An Electrified Vehicle Onboard Microgrid With Pv For Battery Module Balancing And V2g Applications

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AN ELECTRIFIED VEHICLE ONBOARD MICROGRID WITH PV FOR BATTERY MODULE BALANCING AND V2G APPLICATIONS

by

CHEN DUAN

DISSERTATION

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

2020

MAJOR: ELECTRICAL ENGINEERING

Approved By:

____________________________________
Advisor / Date

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____________________________________
DEDICATION

This thesis is dedicated to my parents, my wife, my friends, and all my teachers.
ACKNOWLEDGMENTS

First of all, I would like to express my most sincere gratitude to my advisor, Dr. Caisheng Wang, for his unreserved support, tremendous guidance, and warmest encouragement. Through my study and research journey of pursuing Ph.D., I faced tons of difficulties and had a lot of hard times. Without his help, guidance, and all the knowledge he taught me, I would have never gone through these handicaps and made my research fruitful. I believe his profound knowledge, active attitude towards research and life, will benefit my future career as well as my life.

I also want to extend my gratitude to the members of my thesis committee: Dr. Le Yi Wang, Dr. Feng Lin, and Dr. Da Deng. It would not be possible to carry out my research without their help, guidance, and encouragement. I also would like to thank Wayne State University for providing me all the supports in both study and research, particularly for helping turn my research idea into a patent application.

I would also like to express my gratitude to my colleagues, Dr. Chang Fu, Dr. Jianfei Chen, Mr. Zongzheng Li, Mr. Shidao Wang, Ms. Tingli Hu, Mr. Chenguang Jiang, Mr. Qiang Xu, and Mrs. Hongjun Tao, for all their help and valuable suggestions. Especially, I would like to thank Dr. Zhongyang Zhao, for his insightful suggestions for modeling virtual solar farm.

Ultimately, my thanks go to my beloved parents and wife for their continuous love, care, and support for me. I hope this thesis can be the best gift for them.
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CHAPTER 1 INTRODUCTION

1.1 Electrified Vehicles Worldwide and in the U.S.

Vehicles with partially or fully electrified powertrains are identified as electrified vehicles, or xEV. Depending on the powertrain type, the xEV can be battery electric vehicle (BEV or EV), hybrid/plug-in hybrid electric vehicle (HEV/PHEV), and fuel cell electric vehicle (FCEV). According to the Global EV Outlook 2019 [1-2], the global xEV stock number has reached 3,290.8 thousand by the end of 2018, with an increase of 2,814% compared to 2012. The yearly global xEV stock numbers from 2012 to 2018 are presented in Figure 1.1 [1].

![Figure 1.1: Yearly xEV Global Stock [1]](image)

As the core energy storage system, the battery production and vehicle installation number bloom as well. Figure 1.2 and Figure 1.3 present the vehicle installed battery energy in GWh worldwide and in the U.S., respectively. From the figures, it can be observed by the end of 2018, a total of 198GWh battery packs have been installed
onboard worldwide. The U.S. shares around 20% of the total installed storage energy capacity, which is around 40 GWh. It can also be observed that, as predicted, the total energy of installed xEV battery by the end of 2020 worldwide and in the U.S. will be increased to 247 GWh and 50 GWh, respectively.

Figure 1.2: Vehicle Installed Battery Energy Worldwide [1]

Figure 1.3: Vehicle Installed Battery Energy in the U.S. [1]
1.2 Battery Systems in Various Electrified Vehicles

Battery systems have been widely used in industry, transportation, energy storage applications for more than a century. Battery energy storage has been identified as an enabling technology for transportation electrification and smart grid applications. Battery systems can further catalyze the synergy between electrified vehicles and the electric grid [3]. For example, as shown in Figure 1.4, the battery pack is the only energy source for the EV, which is charged by the grid (G2V) and can provide energy to the electric grid (V2G) when needed.

![Battery Electric Vehicle (BEV) Powertrain Architecture](image)

Figure 1.4: Battery Electric Vehicle (BEV) Powertrain Architecture

While for HEV and PHEV, the battery pack is usually much smaller. This is because most of the energy is supplied by the internal combustion engine (ICE) in those vehicles. The battery is utilized as an energy or power buffer for short-range drives, acceleration, and V2G applications.
For FCEV, the battery pack is still necessary as an energy/power source for stabilizing the DC bus voltage to avoid the stack degradation [29]. In addition, when applying regenerative braking, the battery pack is used to recover some of the braking power; therefore, the overall fuel economy can be improved.
1.3 Literature Review

In this section, a literature review is carried out for the battery imbalance mechanisms, state-of-the-art technologies used in battery balancing, and solar energy utilization for vehicle applications.

1.3.1 Battery Imbalances in Vehicles and Its Mechanisms

In high power applications such as EVs and PHEVs, the battery packs are usually formed by battery modules/cells connected in series to increase the voltage and connected in parallel to increase the capacity. However, due to manufacturing caused variations and varying operation conditions, the imbalances reduce the usable energy [3-7]. The imbalances of a battery pack could lead to adverse outcomes such as early termination of the charging and discharging process [8-10]. Or, it can be even worse: the battery cells/modules that are over-charged or over-discharged could be permanently damaged [4]. To deal with the imbalance issue of battery packs, various battery balancing topologies and control algorithms have been investigated and developed [4-13].

The imbalance between Li-ion battery modules and cells, also called inconsistency, can be caused by two reasons [14]. The first reason is the manufacture error and deviations [15-17, 28], e.g., electrode fabrication, module, and pack assembly, as well as tests. The deviation during the manufacturing process brings inconsistency of capacity, initial state-of-charge (SOC), and internal/wiring resistance to the batteries. These deviations will be enlarged with the driving range of the electric vehicles due to
differences in depth-of-charge (DOD), temperature, among other factors [18-20]. This is the second reason that causes and propagates the inconsistency within battery systems.

A review of the literature on battery imbalance mechanisms has been conducted. The reviewed studies show the inconsistency within battery systems is inevitable and reflected in various parameters. Internal parameter consistency has been discussed in [21-25]. As stated in [15-16], the battery manufacturing process is so complicated that the error/deviations among cells will be dramatically magnified when the cells are assembled into battery modules and packs. Capacitance and internal resistance are the two most important parameters related to battery degradation but impossible to be kept consistent. Because of the production error, the initial capacitance of a cell string usually fits a normal distribution [18]. However, assembling the cell strings to battery modules/pack does not help reduce the deviation. The internal resistance mainly includes two parts: ohmic resistance and polarization resistance. Ohmic resistance is determined by the cathode and anode electrode materials, diaphragm materials, electrolytes, and other components [19]. Polarization resistance is caused by the polarization reactions within a battery module/pack. Polarization resistance is highly dependent on the battery SOC and temperature [25]. Therefore, the SOC imbalance and the temperature difference among battery cells/modules will lead to polarization resistance variations. And as a result, the SOC and temperature delta will be even larger.

1.3.2 Battery Balancing Technologies

To deal with the imbalance issue of battery packs, various battery balancing
topologies and control algorithms have been researched and developed [4-13].

Passive balancing is still one of the most widely used methods in battery management systems (BMS) because of the advantage of low cost [6]. The operating principle of passive balancing is simple: When a single cell/module reaches the charge voltage limit, it will be discharged by a power resistor to allow other cells to be fully charged [5, 6]. However, passive balancing is only applied to the charging process [4] instead of both charge and discharge. In addition to this limitation, the overall efficiency of the battery system with passive balancing is relatively low due to the balancing energy is dissipated as heat.

In contrast, active balancing circuits equalize battery cells by transferring energy from the cells with higher state-of-charge (SOC) to the cells with lower SOC and can be operated during both charge and discharge processes. Three types of state-of-the-art active balancing circuits are summarized in [4]: Capacitive Balancing, Inductive Balancing, and Mixed Active Balancing. For capacitive based active balancing, one or more capacitors are switched in parallel to a cell [11, 12], the energy transfer is the result of a voltage difference between cells. The advantage of capacitive balancing is no complex control algorithm is needed. However, the balancing process is very slow. In addition, the capacitance resistance brings power loss to the battery pack. The inductive balancing uses transformers with air-gapped magnetic cores or inductors to transfer energy between cells. Compared with capacitive balancing, the inductive balancing is able to charge a cell with equal or higher voltage with another cell. But at the same time, the iron loss and copper loss of the inductive components add power
loss to the battery pack as well. The mixed active balancing uses DC/DC converters, e.g., Cŭk converter [13, 26] to transfer energy. For mixed active balancing circuits, the power loss cannot be eliminated due to the resistance of capacitive components, iron and copper loss of inductive components, and the switching loss of MOSFETs. The main disadvantage of the conventional active battery balancing system is the power loss during the balancing operation. The power loss wastes the usable energy of the whole battery pack. For EVs, the result is the drop in driving range. To deal with the power loss issue, some other battery balancing circuits have been studied and developed. For example, in [27], a hierarchical cascaded multi-level inverter was proposed to achieve uniform SOC operation by bypassing low SOC cells; In [30], a cell/module reconfiguration method was adopted to achieve charge balance with fast speed. Research activities have also been conducted to use the low voltage battery as the balancing sink to equalize the high voltage battery cells [31, 32]. Hence, the balancing power loss can be eliminated, and the accessible battery capacity can be improved. However, due to the high cost and complicated control algorithm, none of these novel balancing schemes has been applied widely on electrified vehicle products.

1.3.3 Solar Energy in Transportation Applications

As one of the important renewable energy sources, solar energy has been utilized in different transportation applications. The most successful utilization case of solar energy is space vehicles, including space shuttles and exploration rovers [33-36]. For space vehicles without nuclear reactors, solar energy is the only source for powering
propulsion and electric accessory loads. Another advantage of applying solar power to space vehicles is there is almost no room limit for solar panels. Therefore, the solar energy harvesting system can be designed to meet the maximum power requirements. For example, in [34], the explorer for near-earth asteroids was configured to equipped a 300-kW solar electric propulsion system. Research and experiments have also been done to power aircraft with solar energy [37-41]. In [37], several solar-powered aircraft projects have been reviewed, and the challenges have been summarized. In short, the power density of the solar arrays nowadays is not enough to provide enough dynamic force to lift the aircraft at high altitudes, where the atmospheric density is much lower.

On the other hand, the energy density of the batteries and considerable power loss of other components, e.g., inverter, motor, and propeller, etc. prevents the aircraft from traveling a long distance.

For ground vehicles, there are also benefits available through installing solar panels on the roof. Comparing to conventional fossil fuels and plug-in charging, the vehicles with solar panels can be charged with free, abundant, and rather evenly distributed solar energy [42]. The benefits also apply to the grid. Using real drive data, the analysis in [43] proves that in sunny summer weeks, large-scale solar EVs can help reduce 15%~20% of the charging energy from the grid, and 47%~49% aging of the transformer. There were a lot of projects performed to develop and optimize vehicle onboard solar system [44-52], including vehicles like HEV [50], electric scooter [51], and wheelchair [52] with smaller battery comparing to EV. However, due to the price of the solar arrays and the unstable of the sun irradiance [42,44], vehicular solar panels are still far away from
being widely commercialized. In very recent years, there is some good news: two electric vehicle startups, Lightyear [53] and Sono Motors [54], are kicking off solar-powered electric vehicles. In addition, TESLA has assembled solar panels to its latest pick-up model Cybertruck and claims that the PV can add 15 miles driving range each day [55]. Moreover, PV-supported EV charging stations, especially fast-charging stations, have been richly researched [56-60], and more and more stations are being erected all over the world [61-63]. The benefits of the PV-supported charging station as an accelerator of transportation electrification are clear. With the harvested solar energy, more free and clean electricity can be utilized to charge the vehicles. In addition to that, the power request and ripple from the charging station to the grid can be reduced considerably.

