1. Lithium batteries serve as promising candidates for grid storage if not for the cost. As a result, the reduced cost of second life lithium ion batteries is appealing to stationary energy storage applications since they may be effectively implemented in small-scale applications to deliver high localized fidelity for demand response.

This paper presents the development and preliminary use of a second life battery pack in a Smart Grid-tied Photovoltaic Battery Energy System (referred to as the SYSTEM in the rest of this paper), a system developed for a single family household integrating a PV array, grid back feeding, second life battery storage and a PHEV charging station. The following tasks were accomplished in the following order: 1) battery pack assembly, 2) the integration of a battery management system, 3) the design of an energy management algorithm, which considers a simple grid response, PV energy harvest, house demand and battery safety; 4) and finally the development of an information network for energy management and data acquisition. As illustrated in Figure 1, the project applied a second use of vehicle traction batteries as stationary energy storage into a PV array and vehicle charging equipped smart house.

**System Design**

The system was designed to satisfy the following goals: 1) support the energy demand of a single family household using both utility power and PV panels, 2) optimize grid dependence using battery storage, 3) enable grid back feeding during peak utility cost, 4) charge a PHEV using a Level II charging station.

![Figure 1](image1.png)

Figure 1 shows a stitched photo of the installed system. A smart meter and a smart panel were installed on the side of the house. The garage space is where the battery box, battery and PV inverters, junction boxes and breakers were installed.

![Figure 2](image2.png)

Figure 2 shows a diagram of the system components. One PV string consists of 12 panels in series providing 2.16kW of nominal power output, and was installed on a south facing rooftop at the project house. Each panel was connected to a DC-DC maximum power point tracking (MPPT) converter (TiGo system®) to optimize the output of each PV module. The entire array was then connected to a DC-AC MPPT converter (SMA system®) to convert the DC solar power into AC power for connecting to the main home power bus. The maximum power tracking provides a high solar energy harvesting efficiency considering irradiance fluctuation and partial shading. A battery pack serves as energy storage of the system and uses a bi-directional AC–DC converter to input (output) energy to (from) the main power bus. The battery pack was assembled using 135 units of second life LiFePO4 based cells. The batteries were originally manufactured with a capacity of 40Ah. However, after years of service in a vehicle traction battery, these second life batteries have a remaining capacity of 20~30 Ah. The battery pack has 9 cells in each parallel bank, and 15 banks in series, providing 48V of nominal voltage and 12kWh of nominal energy capacity. Limited by the weakest bank in the pack, the second life battery pack has an accessible capacity of 10kWh, or 58% of its original condition. The battery pack is controlled to absorb excess energy.
production from the PV during off-peak hours, and to partially support the house load during peak times. Additionally, the control algorithm is programmed to maintain a high level of charge in the battery to enable use as a backup power source. A vehicle charging station was installed to provide level II charging to a PHEV. The vehicle is charged daily with an estimated energy demand that may vary between 2kWh to 8kWh. The total rated power is 10kW for the interconnected system.

**Battery Pack Design**

![Diagram of Battery Pack Design](image)

Figure 3. Battery pack: a. schematic diagram; b. picture of balancing box (on the top of battery box); c. picture battery box.

Figure 3 presents the assembled battery pack used in this study. The battery pack was enclosed in the battery box with nine cells connected in parallel to form one battery bank and 15 battery banks stringed in series to form the pack. At each terminal of the battery bank a battery management system (BMS) slave board was installed to sense the battery voltage and temperature. A current sensor was installed at the positive dc terminal to sense the current in and out of the battery pack.

Current, voltage and temperature measurements were reported to the BMS master board (via line 2 in Figure 3(a)). The balancing box, as seen in Figure 3(c)(b), is a small case on the top of the battery box. In the balancing box the passive balancing boards were installed. They are able to shunt part of the charge from a bank in order to eliminate charge imbalance within the battery banks (via line 4 in Figure 3(a)). The balancing boards were located far enough from the battery so that dissipating heat from the boards during balancing will not affect the thermal condition of the battery pack.

![Flow Chart of Battery State-of-Charge Estimation Algorithm](image)

Figure 4. Flow chart of battery state-of-charge estimation algorithm.
A few other mechanical and electrical aspects of the battery pack include: 1) BMS master board control of a safety relay to mitigate excessive voltages or currents; 2) a dc/dc converter which sinks a small portion of battery energy (line 9) to power the BMS (line 8); 3) the BMS sends commands to the dc/ac inverter (line 7) to control the battery current input and output (line 1); and finally 4) each battery cell was applied at least one fusible link to isolate itself from the whole bank in case of over currents.

