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Comparison of Multiple Battery Chemistries in the Cost Minimization of a Residential Vehicle-to-Grid System

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ABSTRACT

The economic feasibility of Vehicle-to-Grid (V2G) technology is subject to a lot of debate due to the battery degradation costs associated with it. In this paper, the daily operational cost of a V2G system is calculated for three different types of Li-ion batteries and one new Li-S battery, and a comparative study is conducted to understand the conditions required to deploy a successful V2G system. Different models are applied in estimating the degradation of batteries with different battery chemistries. The best Li-ion battery for this system is found to be $LiFePO_4$ even though it is the most expensive battery considered. It is also noted that the starting state-of-charge (SOC) relates to the operational costs non-linearly and an optimal starting SOC is calculated for minimizing operational cost. When these Li-ion batteries are replaced by the new double SEI layer Li-S batteries, additional cost benefits of about 17% are expected.

Keywords: Li-ion battery, Li-S battery, Vehicle-to-Grid, Battery degradation

1. INTRODUCTION

In an attempt to reduce the burden of electric vehicle (EV) load on the power grid and also customers' EV charging costs, Vehicle-to-Grid (V2G) technology has been developed for residential users. However, residential V2G implies more frequent charging and discharging to batteries, which brings accelerated degradation to batteries and such a degradation cost needs to be considered in V2G. This paper aims to study the impact of different battery chemistries to residential V2G, where three popular Li-ion batteries and a new type of Li-S battery will be investigated and compared in the V2G energy cost minimization.

In literature, battery degradation has been noted in V2G studies. For example, it is demonstrated in [1] that using EV batteries to store photovoltaic (PV) power for grid load reduction leads to more than 37% battery degradation. This means that V2G would lead to a higher operational cost [2]. Thus, customers may not be willing to participate in V2G due to the accelerated degradation amongst other reasons such as low feed-in tariff and expensive battery packs. To make V2G economically viable for users, substantial subsidies from the grid would be needed to counter the costs associated with V2G [3]. However, these exiting V2G studies usually focus on particular types of EVs or batteries, and it is unclear how the V2G will perform under different battery chemistries.

In this paper, we will focus on the minimization of residential V2G operational costs while taking into consideration multiple battery chemistries and their degradation. The Li-ion battery degradation model used in this study considers the fundamental battery degradation theories including the Arrhenius relationship and the solid electrolyte interphase (SEI) film formation while deriving the required parameters empirically using experimental data [4]. Three types of popular Li-ion battery chemistries will be considered in the energy cost minimization of a residential home which has an EV, a PV system, a home energy storage (battery), and typical electric home appliances. Since there is also a new emerging Li-S battery technology, the Li-S battery with double SEI layers [5], it is also considered in this study although it has not yet been available in the market. This new battery has an extremely slow degradation as shown in Fig. 1 (extrapolated from [5]).

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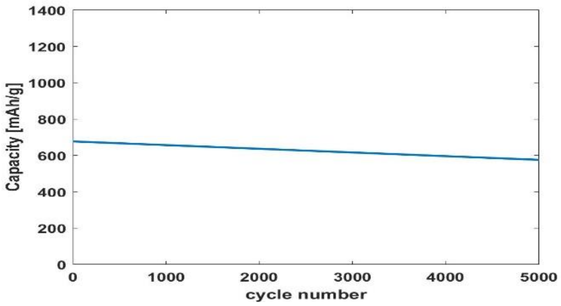

Fig. 1. Degradation of a Li-S battery with double SEI layers

The remaining part of this paper is organized as follows. Section 2 will introduce the residential energy eco-system model applied in this paper, Section 3 is the case study and comparison results, and the last section is the conclusion.

2. RESIDENTIAL ENERGY SYSTEM AND V2G MODEL

The residential energy system with V2G facilities consists of 5 key components, as seen in Fig. 2. The first component is the energy purchased from (or sold to) the grid, the second component is the energy stored and utilized in the home storage unit, the third component is the electric vehicle, the fourth component is the renewable energy generated at home, i.e., solar energy and the fifth component is the load at this home. Due to the presence of renewables and energy storage, this residential energy system is often called residential ecosystem in literature. These components are connected to a central control unit, which minimizes the total energy cost by controlling the power flow between these components.