1.4 Motivation and Scope of Study

According to the literature review, the utilization of conventional battery balancing schemes for electrified vehicles is limited by their disadvantages, especially power loss. There are urging needs for the automotive industry to apply a novel battery balancing technology that can reduce power loss so that the battery life can be extended without bringing ‘range anxiety’ to the vehicle users. On the other hand, although there are some trials on commercializing EV onboard PV have been kicked off, most produced electrified vehicles are still not equipped with solar panels due to high cost and low energy harvesting performance. To provide a solution to these issues, this thesis proposes an electrified vehicle onboard microgrid with PV for battery module balancing.
and V2G applications. By forming a microgrid with onboard components including auxiliary power module (APM), bi-directional charger, and PV, the proposed system is able to perform battery module balancing when solar power is not available as well, and carry out vehicle-to-grid (V2G) functions to enlarge benefits. The system architecture and working principle of the electrified vehicle onboard microgrid will be demonstrated in Chapter 2. To estimate the performance and efficiency of the proposed system, the simulation studies and experimental tests are carried out. In Chapter 2, the modeling and simulation of the proposed system are given, followed by the prototype development and experimental validation of the microgrid.

As another important topic of battery balancing, the balancing criteria have been sufficiently investigated for conventional schemes. However, for novel balancing schemes using energy sources outside of the battery, like APM and PV, balancing criteria and related control algorithms have not been extensively studied. Especially for solar-assisted balancing, when SOCs of all modules are well equalized, the harvesting of solar energy shall not be stopped. Therefore, it is worth developing an advanced algorithm that can maximize battery life with harvested solar energy. In Chapter 3, various balancing criteria and related control algorithms will be discussed and compared through model-based analysis, for both APM and solar balancing.

As demonstrated in the literature review, the charging station is still the most commonly seen application scenarios of solar panels for transportation electrification, instead of onboard vehicle applications. One of the biggest reasons is the rated power of the PV on one vehicle is limited by the roof area. To overcome this issue and find
out the benefits of the proposed system to the electricity grid and utility users, the studies of this thesis have been extended to grid applications. In Chapter 4, a concept named virtual solar farm will be proposed. The idea of virtual solar farm is to aggregate large numbers of EVs for grid support. Although PV on each vehicle can generate only a small amount of solar energy, when the vehicle number becomes big, the total green energy generation will be remarkable. Another solution to address the PV power limitation is to apply a solar-assisted balancing scheme to other battery systems with bigger areas for PV installation, such as a grid energy storage system (ESS). In Chapter 4, followed by the discussion of virtual solar farm, a study on applying solar-assisted battery balancing to telecommunication backup battery pack will be presented. Based on the studies on the 2 key concepts, the proposed system shows convincing results for industry commercialization. The conclusion of the thesis and the discussion of future work are given in Chapter 5.
CHAPTER 2 ELECTRIFIED VEHICLE ONBOARD MICROGRID WITH PV FOR BATTERY MODULE BALANCING AND V2G APPLICATIONS

2.1 System Configuration and Operation

In this chapter, the architecture of the proposed electrified vehicle onboard microgrid with PV for battery module with V2G features will be proposed, following with the system modeling, simulation, and experimental verification.

Figure 2.1 shows the system architecture of the proposed onboard microgrid system. Take a battery pack with 4 modules of an EV as an example. The system is formed by a PV panel, a DC/DC converter, selection switches S1-S8, dual switches/contactors DS1-DS2, mode switches/contactors MS_PV and MS_APM, as well as a bi-directional charger. The auxiliary power module (APM) is also connected to the microgrid. The APM is a 12V battery to power accessories like radio and lights on most EVs. There is always a step-down converter to charge the APM from the battery pack, which is not shown in the figure. The maximum/minimum output voltage of the DC/DC converter should be higher than the battery pack/module terminal voltages, respectively. It can also automatically recognize the input voltage and output terminal voltage, then charge the battery module/pack connected to the output. The selection switches are used to link the battery module that needs to be balanced to the DC/DC converter or bi-directional charger. To achieve the balancing, S1, S2, S4, S6 are connected to the positive terminal of the DC bus, while S3, S5, S7, and S8 are connected to the negative terminal. If the total battery module number is n, the number of switches will be 2n. These switches can be packaged into a small circuit board and integrated into the DC/DC converter, the BMS, or the power distribution box. The bi-directional charger can either act as a
charger with DS2 closed to charge the whole battery pack or perform V2G functionalities when DS1 is closed. The mode switches are utilized to select the energy source for battery balancing: when there is solar power available, MS_PV will be closed; otherwise, the MS_APM will be closed.

![System Architecture Diagram](image)

**Figure 2.1: System Architecture of Electrified Vehicle Onboard Microgrid for Battery Module Balancing & V2G**

When the EV is in driving and there is solar power available, mode switch MS_PV is closed to balance the battery modules with PV. The control unit estimates the voltage or SOC of each battery module and closes the corresponding switches to link the solar panel to the battery module needed to be charged via the DC/DC converter. For example, to charge module 1 (if the SOC of this module was the lowest), S1 and S3 are closed, as shown in Figure 2.2. Only 2 switches will be closed at the same time. The switches linked to the same terminal will never be closed at the same time to avoid short circuit.
Once all the battery modules are balanced to the same voltage or SOC, the whole battery pack will be connected to the DC/DC converter and get charged by closing S1 and S8. Thus, solar energy can still be harvested even if the battery modules are balanced. When the vehicle is parked and charged from the grid and there is solar power available, the system works in the same way, and the bi-directional charger works in the charging mode with DS2 closed. Therefore, the battery modules can be equally charged. In addition, with the help of the solar charging energy, the total charging time and energy from the grid can be reduced. When the battery is fully charged, the selection switches S1-S8 and DS2 will be opened to disconnect the battery from the system, and the bi-directional charger turns into inverter mode with DS1 closed as shown in Figure 2.3. In this scenario, the harvested solar energy will be delivered to the power grid (PV2G), and the battery will be maintained as fully charged. The maximum power harvested from the PV is given by

\[ P_m = (n_s \times V_m) \times (n_p \times I_m) \times \eta_c \quad (2.1) \]

where \( P_m \) is the maximum power delivered to the battery or grid by the PV, \( n_s \) and \( n_p \) are the numbers of series and number of parallel panels in the array. \( V_m \) and \( I_m \) are the voltage and current of each panel under the maximum power point tracking (MPPT). \( \eta_c \) is the efficiency of the DC/DC converter.

In case that the vehicle user is willing to sell more electricity to the grid or needs to power up some off-grid loads such as camping equipment, S1 and S8 will be closed, and the battery pack provides additional power with the PV (or by itself at night), as shown in Figure 2.4. The maximum power that the proposed system could deliver to
the power grid is determined by the bi-directional charger.

Figure 2.2: EV Battery Module Balancing

Figure 2.3: PV2G Operation
When the vehicle is driving or being charged at night or under cloudy weather when solar power is not available, MS_PV is opened and MS_APM is closed to balance the battery modules using energy from APM. In this scenario, the energy from APM will be transferred to the battery module at the lowest SOC/voltage through the DC/DC converter. Since the energy in the APM come from the battery pack eventually, once the battery modules are balanced, MS_APM and all selection switches S1-S8 will be opened to avoid power loss during balancing. The balancing power of this mode is controlled by the output voltage of the DC/DC converter and given as

\[ P_c = \frac{V_o - V_{oc}}{R_{in}} \times V_t \]  

(2.2)

where \( P_c \) is the charging power to the battery at the lowest voltage or SOC. \( V_o \) is the output voltage of the DC/DC converter, \( V_{oc}, R_{in} \) and \( V_t \) are the charged battery module open-circuit voltage, internal resistance and terminal voltage, respectively.
The control flow chart of the onboard microgrid under different operation modes is shown in Figure 2.5. From the flow chart, it can be observed that the battery balancing, either using PV or APM, will not be performed during V2G or PV2G operation. It is also worth noticing that when balancing is being executed, the control unit of the system will process the control algorithm as a circling loop until the system is shut off or the battery is fully charged. During the balancing process, the control unit keeps measuring the modules’ voltages or SOCs to update the decision. If the control unit takes module voltage to make a decision, it will have to open all selection switches to measure the modular voltages. This is because, under this condition, the terminal voltage measured for the charged module is the output voltage of the DC/DC converter.

After being balanced for a certain period $t$, all switches will be opened for a sampling time $T$ and $T=1/f$, where $f$ is the sampling frequency of the voltage measurement. A new decision on the battery module to be balanced will be made based on the module voltage measured on the sampling period $T$. Another reason for doing this is for short-circuit protection. The period $T$ also acts as a dead-band between switches status changing. With the dead-band, switches connected to the same terminal of DC/DC converter or battery modules will not be closed at the same time. It is important that the dead-band $T << t$ for balancing speed and harvesting as much solar energy as possible.
Figure 2.5: Control Flow Chart of the Microgrid
2.2 System Modeling & Simulation

To evaluate the balancing and energy saving performance of the proposed system, as well as to compare with conventional battery balancing systems, a model-based simulation has been carried out. The modeling and simulation diagram is shown in Figure 2.6. The vehicle simulation model is developed in MATLAB/Simulink as a backward model. The input of the model is a standard drive-cycle. The vehicle dynamics subsystem calculates the mechanical power required to overcome road resistance and acceleration resistance. The powertrain subsystem, which includes an electric motor, inverter, and a driveline, calculates the electric power requirement from the mechanical power. The electric power traction load discharges the battery, and the balancing circuit equalizes the battery modules by utilizing both traditional and proposed balancing schemes. The vehicle model parameters are shown in Table 2.1. This vehicle is modeled as an electric utility cart with four 12V rated Li-ion battery modules in series with slightly different capacities but the same initial SOCs.

![Vehicle Modeling and Simulation Diagram](image)

Figure 2.6: Vehicle Modeling and Simulation Diagram

Manhattan Bus Cycle (MBC) is selected as the standard drive-cycle for comparing different battery balancing methodologies under discharging. This is because the top speed of the MBC is less than 25mph, which fits the operating condition of utility vehicles. The vehicle speed, traction power, and battery current rate vs. time of MBC for the simulation vehicle are shown in Figure 2.7 [64].
Table 2.1: Simulation Vehicle Model Parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Curb Weight</td>
<td>344kg</td>
</tr>
<tr>
<td>Driver and Load Weight</td>
<td>100kg</td>
</tr>
<tr>
<td>Vehicle Cross Section</td>
<td>2.37m²</td>
</tr>
<tr>
<td>Drag Coefficient</td>
<td>2.51</td>
</tr>
<tr>
<td>Rolling Friction Coefficient</td>
<td>0.04</td>
</tr>
<tr>
<td>Mass Factor</td>
<td>1.1</td>
</tr>
<tr>
<td>Motor Rated/Max Power</td>
<td>3kW/8kW</td>
</tr>
<tr>
<td>Differential Gear Ratio</td>
<td>16.82</td>
</tr>
<tr>
<td>Driveline Efficiency</td>
<td>98%</td>
</tr>
<tr>
<td>Traction Motor Efficiency (constant)</td>
<td>90%</td>
</tr>
<tr>
<td>Inverter Efficiency</td>
<td>95%</td>
</tr>
<tr>
<td>Balancing Efficiency</td>
<td>95%</td>
</tr>
<tr>
<td>Battery 1 Ah Capacity</td>
<td>50Ah</td>
</tr>
<tr>
<td>Battery 2 Ah Capacity</td>
<td>49Ah</td>
</tr>
<tr>
<td>Battery 3 Ah Capacity</td>
<td>47Ah</td>
</tr>
<tr>
<td>Battery 4 Ah Capacity</td>
<td>48Ah</td>
</tr>
<tr>
<td>Initial SOC</td>
<td>90%</td>
</tr>
<tr>
<td>Battery Internal Resistance</td>
<td>15mΩ</td>
</tr>
</tbody>
</table>
The four battery modules are modeled as internal-resistance circuits ($R_{\text{int}}$ model) in series discharged by the same current. The internal-resistance circuit model of the batteries is shown in Figure 2.8, where $V_{\text{oc}}$ is the open-circuit voltage, and $V_t$ is the terminal voltage of the battery. The open-circuit voltage is calculated from the terminal voltage and the charging/discharging current. Based on the open-circuit voltage, the SOC of a battery can be obtained through a look-up table shown in Fig. 2.9. The curve in Figure 2.9 describes the general SOC-OCV relationship of a Li-ion battery at 20°C. Although the battery modules have different capacities, all the modules are modeled to have the same internal resistance and follow the look-up table in Figure 2.9. Since the battery modules are connected in series to provide a 48V output voltage, a weaker module will have a lower terminal voltage during discharging. The total SOC of the whole battery pack is calculated from equation (2.3). It is worth noticing that battery polarization and temperature effects are not taken into account the internal-resistance
model, which may give less accurate results in real battery modeling and parameter identification. Nevertheless, for vehicle level modeling and battery balancing simulation, the \( R_{int} \) model is able to provide reasonably accurate and convincing results. One of the future tasks of this research is to use a more detailed model and more advanced SOC methods such as the ones developed by the authors and other researchers \([65-69]\) to further verify the method.

\[
SOC_{all} = \frac{C_1 \times SOC_1 + C_2 \times SOC_2 + C_3 \times SOC_3 + C_4 \times SOC_4}{C_1 + C_2 + C_3 + C_4}
\]  

(2.3)

where \( C_1, C_2, C_3 \) and \( C_4 \) are the Ah capacities of the four battery modules, respectively.