**Figure 5. Flow chart of battery state-of-health estimation algorithm.**

State-of-charge (SoC), and state-of-health (SoH) of the battery pack, which during dynamic operation may not be directly measured, are important battery state variables that are needed for battery management. For this battery pack, a multiple-time-scales worst-difference estimation approach was applied for SoC and SoH estimation.
allocates the available computing resources to provide close monitoring of SoC and SoH of that bank. As for the rest of the banks, the scheme estimates their SoC and SoH by comparing them to the worst bank, significantly reducing computing resource demands. Using an equivalent circuit based extended Kalman filter, the estimator provides SoC estimation of the weakest battery bank with the highest accuracy (Detail algorithm presented in section time scale 1 of Figure 4). For the rest of the banks, SoC estimation is provided by comparing the difference between the worst bank and the target bank (Detail algorithm presented in the section time scale 2 of Figure 4). Battery pack capacity and internal resistance degrades as usage accumulates and the algorithm tracks battery SoH by applying a two parameter varying approach(PVA). This evaluates the internal resistance degradation of the worst bank and the capacity degradation of all 15 banks, respectively (Detail algorithm presented in the section Time Scale 3 and the section Time Scale 4 of Figure 5).

Basic on-line estimation results are presented in 6, 7 and 8. The battery pack was tested through a cycle of charge and discharge with voltage profiles of all 15 banks shown in Figure 6. Applying the proposed battery estimator, the system was able to identify SoC and SoH of each battery bank. As shown in Figure 7, the battery estimation algorithm was able to estimate SoC of all 15 banks and successfully identify their differences during cycling. Figure 8 shows that the largest SoC difference among banks was about 10%, of which 5% will generally be compensated by the balancing circuits of the BMS and 5% was caused by SoH imbalance, which cannot be eliminated.

**Monitoring and Data Acquisition**

A data acquisition system was setup as illustrated in Figure 9. A WirelessGlue™ gateway serves as the central gateway that receives information from the battery management system (BMS), SMA®Webbox, Tigo® gateway, and ZigBee radios. The SMA®Webbox logs data of the SMA products, including the DC input from the battery pack, the AC output from the battery charger/discharger, and the AC output from the SMA MPPT PV converter. It also hosts a local HTTP server that can be continuously accessed through the central gateway (Line 4 in Figure 9); similarly, the Tigo® gateway logs output data of each PV panel and transfers the data via wireless communication to the central gateway (Line 7). ZigBee radios connected to the central gateway via Ethernet were installed in the house. They receive data from ZigBee equipped appliances such as smart plugs, smart meter, and a ClipperCreek® vehicle charger (Line 5 and Line 6). The BMS receives voltage, current, and temperature measurements of each battery bank through Line 1, and estimates battery state-of-charge (SoC) and state-of-health (SoH) of the battery pack. Also, the BMS obtains the system operating data from the central gateway, including instant utility price, PV output, and house power demand. Based on the information, the BMS algorithm implements the designated control decision, which is submitted to the central gateway (Line 2) and routed to the battery charger/discharger (Line 4) to operate the battery pack, completing the feedback control loop. Finally, the central gateway assembles all the data from different sources and sends the packaged system information to a server in the cloud.

**Results and Discussion**

The battery pack is operated as an energy buffer shifting energy from the PV production peak to the energy consumption peak. The battery charge and discharge decision is made based on three system variables: 1) battery status, 2) time varying utility price and 3) energy demand subtracting PV production. Take a one-day usage cycle for example, the typical PV production peak occurs from 9am to 4pm, any excess production will be stored in the battery pack during off peak pricing. The energy usage peak typically occurs from 5pm to 9pm. The typical utility time varying price peaks from 1pm to 8pm. A detailed system management decision table is presented in Table 2, where row 1, 2 and 3 are input variables. Row 4 is a list of system actions for Strategy A, and row 5 is a list of system actions for Strategy B. In Strategy A, the battery will receive energy from PV production if PV production is higher than the house power demand and the utility price is not at peak. Then, the battery will discharge to support house load if PV production is insufficient to support the house load, and the utility price is during peak hour. Strategy B, differs from Strategy A in the fact that the battery will receive energy from PV production if the PV production is higher than the house power demand; regardless of the utility price (difference is marked bold in the Table 2). By comparison, Strategy A uses

Page 5 of 8
battery pack to perform peak shifting, while Strategy B also reduces system dependency to the grid, at the cost of higher battery usage.