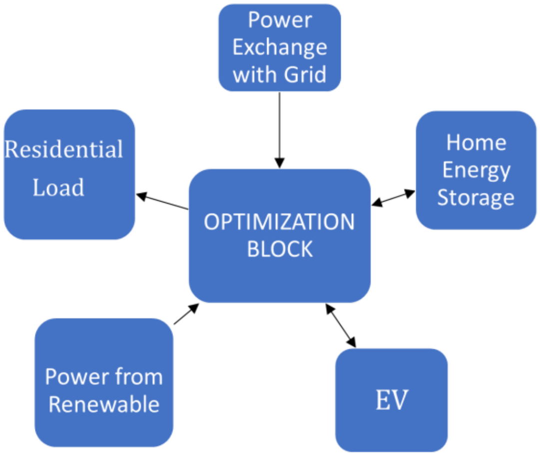

Fig. 2. Residential energy management system

The above system is modelled using a similar one from [6], and it is assumed that a positive power flow from a component means this component consumes this amount of power, while a negative value represents this component supplies power (if applicable). The control period is assumed to be 24 hours, which is sampled every one hour.

The objective, denoted by function f, is to minimize the total energy cost at the residential energy system in Fig. 2, which can be described as follows.

$$\min f = Cost_{Purchase} - Cost_{Sell} + Cost_{Deg}^{EV} + Cost_{Deg}^{HES} \tag{1}$$

where $Cost_{Purchase}$ is the electricity purchasing cost from grid, $Cost_{Sell}$ is the electricity selling income through V2G or battery storage, $Cost_{Deg}^{EV}$ and $Cost_{Deg}^{HES}$ are the degradation costs of the batteries of EV and Home Energy Storage (HES), respectively. Details to calculate the electricity purchase and selling cost can be found from many existing studies, and here we refer to [6] and will not delineate here due to the page limit. The above objective function is subject to many constraints such as power balance, PV generation, EV travel needs, EV and HES battery state-of-charge (SOC) boundaries, etc., which are also discussed in [6]. However, [6] discusses only fixed EV brands and does not consider different battery chemistries. In the following, a very accurate degradation model from [4] is taken to model battery capacity loss for $LiMn_2O_4$ batteries:

$$S_\delta(\delta) = (k_{\delta 1} * \delta * k_{\delta 2} + k_{\delta 3})^{-1} \tag{2}$$

where $k_{\delta 1}$, $k_{\delta 2}$, and $k_{\delta 3}$ are constant coefficients, δ is the depth of discharge (DOD) and $S_\delta(\delta)$ is the number of duty cycles before the battery degrades to 80% capacity. Further to this model, the exponential model for $LiFePO_4$ batteries [7], and the quadratic model for $Li(NiMnCo)O_2$ batteries [8] are also applied in the comparison study. In the degradation calculations, it is assumed that a battery pack will become unfit for service once its capacity degrades to 80% of its original maximum capacity. The following equation is used to calculate SOC.

$$SOC(i) = SOC(i-1) - \frac{P_{EV/HES} * \Delta t}{C_{EV/HES}} \tag{3}$$

where $SOC(i)$ is the SOC at time step i, $P_{EV/HES}$ represents the discharging power from EV or HES, $C_{EV/HES}$ is the corresponding battery capacity of EV or HES, while Δt is the sampling period, i.e., 1 hour in the case study. The degradation cost $Cost_{Deg}$ is thus defined as the product of loss in capacity Q_{loss} (in percentage) over a day and the total cost of the battery ($Cost_{Battery}$).

$$Cost_{Deg} = Q_{loss} \, . \, Cost_{Battery} \tag{4}$$

The objective function in (1) is subject to the above degradation and SOC constraints, along with power balance and load demands as those in [6]. It is solved using Matlab Genetic Algorithm in the case study below.

3. CASE STUDY

The residential eco-system in the study is resembled closely by the Tesla energy Eco-system, thus the EV battery capacity is taken as 75 kWh and the HES capacity is taken as 13 kWh based on available products from Tesla. The residential charging/discharging settings for both EV and HES are controlled at 240V and 16A. The electric loads and solar irradiance data are from San Diego, California. Electricity tariffs are shown in Fig. 3.