The simulation studies have been carried out for 3 scenarios: no-balancing as the baseline, APM-balancing with a 60W constant power, and Solar-Balancing with the balancing power input shown in Figure 2.10, which can be repeated as necessary in the simulation studies. The power curve in Figure 2.10 was recorded from an actual 100W solar panel. The solar panel and the battery have been installed on a vehicle that runs a random city cycle, moves in all directions under the sun, and through building/tree shadows. This makes the solar power data close to the real traffic situation.

![Battery Internal-Resistance Circuit Model](image)

Figure 2.8: Battery Internal-Resistance Circuit Model
For battery discharge simulation of each mode, the vehicle runs 3 MBCs back to back to achieve exactly the same discharging condition. The total driving mileage of 3 MBCs is around 13.22km. For APM-balancing, all the balancing power charged into low SOC modules come from the whole battery pack, with 10% power loss on the circuits. Figure 2.11 shows the battery module SOCs for each mode, with a 50s zoom in plot for dynamic analysis. Table 2.2 shows the final total SOC of the battery pack calculated from equation (2.3) for each balancing mode.

From Figure 2.11, it can be observed that without balancing, the SOC difference
becomes obvious when the battery pack’s overall SOC reaches about 30%. This would result in over-discharging of low SOC battery modules or shrink vehicle mileage if the same cut-off SOC threshold was set for all the battery modules. But with any modes of balancing, the battery module SOC can be equalized, and over-discharging can be avoided. Dynamic operating analysis can be carried out by zooming in a 50s period for each balance mode. From Figure 2.11 (b)-(c), it can be observed for the Solar-Balancing, the short-time balancing response depends on the solar power. The SOC difference can be limited within 0.1% when high solar power is available around 660s. But in the worst case, the SOC difference can also be limited within 0.2%. The APM-Balancing provides a stable balancing response that could also limit the SOC difference within 0.1% on average. The simulation validates that the battery modules can still be equalized effectively with SOC difference <0.2% by Solar-Balancing and APM-Balancing modes. More importantly, the proposed Solar-Balancing could improve the effective capacity of the battery pack by 3.5% every 13.2 km compared to the baseline, as shown in Table 2.2: Total Final SOC For Each Balancing Scheme. The improvement mainly comes from the following aspects: harvesting the solar energy and eliminating the energy loss of internal transfer. For APM-balancing, the SOC shortage is only 0.02% comparing to the baseline.

<table>
<thead>
<tr>
<th>Balancing Scheme</th>
<th>No-Balancing</th>
<th>Solar-Balancing</th>
<th>APM-Balancing</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOC</td>
<td>29%</td>
<td>32.5%</td>
<td>28.78%</td>
</tr>
</tbody>
</table>
(a) Battery Module SOCs of No-Balancing

(b) Battery Module SOCs of Solar-Balancing
Figure 2.11: Battery Module SOCs of 3 Manhattan Bus Cycles.

Constant current charging algorithm is performed for the charging simulation of all 3 modes. All the battery modules are with 20% initial SOC and are charged by 10A constant current from the charger. When the battery pack SOC defined in equation (2.3) reaches 100%, the charging will be terminated. Again, the 60W-fixed balancing power charged into low SOC modules come from the whole battery pack, with a 10% power loss on the circuits for APM-balancing. The solar power input for Solar-Balancing is shown in Figure 2.12. The solar power curve during charging shown in Figure 2.12 was scaled from daylight power of a 3.3kW rated roof solar power system to the 100W onboard panels [70].
Figure 2.12: Scaled Power of a 3.3kW Roof Solar System

Figure 2.13 shows the battery module SOCs for each mode, with a 50s zoom in at the end of charging for dynamic analysis. Table 2.3 shows the total consumed grid energy and charging time for each balancing mode.

(a) Battery Module SOCs of No-Balancing
Figure 2.13: Battery Module SOCs for 10A Constant-Current Charging

(b) Battery Module SOCs of Solar-Balancing

(c) Battery Module SOCs of APM-Balancing
### Table 2.3: Total Consumer Grid Energy and Charging Time

<table>
<thead>
<tr>
<th>Balancing Scheme</th>
<th>No Balancing (Baseline)</th>
<th>Solar-Balancing</th>
<th>APM-Balancing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid Energy</td>
<td>1.966 kWh</td>
<td>1.723 kWh</td>
<td>1.93kWh</td>
</tr>
<tr>
<td>Energy Saved %</td>
<td>0</td>
<td>12.4%</td>
<td>1.83%</td>
</tr>
<tr>
<td>Charging Time</td>
<td>14,400s</td>
<td>12,624s</td>
<td>14,158s</td>
</tr>
<tr>
<td>Time Saved %</td>
<td>0</td>
<td>12.3%</td>
<td>1.68%</td>
</tr>
</tbody>
</table>

From Figure 2.13 (a) it can be observed that without balancing, battery modules 2, 3 and 4 are over-charged to make sure battery module 1 can be fully charged. As a result, the degradation of these 3 modules will be accelerated. In addition, energy and charging time are wasted during this period of time. With Solar-Balancing, the over-charge of the weak module can be suppressed to an ignorable level as shown in Figure 2.13 (b). With the solar energy input and equalization effect, the total grid energy consumption and charging time can be saved by 12.4% and 12.3%, respectively. In case the solar power is not available, by applying the APM-Balancing, all battery modules can be equally charged at the same time, as shown in Figure 2.13 (c). By maximizing the equalization effect to avoid over-charging weak modules, the APM-Balancing can save 1.83% of total grid energy consumption and 1.68% of charging time, respectively.

### 2.3 System Prototyping and Experimental Verification

#### 2.3.1 System Prototyping Development

To experimentally verify the functionality and performance of the proposed system, a prototype has been developed based on the diagram in Figure 2.14 and
integrated into a vehicle. The vehicle is a golf cart with 48V/3kW electric powertrain. Two 18V/50W solar panels are installed on the roof of the cart in parallel with a total of 100 W rated power. The 48V battery pack of the vehicle is formed by four 12V batteries in series. The battery pack can be replaced. The prototype was tested with four 12V/100Ah rated Lead-acid batteries followed by four 12V/50Ah rated Li-ion batteries. The details will be demonstrated in the following subsection. The vehicle prototype is shown in Figure 2.15.

![Figure 2.14: Prototype Configuration](image-url)
The proposed system has been installed onboard of the vehicle and wired to the solar panel as well as the 48V battery pack. The DC-DC converter is a solar controller that can auto-recognize the terminal voltage and tune the output to charge the linked battery maximum to 48V. The solar controller outputs PV voltage when there is no battery connected to it. The bi-directional charger is formed by a 600W grid-tied inverter with 22~60V DC IN - 110V/60Hz AC OUT and a 48V/10A charger. The inverter and charger statuses are controlled by contactor sets DS1 and DS2, and only one of them can be closed at same time. Therefore, the function of a bi-directional charger is emulated. Between the solar controller output and the grid-tied inverter, there is a buck-boost voltage regulator with 10~60V DC IN – 12~80V DC OUT installed. The output of the regulator is set to 48V to stabilize the input voltage for the inverter. It is used to set the V2G max power as well. As shown in Figure 2.12, there are 3 current sensors, and the measured currents are defined as $I_1$, $I_2$, and $I_3$, respectively. The SOC of each battery module can be estimated as
\[ SOC_n = SOC_{n(\text{ini})} + \frac{\int_{0}^{t_1} + S_n \int_{0}^{t_2}}{C_n} \quad (n=1, 2, 3, 4) \] (2.4)

where \( SOC_{n(\text{ini})} \) is the initial SOC of the battery module. \( I_1 \) and \( I_2 \) are the measured currents by the 2 current sensors, respectively, which are defined as positive for charging and negative for discharging. \( S_n \) is the Boolean switching variable for each battery module: \( S_n=1 \) when the corresponding 2 selection switches for the module are closed; otherwise, \( S_n=0 \). \( C_n \) is the battery module rated capacity.

The control unit of the system is a National Instrument (NI) DAQ connected to an onboard desktop. The control unit and desktop onboard are powered by two 100Ah deep-cycle Lead-acid batteries in parallel. The deep-cycle batteries work as APM as well. The NI DAQ estimates the SOC of each battery module and automatically controls switches S1~S8 for battery balancing. Each switch of S1~S8 is formed by 2 DC-Controlled DC solid-state relays connected back to back. This means the drain of internal MOSFETs of two relays are connected, and both the relays are driven by the same gate signal. The mode switches MS_PV, MS_APM, DS1 and DS2 are the same type of relays commanded by the control unit based on the user’s input. The control unit measures the terminal voltages of each battery module for safety. It can also execute voltage-based balancing when needed, or the SOC estimation is failed. Figure 2.16 shows the integrated battery balancing system. There is a screen with GUI for system monitoring, including battery SOC, charging/discharging current as well as operation model selection.
2.3.2 Balancing Test with Lead-acid Battery

In order to experimentally validate the balancing dynamic response and effects of the proposed system, four 12V/100Ah-rated aged Lead-acid batteries in series was tested. Due to the degradation of the battery modules, the rated parameters such as internal resistances and SOC-OCV curve are not reliable anymore. Therefore, in these tests, the battery terminal voltages are used for balancing control.

The prototype was first tested without battery balancing under charging and discharging as a baseline for future comparison. For charging, the battery pack was charged by a 48V Lead-acid charger supplies 10A/50.8V CC-CV mode. Figure 2.17 shows the battery module voltages during a charging period of 220s. From the figure, it can be observed that the voltage of battery 1 is higher than the other 3 batteries, which
means under CC-CV, battery 1 would be over-charged while the rest cannot be fully charged. For discharging, the vehicle was running a random city cycle for 840s without balancing. Figure 2.18 shows the battery voltages during discharging, where battery 1 has the lowest voltage while battery 2 has the highest. From the charging and discharging voltages it can be seen battery 1’s capacity is most degraded while battery 2 keeps the most capacitance. Battery balancing is definitely needed for this pack. It is noted that, for the prototype proposed with Lead-acid batteries, the voltage-based balancing is sufficient to avoid over-charging/discharging of the weak module. In addition, from the dynamic point of view, the recorded voltage data could better demonstrate the balancing effects during short drive cycles.