Table 2. Decision table of system energy flow management.

<table>
<thead>
<tr>
<th></th>
<th>T</th>
<th>F</th>
<th>N</th>
<th>T</th>
<th>F</th>
<th>N</th>
<th>T</th>
<th>F</th>
<th>N</th>
<th>T</th>
<th>F</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>N</td>
<td>T</td>
<td>F</td>
<td>N</td>
<td>T</td>
<td>F</td>
<td>N</td>
<td>T</td>
</tr>
<tr>
<td>2</td>
<td>T</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>C</td>
<td>F</td>
<td>D</td>
<td>S</td>
<td>F</td>
<td>C</td>
<td>D</td>
<td>S</td>
<td>F</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
<td>a</td>
</tr>
<tr>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
</tr>
</tbody>
</table>


Action: F: GRID BACK FEED, S: GRID SUPPLY, C: BATTERY CHARGE, D: BATTERY DISCHARGE.

Back to the grid. As shown Figure 10. from midnight to 10am, both the PV array and battery pack were in silent mode. The house energy usage was fully supported by the grid. From 10am to 5pm, the house energy demand was supported by both the PV and grid. When the PV output was higher than the house demand, excess energy of the PV was used to charge the battery. From 5pm to 8pm, the house energy usage peak arrived, and the battery discharged to support the load demand with an efficiency near 85%. At the same time, the PV supported the energy demand with the remaining sunlight. Any excessive production was sent back to the grid. When the peak pricing finished at 8pm, the battery stopped discharging. Indicated by the energy source pie chart Figure10 (b), 63% the house energy usage was covered by the PV array production (7.2kWh). With the battery pack enabled peak shifting, the peak usage during the nighttime was covered by the PV energy or battery stored PV energy (0.9kWh from direct PV energy, 0.9kWh from battery discharge energy). As shown in the energy consumption pie chart in Figure 10, the house energy demand in that day consisted of 17% peak pricing usage (3.2kWh), 47% partial peak usage (8.4kWh), and 35% off peak usage (6.4kWh). Using the energy management of Strategy A, the PV energy was sent back to the grid to obtain more optimal economics. Meanwhile the battery usage was less. The energy system operated by this strategy can have a smaller size battery pack, but will have a larger grid dependence.

Figure 10. Sample of system operation using Strategy A: a) Plots of power draw and supply. b) Energy supplied as a function of the source. c) Pie chart of energy consumption based on price of usage.

Figure 10 shows the energy operation using energy management Strategy A on November 29th, 2013. At peak hours, instead of charging the battery, the PV output was fed back to the grid. As shown Figure 10. from midnight to 10am, both the PV array and battery pack were in silent mode. The house energy usage was fully supported by the grid. From 10am to 5pm, the house energy demand was supported by both the PV and grid. When the PV output was higher than the house demand, excess energy of the PV was used to charge the battery. From 5pm to 8pm, the house energy usage peak arrived, and the battery discharged to support the load demand with an efficiency near 85%. At the same time, the PV supported the energy demand with the remaining sunlight. Any excessive production was sent back to the grid. When the peak pricing finished at 8pm, the battery stopped discharging. Indicated by the energy source pie chart Figure10 (b), 63% the house energy usage was covered by the PV array production (7.2kWh). With the battery pack enabled peak shifting, the peak usage during the nighttime was covered by the PV energy or battery stored PV energy (0.9kWh from direct PV energy, 0.9kWh from battery discharge energy). As shown in the energy consumption pie chart in Figure 10, the house energy demand in that day consisted of 17% peak pricing usage (3.2kWh), 47% partial peak usage (8.4kWh), and 35% off peak usage (6.4kWh). Using the energy management of Strategy A, the PV energy was sent back to the grid to obtain more optimal economics. Meanwhile the battery usage was less. The energy system operated by this strategy can have a smaller size battery pack, but will have a larger grid dependence.