![Figure 2.17: Battery Module Voltages during Charging W/O Balancing.](image1)

![Figure 2.18: Battery Module Voltages during Charging W/O Balancing](image2)
For the Solar-Balancing mode, the output voltage of the DC/DC converter is set to auto-recognition and no current limitation. The vehicle ran under a sunny day for this mode of testing. Figure 2.19 shows the data of the Solar-Balancing mode for one road test. It is noted the balancing current shown in the figures are the measured $I_2$ in Figure 2.14. From the switching status, it can be observed the designed system works properly on selecting different battery modules for charging. The battery pack was well balanced with 6~7A current from the solar panel. For APM-Balancing mode, the output voltage and current of the DC/DC converter are set to 15V and 4A, respectively (60W power limit). This safety limit is needed because, unlike solar panel, the APM could provide damaging current when the APM powered DC/DC converter’s output voltage is considerably higher than the battery module terminal voltage, considering voltage drop during discharging. Figure 2.20 shows the data of the APM-Balancing mode under one road test. Although the voltage differences between the battery modules are slightly larger than the Solar-Balancing mode due to the current limitation, the balancing performance is still remarkable compared to the case of no-balancing. This result also proves that when the solar current drops to 2~3A due to cloud or building/tree shadows, the system can still provide effective balancing.
Figure 2.19: Battery Module Voltages during Discharging with Solar-Balancing.

Figure 2.20: Battery Module Voltages during Discharging with APM-Balancing.

For Solar-Balancing testing under charging, the vehicle was parked outdoor and being charged by the same CC-CV plug-in charger. Figure 2.21 shows the data of a 250s charging period, from where it can be observed that the voltage difference is suppressed to <0.2V with 5.5–6A current from PV. The testing results for APM-
Balancing testing under charging is shown in Figure 2.22. With 3–4A balancing current from APM, the voltage difference between modules is suppressed to <0.3V.

Based on the testing results for 100Ah rated batteries with both Solar-Balancing and APM-Balancing, it can be concluded that the proposed system is able to effectively balance the battery modules under charging and discharging.

Figure 2.21: Battery Module Voltages during Charging with Solar-balancing

Figure 2.22: Battery Module Voltages during Charging with APM-balancing
2.3.3 Test With Li-ion Battery and V2G Applications

Once the balancing performance of the proposed system had been verified with 100Ah-rated Lead-acid batteries, the battery pack was replaced by four 12V/50Ah-rated Li-ion batteries in series. The Li-ion batteries are with digital SOC display; therefore, the battery module SOCs can be estimated by applying equation (2.4). Along with PV2G and V2G functionalities, the transitions dynamics and SOC-based balancing can be tested.

To test Solar-Balancing and PV2G operation, firstly, the battery modules 1, 2, 3, and 4 are discharged to a SOC of 0.3, 0.29, 0.3, and 0.31, respectively. The testing begins outdoor with 10A constant-current charging. The charging stop SOC is set to 0.4. Figure 2.23 (a) shows the curves of the battery module SOCs, measured currents, and switch operation sequences during a period of 3,000s. From the figure, it can be observed that during the charging period, the modules are gradually balanced by the input current I2 from PV. When the overall SOC reaches 0.4, the system terminates charging and perform PV2G. Figure 2.23 (b) shows the voltage and current output of the inverter to the grid at the moment when the PV2G power is 72W. At the same time, the battery is disconnected from the system to maintain the SOC.
For APM-Balancing and V2G operation testing, firstly, the battery modules 1, 2, 3, and 4 start at an initial SOC of 0.6, 0.61, 0.59, and 0.6, respectively. The testing begins with APM module balancing. The charging stop SOC is set to 0.7. The maximum balancing power is set to 60W. Figure 2.24 (a) shows the curves of the battery module SOCs, measured currents, and switch operation sequences during a period of 3500s.
From the figure, it can be observed that, during the balancing period, the modules are gradually equalized by the balancing current $I_2$. When the overall SOC reaches 0.7, the system stops charging and turns to V2G mode. Figure 2.24 (b) shows the voltage and current outputs of the inverter to the grid at the moment with 310W of V2G power.

(a) Battery Module SOCs, Currents and Switching Status

(b) Inverter Output Voltage and Current.

Figure 2.24: Testing Results for APM-Balancing & V2G.
2.4 Summary

In this chapter, an electrified vehicle onboard microgrid with PV for battery module balancing and V2G has been proposed. With selection switches and mode contactors, the proposed microgrid is able to charge the battery module with lowest SOC via PV or APM. The microgrid can supply electric power from PV with or without battery to grid through bi-directional charger. Basic control algorithms for the microgrid under charge and discharge have been developed. Real solar data-based simulation was carried out and verified that the microgrid is able to limit the SOC difference between 0.1%~0.2%. With solar energy harvesting during balancing process, the microgrid helps increasing the effective capacity for 3.5% every 13.2 km for a utility cart with 50Ah-rated Li-ion battery pack during discharging. For vehicle charging with Solar-Balancing, the over-charge of the weak module can be suppressed to an ignorable level. With the solar energy input and equalization effect, the total grid energy consumption and charging time can be saved by 12.4% and 12.3%, respectively. In case the solar power is not available, all battery modules can be equally charged at the same time with APM-Balancing. By avoiding over-charging weak modules, the APM-Balancing can save 1.83% of total grid energy consumption and 1.68% of charging time, respectively.

Mule vehicle with microgrid prototype integrated was developed to validate developed functionalities and performance. Both Lead-acid and Li-ion battery packs have been tested. Testing results verified that the proposed microgrid can balance Lead-acid/Li-ion modules based on voltage measurement / SOC estimation with solar and APM balancing. In addition, the proposed system successfully delivered electric power
to electricity grid via V2G and PV2G.
CHAPTER 3 BATTERY BALANCING ALGORITHM OPTIMIZATION FOR MAXIMIZING BATTERY LIFE

3.1 Battery Balancing Criteria

In this chapter, the different criteria for battery balancing will be discussed, following the model-based analysis of applying different criteria to the proposed system. Based on the model-based analysis results, it is suggested to apply SOC balancing when there is no solar power available and APM is utilized. When the PV is able to provide balancing power, it is suggested to apply SOC-SOH balancing to maximize battery life.

3.1.1 Voltage / SOC Balancing

Voltage balancing techniques have been widely used in battery systems [70-73] because of simple detection and control. The only measurement needed for this scheme is the battery cell/module terminal voltages. For passive balancing, the battery cells or modules with higher terminal voltages will be discharged by power resistors. While for active balancing, the cells or modules with the lowest voltages will be charged by the balancing circuit. However, due to the battery degradation, the voltage balancing does not guarantee balanced SOC [8][74]. Take the internal resistance model of a battery in Figure 2.7 as an example. The battery terminal voltage can be represented as

\[ V_i = \begin{cases} V_{oc} + I_{char}R_s & \text{(Charging)} \\ V_{oc} - I_{dis}R_s & \text{(Discharging)} \end{cases} \]  

(3.1)

where \( V_{oc} \) is the battery open circuit voltage, and can be determined from SOC based on SOC-OCV curves like Figure 2.8. \( I_{char} \) and \( I_{dis} \) are the absolute value of charging and discharging current, respectively. \( R_s \) is the battery internal resistance. Once the battery
internal resistance and SOC-OCV curve imbalanced due to temperature, degradation, and other reasons [8][75], the terminal voltage will no longer be a good indicator of battery SOC. In this case, the over-charge and over-discharge could happen because of failing to balance SOCs.

To deal with this issue, SOC balancing has been well researched and applied to a lot of battery systems. By combining advanced battery parameters extraction techniques like Kalman filters [65][76-77], neural networks [78-80], among others, the battery SOC is able to be estimated accurately with degradation effects. Based on the estimated SOC, the balancing circuit discharges battery cells/modules with higher SOCs for passive balancing, and charges the cell/module with the lowest SOC for active balancing.

3.1.2 Depth-of-Charge (DOD) In Ah Balancing

Recently, a novel battery balancing algorithm based on DOD (Ah) has been proposed. This technique estimates battery SOC and usable capacity to calculate and balance discharged capacity [81]. This DOD (Ah)-based balancing scheme is claimed to bring the following advantages to the battery system: Firstly, the energy wastes during passive SOC balancing for battery cells/modules with imbalanced capacity can be eliminated. For example, to balance 2 battery modules with 45Ah/100% SOC and 50Ah / 95% SOC in series, the 45Ah battery will be discharged by resistor to 95% SOC before vehicle driving discharge. When the 45Ah battery reaches 0% SOC and the vehicle driving discharge is cut off, the total discharged capacity is 42.75Ah. This
means the 50Ah battery still has 50Ah x 95% - 42.75Ah = 4.75Ah usable capacity. However, to make sure both batteries can be fully charged, the 4.75Ah capacity has to be discharged by a resistor. By performing DOD (Ah)-based balancing scheme, this part of usable capacity can be kept. In addition, there is no need to balance the modules during charging, as the used capacities of each battery to be charged have been equalized. The second advantage claimed for this technique is that the cycle life imbalance between the batteries can be reduced. As the battery cycle life has a tight relationship with DOD [82-83], equalizing the DOD on each cycle can help balance the battery life cycles.

It is noting that, for passive balancing, this method is easier to be implemented as all battery cells/modules with higher DODs (Ah) can be discharged at the same time. To apply this method to active balancing or the proposed Solar-Balancing and APM-Balancing, the system shall identify the battery DODs (Ah) based on estimated usable capacities and SOCs, then charge the module with the highest DOD (Ah).

3.1.3 State-Of-Health (SOH) Balancing

Another important battery balancing criterion is SOH. Balancing the SOHs of battery cells/modules of a pack can extend the overall pack life by avoiding the weakest cell/module reaches end-of-life (EOL) in advance of others. In addition, the SOH balancing can help all cells/modules hit the EOL around the same time, which means all the cells/modules are sufficiently used before becoming dead.

As demonstrated in Section 3.1.2, the battery SOH has a tight relationship with
DOD. Therefore, most battery SOH balancing solutions are designed to request more power from strong cells/modules, and less power from weak cells/modules. For example, in [84], a control algorithm to balance modules’ SOH by distributing power requests using multilevel-converter between energy storage system batteries was proposed. While in [85], a battery SOH balancing system for electric vehicles was developed. This system has an isolated DC/DC converter on each cell that can transfer energy from the cell to the 12V bus. The transferred energy from each cell is defined based on the accessory energy requests and cell SOH. It is claimed the proposed system is able to reduce the cell capacity imbalance by 1.5% comparing to conventional passive methods.

Since the proposed system in this thesis is not able to distribute discharging power between the modules, the SOH balancing will be implemented in another way and named SOC-SOH balancing. In short, when performing Solar-Balancing, the system charges the battery module with the lowest SOH by PV when SOCs of modules are balanced. For APM-Balancing, the SOC-SOH balancing will not be processed. This is because, for APM-Balancing, the balancing circuits turn off when SOCs are balanced to prevent power loss that reduces the driving range.

3.2 Model-Based Analysis

In order to determine the best battery balancing algorithm for the proposed balancing system, model-based analysis has been carried out and will be discussed in this section. With the model-based analysis, the driving and solar condition can be fixed for different
balancing algorithms. Therefore, the results are comparable to each other. In addition, the analysis period can be dramatically reduced as the whole life cycle of the batteries is simulated.

3.2.1 Li-ion Battery Modeling

The Li-ion battery model is developed based on Matlab/Simulink [86-87]. The equivalent circuit of the battery model is shown in Figure 3.1.

![Figure 3.1: Battery Equivalent Circuit Model [86]](image)

For Li-ion batteries, the electromotive force for discharging and charging can be represented by (3.2) and (3.3), respectively.

\[
 f_1 (it, i^*, i) = E_0 - K \cdot \frac{Q}{it} \cdot i^* - K \cdot \frac{Q}{it} \cdot it + A \cdot e^{-B \cdot it} \quad (3.2)
\]

\[
 f_2 (it, i^*, i) = E_0 - K \cdot \frac{Q}{it+0.1Q} \cdot i^* - K \cdot \frac{Q}{it} \cdot it + A \cdot e^{-B \cdot it} \quad (3.3)
\]

where \(E_0\) is the battery rated voltage; \(K\) is the polarization resistance; \(i^*\) is the low
frequency current dynamics; \(i\) is the battery current; \(i_t\) is the extracted current; \(Q\) is the maximum battery capacity; \(A\) and \(B\) are exponential voltage and capacity, respectively [87].

The SOH of the battery is determined by (3.4).

\[
SOH = \min (SOH_R, SOH_Q) \tag{3.4}
\]

where \(SOH_R\) and \(SOH_Q\) are the SOH calculated from internal-resistance growth and useable capacity degradation, respectively. \(SOH_R\) and \(SOH_Q\) can be represented by (3.5) and (3.6).

\[
SOH_R = \frac{Q(n)-Q_{EOL}}{Q_{BOL}-Q_{EOL}} \tag{3.5}
\]

\[
SOH_Q = \frac{R_{EOL}-R(n)}{R_{EOL}=R_{BOL}} \tag{3.6}
\]

where \(Q_{BOL}\) and \(Q_{EOL}\) are the useable capacity of the battery at begin-of-life and end-of-life, respectively, the \(Q_{EOL}\) is defined as 80% of the \(Q_{BOL}\) [88-89]. \(R_{BOL}\) and \(R_{EOL}\) are the internal resistance of the battery at begin-of-life and end-of-life, respectively, the \(R_{EOL}\) is defined as 133% of the \(R_{BOL}\) [90]. \(Q(n)\) and \(R(n)\) are the useable capacities and internal resistance of the battery at \(n\)th cycle. \(Q(n)\) and \(R(n)\) are calculated from (3.7) and (3.8), respectively.

\[
Q(n) = \begin{cases} 
Q_{BOL} - \varepsilon(n) \cdot (Q_{BOL} - Q_{EOL}) & \text{if } \frac{k}{2} \neq 0 \\
Q(n-1) & \text{otherwise}
\end{cases} \tag{3.7}
\]

\[
R(n) = \begin{cases} 
R_{BOL} + \varepsilon(n) \cdot (R_{EOL} - R_{BOL}) & \text{if } \frac{k}{2} \neq 0 \\
R(n-1) & \text{otherwise}
\end{cases} \tag{3.8}
\]

With \(n = kT_h \quad (k = 1,2,3,\ldots)\)
where $T_h$ is the half-cycle duration in second. A complete cycle is obtained when the battery is fully discharged and charged or conversely; The battery aging factor $\varepsilon$ is expressed as (3.9).

$$
\varepsilon(n) = \begin{cases} 
\varepsilon(n-1) + 
\frac{0.5}{N(n-1)} \left( 2 - \frac{DOD(n-2) + DOD(n)}{DOD(n-1)} \right) & \text{if } k \neq 0 \\
\varepsilon(n-1) & \text{otherwise}
\end{cases} \quad (3.9)
$$

where $DOD$ is the battery DOD (%) after a half-cycle duration. $N$ is the maximum number of cycles and is given by (3.10).

$$
N(n) = H(DOD(n))^{\xi} \cdot e^{-\psi\left(\frac{1}{T_{ref}} - \frac{1}{T_a(n)}\right)} \cdot (I_{dis\_ave}(n))^{-Y_1} \cdot (I_{ch\_ave}(n))^{-Y_2} \quad (3.10)
$$

where $H$ is the cycle number constant; $\xi$ is the exponent factor for the DOD; $\psi$ is Arrhenius rate constant for the cycle number; $I_{dis\_ave}$ is the average discharge current in A during a half cycle duration. $I_{ch\_ave}$ is the average charge current in A during a half cycle duration. $Y_1$ is the exponent factor for the discharge current. $Y_2$ is the exponent factor for the charge current.

### 3.2.2 Charge / Discharge Cycle and Control Modeling

With the equivalent battery circuit and aging effects modeled in Section 3.2.1, the battery life estimation model with different balancing criteria have been developed. The battery pack model is formed by four 12V-rated Li-ion modules in series. The initial parameters of each module are shown in Table 3.1: Battery Module Parameters for End-of-life Simulation. It is noticing that with the defined parameters, the battery module to be balanced initially for SOC and DOD (Ah) balancing will be different: for SOC
balancing, Battery 2 shall be charged; However, for DOD (Ah) balancing, Battery 1 with maximum DOD (Ah) in capacity shall be charged. Doing so, the SOC and DOD (Ah) balancing will not act as one scheme.

<table>
<thead>
<tr>
<th>Module Number</th>
<th>Initial Capacity</th>
<th>Initial SOC</th>
<th>Initial Resistance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery 1</td>
<td>50 Ah</td>
<td>0.91</td>
<td>31.5 mΩ</td>
</tr>
<tr>
<td>Battery 2</td>
<td>44 Ah</td>
<td>0.9</td>
<td>31.6 mΩ</td>
</tr>
<tr>
<td>Battery 3</td>
<td>45 Ah</td>
<td>0.92</td>
<td>31.52 mΩ</td>
</tr>
<tr>
<td>Battery 4</td>
<td>49 Ah</td>
<td>0.93</td>
<td>31.5 mΩ</td>
</tr>
</tbody>
</table>

Table 3.1: Battery Module Parameters for End-of-life Simulation

For each cycle, the overall SOC of the battery pack calculated from (2.3) was discharged to 0.2 by the current shown in Figure 2.7. Hence, the discharging condition of vehicle driving was determined. Then, the battery pack was charged to full by a 10A constant-current charger. For APM-Balancing, the balancing current was fixed at 5A on both charging and discharging, as researches have proved that 0.1C-rate balancing current is more than enough for battery module balancing maintenance [31]. For Solar-Balancing, different levels of solar power input during charging and discharging at each cycle were simulated. This is because the ideal solar conditions in Figure 2.10 and Figure 2.12 will not be available all the time, considering the scenarios that the vehicle is driving in cloudy days and charged at nights. Therefore, test cases with Solar-
Balancing power during discharging and charging to be 10%, 20%, 30%, ..., of the recorded values in Figure 2.10 and Figure 2.12 have been generated to form a matrix.

The control algorithms for voltage and SOC balancing are the same as shown in Figure 2.6. When performing APM-Balancing, the balancing circuits will be turned off once all the modules are balanced to save usable energy. While for Solar-Balancing, all modules will be charged by the PV when their voltages or SOCs are balanced. The standby condition was not taken into consideration for any model-based analysis as the battery was simulated to run charge/discharge cycles back to back.

The control flowchart of DOD (Ah) balancing is shown in Figure 3.2. During battery discharging, the balancing circuits charge the module with maximum DOD (Ah) in capacity with PV when solar is available. Once the DODs for all modules are balanced, S1 and S8 will be closed to charge all modules to harvest more solar energy. If the solar power is unavailable, the balancing circuits will be turned off once all the modules’ DODs are balanced by the APM. It is worth noticing that at charging, this control algorithm performs SOC balancing to make sure all modules can be equally charged to full in case the DODs were not well balanced during discharging.

The control flowchart of SOC-SOH balancing is shown in Figure 3.3. Different from conventional SOH balancing, the algorithm has been modified to be suited for the proposed system: the SOC balancing still has the highest priority. When performing Solar-Balancing, the battery module with the lowest SOH will be charged to suppress DOD when the SOCs are balanced. Likewise, when performing APM-Balancing, the balancing circuits turn off when all modules’ SOCs are balanced to avoid driving range
drop. When the battery pack is under charging, only SOC balancing will be performed to guarantee all modules can be equally charged.

Figure 3.2: Control Flow Chart of the DOD in Ah Balancing
Figure 3.3: Control Flow Chart of the SOC-SOH Balancing
3.2.2 Simulation Results and Discussion

To estimate the battery life improvement of each criterion, the model-based simulations were run separately for APM-Balancing and Solar-Balancing, except SOC-SOH balancing that is not applicable to APM-Balancing. First of all, cycles without any balancing scheme was simulated as the baseline. For APM-Balancing of each criterion, all the balancing power comes from the whole battery pack with a 20% power loss on step-down converter and balancing circuit. The battery pack ran charge/discharge cycles back to back until SOH of the weakest module, Battery 2, reached 0. At this time, the whole battery pack was considered at EOL and the cycle life as well as standard deviations (SD) of each module’s SOH were recorded. Table 3.2 shows the simulation results of APM-Balancing of each criterion and their comparisons with the baseline.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Total Cycles at EOL</th>
<th>Total Improvement %</th>
<th>SOH SD at EOL</th>
<th>SOH Reduction SD %</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Balancing (Baseline)</td>
<td>2068</td>
<td>0</td>
<td>0.092</td>
<td>0</td>
</tr>
<tr>
<td>Voltage</td>
<td>2262</td>
<td>9.3%</td>
<td>0.05</td>
<td>45.6%</td>
</tr>
<tr>
<td>SOC</td>
<td>2633</td>
<td>27.3%</td>
<td>0.0078</td>
<td>91.5%</td>
</tr>
<tr>
<td>DOD (Ah)</td>
<td>2029</td>
<td>-1.89%</td>
<td>0.092</td>
<td>0</td>
</tr>
</tbody>
</table>

From Table 3.2, it can be observed that with APM-Balancing in the whole battery cycle life, the SOC balancing brings the best life improvement as high as 27.3%, and the SOH imbalance can be suppressed by 91.5% at EOL. On the other hand, the voltage balancing can only improve 9.3% on the life cycle and reduce the SOH imbalance by
45.6%. The reason was stated in the previous section: due to the capacity degradation and internal resistance growth, the terminal voltage will no longer be a good indicator of SOC with aging effects.

The DOD (Ah) balancing does not help in improving the battery life or suppressing SOH imbalance. In contrast, it drops the battery cycle life by 1.89%. To analyze the reason, 2 cycles simulation with initial condition stated in Table 3.1 was studied. Figure 3.4 shows the DOD (Ah) of each battery module. From Figure 3.4, it can be observed with 5A balancing current, the DOD (Ah) of each module can be balanced well. It is worth noting that the balancing was not performed at charging as the discharged capacities of each module have been equalized. This is proved by Figure 3.5, which was obtained by integrating the balancing current charged to each module to show the balancing capacities. Figure 3.5 and the sub-figure zooming at the end of discharge shows that the Battery 1 instead of Battery 2 obtained the most balancing current. Therefore, this balancing scheme didn’t help Battery 2, the weakest module reducing the most DOD. Based on the simulation and analysis above, it can be concluded that the DOD (Ah) balancing is not applicable to the proposed system. Therefore, the simulation of DOD (Ah) balancing for Solar-Balancing was skipped.
As mentioned in the previous section, simulations with various balancing criteria have been performed, with different levels of solar power input during charging and discharging at each cycle. Each test case has been simulated till the SOH of Battery 2
reaches 0. Then the total charge-discharge cycle numbers, as well as the SOH standard deviation, are compared to the baseline case.

Figure 3.6 and Figure 3.7 show the cycle number improvement and the SOH standard deviation reduction percentages of voltage balancing, respectively. From Figure 3.6, it can be observed when the average solar balancing power during discharge through battery life beyond 20% of the ideal values, the overall cycles can be improved by 4%–6%. However, the solar power level during charge does not help much in extending battery life. On the other hand, the SOH imbalance suppression highly depends on the balancing performance by solar power during battery discharge. In best cases, the SOH standard deviation can be reduced by more than 90%.

Figure 3.6: Life Cycles Percentage Improvement from Baseline of Voltage Balancing
The simulation results for SOC balancing are shown in Figure 3.8 and Figure 3.9.

By comparing Figure 3.8 and Figure 3.6, it can be found that, with SOC balancing, the best improvement areas are enlarged. For example, to achieve >5% of life improvement for voltage balancing, the average solar power during discharging shall be >45% of the recorded power. However, when applying SOC balancing, 32% of the recorded solar power during discharging can guarantee at least a life extension of 5%. In addition, for voltage balancing, the maximum life improvement of 6% occurs with 60%~80% of recorded solar power during discharging and at least 20% of solar power during charging. But for SOC balancing, when the solar power during discharging falls into 50%~80% of the recorded value, 6% life extension can be achieved regardless of the balancing performance during charge. This effect benefits most vehicles that are
charged at night. The SOH imbalance suppression performance of SOC balancing is also improved comparing to voltage balancing, as shown in Figure 3.9. It is worth noting that for voltage and SOC balancing when the solar power levels beyond 80% of the recorded value, the life improvement percentage drops from around 6% to 5%. This is because that, with more solar power harvested, the driving range as well as the discharging time of each cycle was extended. As represented in equation (3.7) and (3.8), the battery degradation will be accelerated with a longer half-cycle duration. And the simulation result implies that 80% of the recorded solar power is the margin that the longer discharge time starts to cancel the benefits of voltage and SOC balancing.