Figure 11. Sample of system operation using Strategy B: a) Plots of power draw and supply over an entire day. b) Energy supplied as a function of the source. c) Pie chart of energy based on price of usage.
Figure 11 illustrates the functionality of Strategy B for usage data on December 1st, 2013. As shown in the Figure 11.a, from midnight to 10 am, both the PV array and the battery pack were in silent mode, and the house energy usage was fully supported by the grid. From 10am to 5pm, the house energy demand was fully supported by the PV array output, and excess energy of the PV was used to charge the battery. From 5pm to 8pm, the house energy usage peak arrived, overlapping with the utility peak pricing hour. The battery discharged to support the load demand at efficiencies of approximately 85%. When the peak pricing stopped past 8pm, the battery stopped discharging. Indicated by the energy source pie chart of Figure 11.b), 63% of the house energy usage was covered by the PV array production (6.8kWh), and with the battery pack enabled peak shifting capability, the peak usage during the evening hours was covered by the battery stored PV energy (3 kWh). As shown in the energy consumption pie chart in Figure 11.c), the house energy demand during that day consisted of 30% peak pricing usage (3.2 kWh), 20% at partial peak usage (2.4 kWh), and 50% at off peak usage (5.7 kWh). Using the energy management strategy b, the over produced PV energy will always be used to charge the battery. Battery usage is more than strategy b. The energy system operated by this strategy will need a bigger battery pack, but the system will have a smaller grid dependency.

Table 3. System operation statistics from 12/01/2013 to 12/30/2013

| PV System | Energy Harvested | 218.3 kWh |
| Battery Pack | Peak Usage Shifted | 63 kWh |
| Battery Pack | Peak Usage Bill Saved (@0.3$/kWh) | $18.90 |
| Battery Pack | Extended Battery Life | 11 Cycles |
| Grid Interaction | Electricity Bill Saved (@0.15$/kWh) | $32.7 |

The system directly provides solar energy when available in the daytime, and reduces a portion of the evening peak load using the stored solar energy that resides in the battery. Over the course of one month of operation with Strategy A at the location of Davis, CA. The system produced 218.3kWh of renewable energy. This results in an equivalent CO2 savings equal to 371.1lbs. The battery system provided PV energy shifting of 63kWh, equivalent to $18.90 savings. Placing the battery into this second application enabled the use of 11 additional cycles. Overall the system has saved $32.7 per month in reduced sunlight wintertime operation.

Conclusions

In this paper, an application was achieved using second life lithium ion vehicle traction batteries as stationary energy storage. With a proper management algorithm and hardware, used lithium batteries can be utilized as stationary energy storage with competitive performance with the exception of battery pack imbalance at high state of charge and slightly lower round trip efficiency compared to a new battery pack. A complete design document was presented integrating second life battery storage into a PV array and smart grid equipped single family house. System operation test results reveal that a system with 10kWh battery pack and 2.16 kW PV array can provide effective load shifting of a single family house with 25kWh daily energy demand. The daily energy throughput of the battery pack is only 2 to 3kWh in both a good weather scenario and a bad weather scenario. In the future, life cycle assessment and aspects of battery life extension, economic benefit, and environmental impact of the system will be studied. Meanwhile, more advanced energy source and demand predictive management algorithms will be investigated using this platform.

References


Acknowledgments

The authors gratefully acknowledge the support of California Solar Initiative (CSI) in funding this research project.

Definitions/Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHEV</td>
<td>Plug-in hybrid electric vehicle</td>
</tr>
<tr>
<td>EV</td>
<td>Electric vehicle</td>
</tr>
<tr>
<td>DoD</td>
<td>Battery depth of discharge</td>
</tr>
<tr>
<td>SoC</td>
<td>Battery state of charge</td>
</tr>
<tr>
<td>SoH</td>
<td>Battery state of health</td>
</tr>
<tr>
<td>ICE</td>
<td>Internal combustion engine</td>
</tr>
<tr>
<td>BMS</td>
<td>Battery management system</td>
</tr>
<tr>
<td>PV</td>
<td>Photovoltaic</td>
</tr>
<tr>
<td>MPPT</td>
<td>Maximum power point tracing</td>
</tr>
<tr>
<td>EKF</td>
<td>Extended Kalman filter</td>
</tr>
<tr>
<td>PVA</td>
<td>Parameter varying approach</td>
</tr>
</tbody>
</table>