Figure 3.8: Life cycles Percentage Improvement from Baseline of SOC Balancing
Figure 3.10 and Figure 3.11 show the life cycle improvement and the SOH standard deviation reduction percentage at EOL of SOC-SOH balancing, respectively. By comparing Figure 3.10 and Figure 3.8, it can be found the implemented SOC-SOH balancing algorithm during discharge further optimizes the battery life improvement. Firstly the maximum life improvement percentage is increased to around 7%-8%. Secondly, when the balancing solar power during discharge beyond the 80% margin, the maximum life extension of 8% can still be achieved in most areas. This means the degradation acceleration from longer discharge time on each cycle has been counteracted. Therefore, the utilization of solar power can be maximized without additional hardware. In addition, the comparison between Figure 3.11 and Figure 3.9 shows that with SOC-SOH balancing, a 90% reduction on SOH standard deviation at
EOL can be achieved with $\geq 90\%$ of ideal solar power during discharge, regardless of the balancing performance during charge.

Based on the simulation and analysis for APM-Balancing and Solar-Balancing for each criterion, the following conclusion can be made for the proposed system: For APM-Balancing that needs to turn off the balancing circuit when all modules are balanced, the best criterion for balancing is SOC based. While for the Solar-Balancing mode that is designed to harvest as much solar power as possible, it is recommended to charge the battery module with the lowest SOH via PV when the SOCs are balanced during discharge.

![Figure 3.10: Life Cycles Percentage Improvement from Baseline of SOC-SOH Balancing](image-url)
In this chapter, different criteria for battery balancing and their implementations in the proposed microgrid have been studied. The studied balancing criteria include conventional voltage/SOC, DOD (Ah) and SOC-SOH for Solar Balancing. To estimate performances on battery life extension of each criterion, model-based analysis has been carried out for a Li-ion pack with inconsistency modules. Same charge/discharge profile and solar conditions were applied to simulations of each criterion.

The model-based analysis results show that for APM-Balancing, the SOC is the best criterion that could bring 27.3% of cycle life improvement and 91.5% of SOH standard deviation reduction at EOL from the baseline. The analysis results also prove...
that the DOD (Ah) balancing is not applicable to the proposed microgrid. Therefore, the analysis of the DOD (Ah) balancing for Solar-Balancing was skipped.

For Solar-Balancing, different levels of solar power input during charging and discharging at each cycle were simulated for each criterion. The simulation results show that the SOC-SOH balancing has best performance on maximizing battery life and minimizing SOH standard deviation at EOL. With SOC-SOH balancing, the maximum life improvement percentage is increased to around 7%~8%. In addition, the degradation acceleration from longer discharge time can be counteracted with SOC-SOH balancing, which makes the harvested solar energy sufficiently extend both the driving range and battery life.
CHAPTER 4 ELECTRICITY GRID-TIED APPLICATIONS OF THE ONBOARD MICROGRID

4.1 Virtual Solar Farm (VSF)

In this chapter, the electricity grid-tied applications of the proposed onboard microgrid will be studied. Firstly, the concept of virtual solar farm (VSF) will be proposed, followed by a real solar data-based simulation. Then, the counterpart of the vehicle microgrid for the customer-side energy storage system will be proposed and analyzed.

4.1.1 Virtual Solar Farm Diagram

As stated in Chapter 2, the EVs with the proposed onboard microgrid can supply the harvested solar energy to the grid along with the battery. When the vehicles are connected to the grid and form a virtual power plant (VPP) [91], all the vehicles equipped with the proposed system actually form a virtual solar farm (VSF). This VSF does not require land and construction. The hardware of the VSF, including PV panels, grid-tied inverters, and the battery energy storage systems are decentralized into each vehicle. Therefore, the total costs are shared by the EV users. By installing the onboard microgrid with PV, the vehicle users have their battery life extended. In addition, the additional cost can be compensated by selling electricity to the grid. For shared vehicle operators, there will be a number of electric vehicles standing by for a certain period of time. With the proposed system, the standing-by vehicles could generate some economic benefits for the operator as well. More importantly, each of the vehicles is able to control the charge/discharge (V2G) power based on its own state and behavior.
to participate in the electricity market [92]. There will be no extra control needed for solar energy harvesting. Therefore, the VSF can have high flexibility. The schematic diagram of a VSF is shown in Figure 4.1.

![Figure 4.1: A Virtual Solar Farm Consisting of EVs with the Proposed PV Systems.](image)

From Figure 4.1, it can be seen the aggregated EVs will be under one of three operation conditions: V2G (EV1), EV Charging (EV2), and PV2G (EV3). For the vehicles performing V2G, the generated solar power will be supplied to the grid along with the power from batteries. For vehicles performing PV2G, the batteries are not being charged or discharged due to electricity price or other reasons, and the systems deliver the harvested solar power to the grid. While for the vehicles being charged, the solar panel, together with the grid, charges the vehicle batteries. Therefore, the total equivalent generated solar power of the VSF can be defined as equation (4.1).
\[ P_{S,VSF} = \sum_{i=1}^{N_{V2G}} P_{S,i} + \sum_{j=1}^{N_{char}} P_{S,j} \] (4.1)

where \( P_{S,i} \) is the generated solar power of \( EV_i \) that is performing PV2G or being discharged via V2G. \( P_{S,j} \) is the harvested solar power of \( EV_j \) that is being charged. It is worth noticing that, although \( P_{S,j} \) is not delivered to the grid, it saves the charging power that was supposed to be consumed from the grid.

### 4.1.2 Modeling & Simulation of VSF

#### 4.1.2.1 EV Behavior Model

Simulation studies have been carried out to estimate the solar power and energy generation performance of the VSF. The key behaviors affecting the aggregation of EVs to participate in the VSF includes the arrival and departure time, assuming the vehicles will be connected to the grid at arrival. Truncated Gaussian has been used to model the EVs’ arrival and departure as equation (4.2) [92].

\[ t_{arv/dep} = f_{TG}(x; \mu_{arv/dep}, \sigma_{arv/dep}, t^{min}, t^{max}) \] (4.2)

where \( \mu_{arv/dep} \) is the mean time for arrival/departure; \( \sigma_{arv/dep} \) is the standard deviation; \( t^{min} \) and \( t^{max} \) are the minimum (earliest) and maximum (latest) time of arrival and departure, respectively. Based on the research of [93] and [94], the parameters of EVs’ behavior probability distributions are listed in Table 4.1. The corresponding distributions are plotted in Figure 4.2.
### Table 4.1: Parameters of EV Behaviors’ Distributions

<table>
<thead>
<tr>
<th>Description</th>
<th>Arrival Time (hour in a day)</th>
<th>Departure Time (hour in a day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>8.5 (8:30 AM)</td>
<td>17.5 (5:00 PM)</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Min (Earliest)</td>
<td>6 (6:00 AM)</td>
<td>13 (1:00 PM)</td>
</tr>
<tr>
<td>Max (Latest)</td>
<td>13 (1:00 PM)</td>
<td>22 (10:00 PM)</td>
</tr>
</tbody>
</table>

Figure 4.2: Distribution of EV Arrival and Departure Times.

In this research, 10,000 vehicles have been simulated based on the distribution and aggregated to form a VSF. From Figure 4.2, it can be observed that most EV users go to work around 8.5 (8:30 AM) and leave at around 17.5 (5:30 PM). Therefore, the vehicle types of simulation study can be defined as passenger cars for daily commute and aggregated to participate in an electricity market at work places.

#### 4.1.2.2 Solar Condition Model

The solar condition has been modeled based on the real data recorded from a building roof solar system in Detroit, Michigan [70]. Solar power data of 12 days in
each month from December 2016 to November 2017 have been applied. In Figure 4.3 (a)-(d), the curves are the scaled-down output power profile from the real 3.3kW building roof-solar system to a 300W rated solar panel that fits the top area of most passenger cars [95], along with date and weather. Due to building/tree shadowing and solar zenith angle, the vehicles can harvest only 67% and 82.3% of the recorded available solar energy in January and July, respectively [95]. To estimate the available solar power for EVs in other months, linear interpolation has been applied. The attrition rates of recorded solar in each month are shown in Table 4.2. It is worth noticing that with 10,000 vehicles equipped with 300W PV on each roof, the overall VSF rated power is 3MW, which means the VSF can be classified as a utility solar farm [96].

(a): Recorded Solar Power of 3 days in winter 2017
(b): Recorded Solar Power of 3 days in Spring 2017

(C): Recorded Solar Power of 3 days in Summer 2017
(D): Recorded Solar Power of 3 days in Fall 2017

Figure 4.3: Scaled Solar Power from 3.3kW Roof PV in 12 Days of 2016~2017
Table 4.2: Solar Attrition Rate from Roof to EV of Each Month

<table>
<thead>
<tr>
<th>Month</th>
<th>Solar Attrition Rate from Roof to EV</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>33%</td>
</tr>
<tr>
<td>February</td>
<td>30.38%</td>
</tr>
<tr>
<td>March</td>
<td>27.76%</td>
</tr>
<tr>
<td>April</td>
<td>25.14%</td>
</tr>
<tr>
<td>May</td>
<td>22.52%</td>
</tr>
<tr>
<td>June</td>
<td>19.9%</td>
</tr>
<tr>
<td>July</td>
<td>17.3%</td>
</tr>
<tr>
<td>August</td>
<td>19.9%</td>
</tr>
<tr>
<td>September</td>
<td>22.52%</td>
</tr>
<tr>
<td>October</td>
<td>25.14%</td>
</tr>
<tr>
<td>November</td>
<td>27.76%</td>
</tr>
<tr>
<td>December</td>
<td>30.38%</td>
</tr>
</tbody>
</table>

4.1.2.3 Simulation Results and Discussion

Based on the EVs’ behavior model and solar irradiation model, simulation studies with a total number of 10,000 EVs with the onboard microgrid have been carried out for the 12 days. By identifying the vehicles’ arrival and departure times, the total equivalent generated solar powers can be estimated. Figure 4.4 shows the equivalent generated solar power of the simulated VSF formed by 10,000 EVs in the 12 days.
(a): Equivalent Solar Power of a 10,000 EVs Formed VSF of 3 days in winter 2017

(b): Equivalent Solar Power of a 10,000 EVs Formed VSF of 3 days in Spring 2017

(c): Equivalent Solar Power of a 10,000 EVs Formed VSF of 3 days in Summer 2017
Figure 4.4: Equivalent Solar Power of a 10,000 EVs Formed VSF

From Figure 4.4, it can be observed that the peak power of the VSF reaches 1MW and 0.6~0.8MW in summer and winter, respectively. It is worth noticing that the VSF supplies maximum power around noon when the grid reaches peak electricity consumption. Therefore, the VSF can help to mitigate the grid pressure as well. By integrating the power curve, the VSF equivalent solar energy generation of each date can be obtained. The equivalent generated solar energy of the simulated 12 days is shown in Table 4.3 along with the saved CO\textsubscript{2} emission [97]. Taking season and weather factors into account, a VSF formed by 10,000 EVs can help generate 3,440 kWh clean energy and save 2,432 kg CO\textsubscript{2} per day on average.
Table 4.3 VSF Equivalence Solar Energy Generation and CO$_2$ Emission Reduction

<table>
<thead>
<tr>
<th>Date</th>
<th>Generated Solar Energy</th>
<th>Saved CO$_2$ Emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>12/31/2016</td>
<td>1,898 kWh</td>
<td>1,342 kg</td>
</tr>
<tr>
<td>01/13/2017</td>
<td>1,785 kWh</td>
<td>1,262 kg</td>
</tr>
<tr>
<td>02/18/2017</td>
<td>4,097 kWh</td>
<td>2,897 kg</td>
</tr>
<tr>
<td>03/14/2017</td>
<td>2,343 kWh</td>
<td>1,657 kg</td>
</tr>
<tr>
<td>04/17/2017</td>
<td>4,471 kWh</td>
<td>3,161 kg</td>
</tr>
<tr>
<td>05/15/2017</td>
<td>5,594 kWh</td>
<td>3,955 kg</td>
</tr>
<tr>
<td>06/12/2017</td>
<td>5,455 kWh</td>
<td>3,857 kg</td>
</tr>
<tr>
<td>07/15/2017</td>
<td>4,289 kWh</td>
<td>3,032 kg</td>
</tr>
<tr>
<td>08/15/2017</td>
<td>4,937 kWh</td>
<td>3,491 kg</td>
</tr>
<tr>
<td>09/16/2017</td>
<td>4,699 kWh</td>
<td>3,322 kg</td>
</tr>
<tr>
<td>10/19/2017</td>
<td>4,242 kWh</td>
<td>2,999 kg</td>
</tr>
<tr>
<td>11/14/2017</td>
<td>2,918 kWh</td>
<td>2,063 kg</td>
</tr>
<tr>
<td>Average</td>
<td>3,440 kWh</td>
<td>2,432 kg</td>
</tr>
</tbody>
</table>

4.2 Utilization of Backup Battery for Minimizing TOU Charge with Onboard Solar-assisted balancing

Battery systems, or energy storage systems (ESS), are widely applied on both the grid-side and energy customer-side for load leveling, peak shifting, fluctuation suppression, among other functions [98]. For devices of great significance that need to be operated continuously, for example, telecommunication stations, battery systems are utilized as a backup power source. This kind of backup power source is usually
designed with a high capacity margin but only performs its function when a power outage happens. In this section, a concept of converting telecommunication backup ESS to general ESS for minimizing Time-of-use (TOU) electricity charge with onboard solar-assisted balancing will be proposed and analyzed.

4.2.1 Conversion of Telecommunication Station Backup ESS

A typical backup ESS for telecommunication stations are usually assembled as shown in Figure 4.5. The ESS is charged by the grid through a charger and maintained as fully charged. In case the power outage happened, the uninterruptible power supply (UPS), which is a small battery pack with an inverter, will supply the AC load for a short period of time. At the same time, the supervisor controller closes the switch S_ESS so that the load can be powered by the ESS. Depending on the capacity of the ESS, the loads of telecommunication devices can be powered up to hours before the grid power backs on. The required rated capacity of an ESS for a specific telecommunication station can be calculated by equation (4.3) [99].

$$Q \geq \frac{KI \eta}{1+\alpha(\eta-25)}$$

(4.3)

where $Q$ is the required rated capacity of the designed telecommunication station backup ESS; $K$ is the safety coefficient fixed at 1.25; $I$ is the constant discharge DC current; $T$ is the designed hours for continuous discharge; $\eta$ is the discharge coefficient, $\alpha$ is the battery temperature coefficient, and $t$ is the minimum ambient temperature of the station. Take an example of a station that requires the ESS to continuously work for 3 hours at a discharging rate of 347A DC per hour, and the minimum ambient
temperature is \(-20^\circ\text{C}\). \(\eta\) and \(\alpha\) equal to 0.75 and 0.008, respectively, for Lead-acid batteries [99]. The total capacity will be 2,712.67Ah. However, the required discharge capacity is only 1,041Ah, which means almost \(2/3\) of the rated capacity will be wasted if there was no extreme temperature, battery degradation, and power outage.

Figure 4.5: Conventional Backup ESS for Telecommunication Devices

To better utilize the useable capacity of the backup ESS, a novel system architecture is proposed, as shown in Figure 4.6. With the proposed architecture, the system is able to minimize the electricity bill. During the hours with low TOU electricity prices, the loads are powered by the grid, and the ESS is also charged by the grid as needed. When the time approaches high TOU fee hours, the S_ESS will be closed, followed by the opening of S_AC, the power source is switched to the ESS. When the time approaches low TOU fee hours again, the S_AC will be closed, followed by the opening of the S_ESS, to switch the power source back to the grid. It is worth noticing that the minimum usable capacity of the ESS at any time should be enough for backup use. Taking the same 2,712.67Ah telecommunication station ESS as an example, the usable battery capacity should not be discharged below 1,041Ah. In case a power outage happens, the proposed system works the same way as conventional ones to
utilize the ESS as a backup power source. Since the ESS in the proposed system operates much more charge and discharge cycles than in conventional types, battery balancing will be necessary to extend the overall cycle life. Therefore, the solar-assisted battery balancing scheme will be the best solution for energy saving. As shown in Figure 4.6, the PV is connected to the DC/DC converter and switch box assembly like in the vehicle applications aforementioned. A supervisory controller estimates the battery SOC and closes the corresponding selection switches to charge the weakest battery via PV during charge and discharge when solar power is available. The PV can be installed on the top of the ESS for outdoor telecommunications devices as shown by the perspective in Figure 4.7.

Figure 4.6: Proposed ESS With Solar-assisted Balancing

Figure 4.7: Perspective of Proposed ESS With Solar-assisted Balancing
4.2.2 Modeling of Converted ESS with Solar-assisted Balancing

To analyze the feasibility and performance of the proposed telecommunication ESS with solar-assisted balancing, a simulation model has been developed in MATLAB/Simulink environment by adopting the parameters mentioned before. The required ESS rated capacity and voltage is 2,712.67Ah and 48VDC, respectively. From the battery supplier’s category [100], a 3,000Ah/48V battery pack is selected. The whole battery pack is formed by 2 strings in parallel, and each string has four 1,500Ah/12V Lead-acid battery modules in series. The rated PV power for battery balancing is set to 500W with 3.5m² top area available for PV installation. The electric architecture of the ESS with solar-assisted balancing is shown in Figure 4.8. The control algorithm for the system is similar to its counterpart in the vehicle applications: 2 specific switches will be closed to charge the battery module with the lowest SOC via PV at one time (e.g. S2 and S5 for Module 1) during either charge or discharge; If all 8 battery modules were well balanced and there was still solar power available, the top and bottom switches will be closed to charge the whole battery pack. When the battery pack has been fully charged, all the switches should be opened to prevent over-charge. With bi-directional charger, the harvested solar energy can be sent to grid when the battery is fully charged.
The charge and discharge profile of the proposed ESS is determined based on TOU price in Detroit, Michigan [101], as shown in Figure 4.9. From Figure 4.9, it can be observed the TOU price approaches peak value from 3pm to 7pm on weekdays. Therefore, on weekdays, the ESS is designed to be discharged at 347A DC for powering the loads from 3pm to 7pm and charged for the rest of the day. By assuming there is no power outage happens, the charge current is set to 72A. With 72A charge current, the whole battery pack can be fully charged 0.5~1 hour in advance of discharge begins. This charging profile brings two advantages for the ESS: 1) the battery can be warmed up by charge current under extremely low temperatures so that the capacity loss can be prevented; 2) By finishing the charge before 2 pm to 3 pm, the solar energy can be sufficiently harvested. Especially around the end of charge, the solar power reaches its peak in a day. Therefore, the balancing effects can be maximized.
As mentioned before, the system has been modeled in MATLAB/Simulink environment. The batteries are modeled in the same way as demonstrated in Chapter 3 as Lead-acid modules. The rated capacities and internal resistances of the modeled batteries are shown in Table 4.4. The available solar powers in 12 selected days are scaled from the curves in Figure 4.3 to the 500W rated PV. Because this ESS is designed for telecommunication devices on building roofs, the power losses due to building/tree shadowing and sun zenith angle are ignored.
Table 4.4: Rated Capacities and Internal Resistances of Modeled ESS Batteries

<table>
<thead>
<tr>
<th>Battery Number</th>
<th>Rated Capacity</th>
<th>Internal Resistance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery 1</td>
<td>1,500 Ah</td>
<td>4.50 m Ω</td>
</tr>
<tr>
<td>Battery 2</td>
<td>1,490 Ah</td>
<td>4.48 m Ω</td>
</tr>
<tr>
<td>Battery 3</td>
<td>1,495 Ah</td>
<td>4.49 m Ω</td>
</tr>
<tr>
<td>Battery 4</td>
<td>1,492 Ah</td>
<td>4.47 m Ω</td>
</tr>
<tr>
<td>Battery 5</td>
<td>1,496 Ah</td>
<td>4.48 m Ω</td>
</tr>
<tr>
<td>Battery 6</td>
<td>1,499 Ah</td>
<td>4.49 m Ω</td>
</tr>
<tr>
<td>Battery 7</td>
<td>1,498 Ah</td>
<td>4.49 m Ω</td>
</tr>
<tr>
<td>Battery 8</td>
<td>1,551 Ah</td>
<td>4.51 m Ω</td>
</tr>
</tbody>
</table>

4.2.3 Simulation Results & Discussion

The modeled ESS with solar-assisted battery balancing has been simulated for 13 charge-discharge cycles. One of the cycles was simulated without solar-assisted balancing, as the baseline for balancing performance comparison. The rest 12 cycles were simulated with the recorded and scaled solar power in 12 days from December 2016 to November 2017. Each of the cycles is 24 hours long, and all of them are assumed as weekdays; hence, the ESS discharges during high TOU fee hours. The battery SOCs of the baseline cycle is shown in Figure 4.10, with subplots zoomed into the end of ESS charge and discharge.
Figure 4.10: Battery SOCs of Converted ESS W/O Solar-assisted Balancing

From Figure 4.10, it can be observed at the beginning and end of the cycle, the ESS can be charged to the same SOC. In addition, the ESS can be fully charged around an hour before discharge starts. These findings verified that the designed charge/discharge profile is able to support the continuous operation of the ESS for TOU optimization. The second and third subplots of Figure 4.10 show that without balancing, the maximum SOC differences between modules at end of charge and end of discharge are around 0.3% and 1%, respectively. The battery SOCs of the 12 cycles with solar-assisted balancing are shown in Figure 4.11 (a)-(l). From Figure 4.11, it can be observed with solar-assisted balancing, the maximum SOC difference between modules at the end of charge and discharge can be suppressed to less than 0.1%~0.15% and less than 0.04%~0.3%, respectively, depending on the solar condition. This simulation results verify that the proposed solar-assisted balancing scheme can equalize the SOCs of the ESS daily operation. Therefore, the overall life of the ESS modules can be balanced and extended.
(a) Battery SOCs of Converted ESS with Solar Data from 12/31/2016

(b) Battery SOCs of Converted ESS with Solar Data from 01/13/2017

(c) Battery SOCs of Converted ESS with Solar Data from 02/18/2017
(d) Battery SOCs of Converted ESS with Solar Data from 03/14/2017

(e) Battery SOCs of Converted ESS with Solar Data from 04/17/2017

(f) Battery SOCs of Converted ESS with Solar Data from 05/15/2017
(g) Battery SOCs of Converted ESS with Solar Data from 06/12/2017

(h) Battery SOCs of Converted ESS with Solar Data from 07/15/2017

(i) Battery SOCs of Converted ESS with Solar Data from 08/15/2017
(j) Battery SOCs of Converted ESS with Solar Data from 09/16/2017

(k) Battery SOCs of Converted ESS with Solar Data from 10/19/2017

(l) Battery SOCs of Converted ESS with Solar Data from 11/14/2017

Figure 4.11: Battery SOCs of Converted ESS With Solar-assisted Balancing
Table 4.5 shows the total electricity charge of the simulated cycles, as well as the cost of the conventional power supply of the studied telecommunication station, where the ESS is not operated and all the devices are powered by the grid. In addition, the usable capacities of the ESS at the end of discharge of each cycle are also shown. The usable capacity of each cycle is limited by the module with the least usable capacity in each string and is defined by equation (4.4).

\[ Q_{\text{usable}} = \sum_{i=0}^{n} \min(Q_{i,j} \cdot SOC_{i,j}) \]  

(4.4)

where \( Q_{i,j} \) is the rated capacity of the \( j^{th} \) battery module in the \( i^{th} \) string in parallel; \( SOC_{i,j} \) is the SOC at the end of discharge of the \( j^{th} \) battery module in the \( i^{th} \) string in parallel;

<table>
<thead>
<tr>
<th>Simulated Cycle</th>
<th>Total Bill Charge</th>
<th>Usable Capacity at the end of Discharge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>$35.85$ (Weekdays)</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>$88.08$ (Critical Peak)</td>
<td></td>
</tr>
<tr>
<td>No Solar Balancing</td>
<td>$29.90$</td>
<td>1,465 Ah</td>
</tr>
<tr>
<td>12/31/2016</td>
<td>$29.84$</td>
<td>1,603 Ah</td>
</tr>
<tr>
<td>01/13/2017</td>
<td>$29.83$</td>
<td>1,605 Ah</td>
</tr>
<tr>
<td>02/18/2017</td>
<td>$29.78$</td>
<td>1,628 Ah</td>
</tr>
<tr>
<td>03/14/2017</td>
<td>$29.86$</td>
<td>1,623 Ah</td>
</tr>
<tr>
<td>04/17/2017</td>
<td>$29.78$</td>
<td>1,634 Ah</td>
</tr>
<tr>
<td>05/15/2017</td>
<td>$29.78$</td>
<td>1,647 Ah</td>
</tr>
<tr>
<td>06/12/2017</td>
<td>$29.78$</td>
<td>1,645 Ah</td>
</tr>
<tr>
<td>07/15/2017</td>
<td>$29.78$</td>
<td>1,644 Ah</td>
</tr>
<tr>
<td>08/15/2017</td>
<td>$29.79$</td>
<td>1,641 Ah</td>
</tr>
<tr>
<td>Date</td>
<td>Cost</td>
<td>Capacity</td>
</tr>
<tr>
<td>-----------</td>
<td>------</td>
<td>----------</td>
</tr>
<tr>
<td>09/16/2017</td>
<td>$29.80</td>
<td>1,640 Ah</td>
</tr>
<tr>
<td>10/19/2017</td>
<td>$29.80</td>
<td>1,633 Ah</td>
</tr>
<tr>
<td>11/14/2017</td>
<td>$29.81</td>
<td>1,616 Ah</td>
</tr>
</tbody>
</table>

As shown in Table 4.5, the converted ESS system can reduce the electricity charge by powering the telecommunication devices using battery during high TOU price hours. Taking an average of 12 simulated cycles with solar-assisted balancing, the bill charge can be reduced by 16.8% at weekdays, and by 66.2% if with critical peak events. On the other hand, the solar-assisted battery balancing scheme helped increase the usable capacity at end of discharge from 1,465 Ah to 1,630 Ah on average. With this improvement, the converted ESS has more capacity for power outage backup that requires 1,041 Ah usable capacity at any time. It is noticing that all the simulations are based on the assumption that the ESS is at begin-of-life (BOL) and it always works within proper temperature range with thermal management system. Further analysis for battery temperature management and capacity degradation are to be done in future.

4.3 Summary

In this chapter, the potential applications of the proposed microgrid on electricity grid and utility users have been studied. First the concept of virtual solar farm was proposed. A virtual solar farm is aggregated by a big number of EVs equipped with the microgrid and participate in an electricity market. Depends on the vehicle status, the harvested solar energy can be either charged to the vehicle batteries, which saves same amount of energy from grid, or supplied to the grid. Vehicle user behavior-based
simulation with 10,000 EVs have been carried out with real solar data of 12 days from December 2016 to November 2017. Simulation results show that the aggregated virtual solar farm can generate 3,440 kWh clean energy and save 2,432 kg CO2 per day on average.

Another application of the proposed microgrid is the utility energy storage system (ESS). In this chapter, a case study on converting telecommunication backup ESS to general ESS with solar-assisted balancing for minimizing Time-of-use (TOU) electricity charge was carried out. By re-designing the electrical architecture of a telecommunication back up ESS and adding the solar-assisted battery balancing scheme, the proposed system can power the devices with ESS during high TOU fee hours with keeping enough usable capacity all the time for power outage backup. The results of 12 simulated cycles with solar-assisted balancing shows that the bill charge can be reduced by 16.8% at weekdays, and by 66.2% if with critical peak events. On the other hand, the solar-assisted battery balancing scheme helped increase the usable capacity for power outage backup. For balancing performance, the simulation results verified that with solar-assisted balancing, the maximum SOC difference between modules at the end of charge and discharge can be suppressed to less than 0.1%~0.15% and less than 0.04%~0.3%, respectively, depending on the solar condition.
CHAPTER 5 CONCLUSIONS AND FUTURE WORK

In this thesis, an electrified vehicle onboard microgrid with PV for battery module balancing and V2G operations has been proposed. Either when the vehicle is moving or parking, the proposed system can balance the battery modules with the vehicle roof PV or the APM when solar power is not available. When the battery is fully charged, or there is a specific request from the user, the proposed system can deliver energy from the battery pack with PV to the grid or off-grid loads. Vehicle level simulations have been performed with real solar data, based on which the balancing and energy saving performance has been estimated. A prototype vehicle has been developed and tested, which experimentally verified the battery balancing effects of the proposed system for both Lead-acid and Li-ion battery packs. Vehicle-to-grid (V2G) and PV-to-grid (PV2G) functions have been tested and validated as well.

To optimize the control algorithms for maximizing battery life, different battery module balancing criteria have been studied for the proposed system, including conventional voltage/SOC, DOD (Ah) based, and SOC-SOH for solar balancing. In order to compare the balancing performance of each criterion on extending overall battery life and suppressing SOH imbalance at end-of-life (EOL), model-based analysis has been carried out with the vehicle discharge profile from MBC drive cycles. Based on the results of the model-based analysis, it is concluded that for APM balancing, the SOC is the best equalization criterion for extending battery life and suppressing SOH imbalance at EOL. When solar power is available, the proposed SOC-SOH balancing
algorithm is suggested. With the SOC-SOH balancing, the PV charges the battery module with the lowest SOH when the SOCs are well balanced during discharge. If the SOHs are balanced as well, the PV charges the whole battery pack. With the SOC-SOH balancing strategy, the battery life extension and SOH imbalance suppression can be maximized without wasting available solar energy.

It is worth noticing that the proposed system can benefit not only the electrified vehicles but also the electricity grid and utility users. Firstly, by charging the battery with solar power and applying PV2G, vehicles equipped with the proposed system can help reduce the electricity consumption from the grid. Thus, green gas emission can be reduced as a result. Based on this fact, the concept of virtual solar farm (VSF) has been proposed. Simulations have been carried out for a VSF formed by 10,000 vehicles equipped with the proposed system. User behaviors on daily commute have been embedded in the simulations. With the recorded solar data of 12 days in each month from December 2016 to November 2017, the simulation results verified that this size of VSF could generate 3,440 kWh energy and reduce 2,432 kg CO2 per day on average.

Another important application of the proposed solar-assisted balancing scheme is for electrical energy storage systems (ESS). For example, the user-side battery packs such as backup power supply for communication stations. When converting a backup battery of a communication station to a general ESS for time-of-use (TOU) bill reduction, the solar-assisted balancing scheme is remarkably helpful to balance the battery SOCs from daily charge/discharge cycles. In addition, by harvesting solar Energy, the converted ESS has more backup capacity for continuous discharging when a power outage
happens. These effects and performance have been verified by simulation as well.

In order to further improve the battery balancing system with PV and its applications, there can be several future extensions to the presented research work: 1) Optimize the battery balancing criterion selection by taking battery temperature and thermal effects into account. By considering thermal effects on Li-ion battery degradation, a better balancing algorithm closer to real applications can be developed for both APM and solar balancing. 2) As more EVs are participating in the electricity market and various of incentive schemes are developed to change the behaviors of vehicle users based on grid conditions, a special incentive scheme can be designed based on weather conditions and sunset/sunrise time to maximize users’ profit and solar energy generation. 3) Develop a more accurate battery model with thermal effects to optimize the charge/discharge profile of the converted telecommunication backup ESS so that the battery temperature can be better managed and solar energy can be harvested more effectively. Based on the expected model, battery life with solar-assisted balancing can be estimated for the converted telecommunication ESS.
REFERENCE


[16] Baumhöfer, Thorsten, et al. “Production caused variation in capacity aging trend and correlation to initial cell performance.” *Journal of Power Sources*, vol.247,


[50] Abdelhamid, Mahmoud, Srikanth Pilla, Rajendra Singh, Intiaz Haque, and Zoran Filipi, “A comprehensive optimized model for on-board solar


[55] “Tesla Cybertruck will have solar roof option to add 15 miles of range per day,” https://electrek.co/2019/11/22/tesla-cybertruck-solar-roof-option-add-range/


pp. 1-8, 2009


[65] Chenguang Jiang, Allan Taylor, Chen Duan, and Kevin Bai, “Extended Kalman
Filter based battery state of charge (SOC) estimation for electric vehicles,”
Transportation Electrification Conference and Expo (ITEC), IEEE, pp. 1-5. 2013.


[86] Matlab/Simulink Library – Implement generic battery model


[101] “Pricing Option DTE Energy,”

ABSTRACT

AN ELECTRIFIED VEHICLE ONBOARD MICROGRID WITH PV FOR BATTERY MODULE BALANCING AND V2G APPLICATIONS

by

Chen Duan

December 2020

Advisor: Dr. Caisheng Wang

Major: Electrical and Computer Engineering

Degree: Doctor of Philosophy

As the energy storage system and the synergy buffer between electrified vehicles (or xEV) and the grid, batteries have been widely used in electric vehicles (EV), hybrid/plug-in hybrid electric vehicles (PHEV), and fuel cell electric vehicles (FCEV). With the booming market of xEV worldwide, the battery production and vehicle installation thrive as well. However, due to inevitable manufacturing errors and inconsistent conditions during operation, battery imbalances take place on modules and cells of a pack. The battery imbalances could result in several damaging effects, including over-charge and over-discharge. To deal with the imbalance issue of battery packs, various battery balancing topologies and control algorithms have been studied and developed, including passive balancing, active balancing, and other schemes. Because of cost, complexity, among other factors, passive balancing is still the most popular solution for xEVs. However, passive balancing brings power loss and cannot be applied during discharging. To provide a better solution for battery balancing, especially module
balancing for xEVs, in this thesis, an onboard microgrid with solar panel (PV) for battery module balancing and vehicle-to-grid (V2G) applications is proposed and investigated. With the proposed microgrid, the vehicle battery modules can be balanced with the roof PV or the auxiliary power module (APM) when solar power is not available. When the battery is fully charged, or there is a specific request from the user, the proposed system can deliver the electrical energy from the PV with or without the battery to the grid or off-grid loads.

In this thesis, various battery balancing criteria are studied for the proposed system, including conventional voltage/state-of-charge (SOC), depth-of-discharge (DOD in Ah, and SOC-SOH for solar balancing. Based on the results of the model-based analysis, it is found that for APM balancing, SOC is the best equalization criterion for extending battery life and suppressing SOH imbalance at the end of life (EOL) of the battery pack. When solar power is available, the proposed SOC-SOH balancing algorithm is suggested. With the SOC-SOH balancing, the PV charges the battery module with the lowest SOH when the SOCs are well balanced during discharge.

In this thesis, the benefits of the proposed system on the grid and derivative counterparts for utility applications are studied as well. Based on the effects of vehicle aggregation, the concept of virtual solar farm (VSF) is proposed. Simulations are carried out for a VSF formed by 10,000 vehicles equipped with the proposed system and verified that a substantial amount of clean energy can be generated. On the utility user side, a study on converting a backup battery of a communication station to a general energy storage system (ESS) for time-of-use (TOU) bill reduction is carried out.
Real solar data-based simulation verifies that the solar-assisted balancing scheme helps balance the battery SOCs from daily charge/discharge cycles and keeps more redundant capacity for continuous discharging when a power outage happens.
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