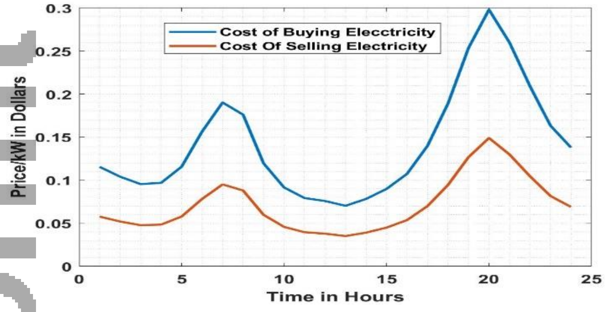

Figure 1: Electricity Tariffs

The SOCs for EV and HES are assumed to be within 20% and 80%, which is the normal working range required by manufacturers. The SOC of the EV in the morning must be at least 50% to ensure possible daily travel needs. The following three types of Li-ion battery chemistries and the corresponding costs are considered.

Battery Chemistry	Unit price ($/kWh)	Cost of EV battery ($)	Cost of HES battery ($)
$LiMn_2O_4$	240	18,000	3,120
$Li(NiMnCo)O_2$	210	15,750	2,730
$LiFePO_4$	270	20,250	3,510

Table 1: List of Batteries

Now solving the cost minimization model mentioned in the previous section for each of the three types of Li-ion batteries, we find the corresponding daily operational costs as tabulated in Table 2, where we assume the EV and HES have the same type of battery chemistry.

As evident, the optimal solutions suggest that using the $LiFePO_4$ battery for both EV and HES will have the least operational cost despite being the most expensive of the three battery choices. $LiMn_2O_4$ is also a good choice as its daily operational cost is only slightly higher than $LiFePO_4$ while its investment cost is lower than $LiFePO_4$.

Battery Chemistry	Daily operation cost ($/day)
$LiMn_2O_4$	1.983
$Li(NiMnCo)O_2$	2.235
$LiFePO_4$	1.982

Table 2. Daily operational cost for different batteries

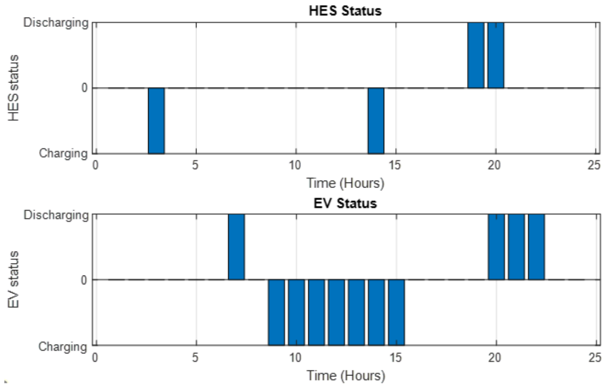

Figure 4: EV and HES battery status

Fig. 4 shows the charging/discharging status of EV and HES using $LiFePO_4$, where EV is charged during the low tariff hours of the day and then discharged during the high tariff hours to generate a net profit for the exchange of energy. A byproduct of this is the flattening of the grid load curve which has been discussed in many existing studies. The cost of operation using this V2G system is found to be $1.982/day.

We now consider the new Li-S battery with double SEI layers and its degradation behaviour shown in Fig. 1 to estimate the daily degradation, where it is assumed that the battery has one full (i.e., 80%) charging/discharging cycle each day. Also, the cost of Li-S is considered equal to the average cost of the three Li-ion chemistries, since this battery is currently not introduced in the market. This assumption will give a more conservative cost estimation since Li-S battery is usually cheaper than Li-ion batteries. Regardless of these undermining assumptions, the daily operation cost with Li-S batteries for EV and HES is found to be $1.642, which is lower than the best-case Li-ion chemistry by about 17%. This is due to the excellent and near flat battery degradation properties of Li-S battery. For this Li-S battery, the optimal solution gives the same charging/discharging schedules as $LiFePO_4$, however, the corresponding SOC changes of Li-S and $LiFePO_4$ are quite different.

All the above operational costs are obtained assuming the home energy system is controlled by the optimization model in Section 2. If it is not optimally controlled, then typically V2G is not meaningful for EV due to the lack of control. In this case, the daily operating cost for the case of $LiFePO_4$ battery is \$2.782. Compared to this baseline case, the above recommended Li-S and $LiFePO_4$ batteries have significant cost savings.

Daily operational cost calculated above indeed relies also on the initial SOC. For example, for $LiFePO_4$ batteries, the following Fig. 5 shows the 50% initial SOC of EV has the least daily operational cost.

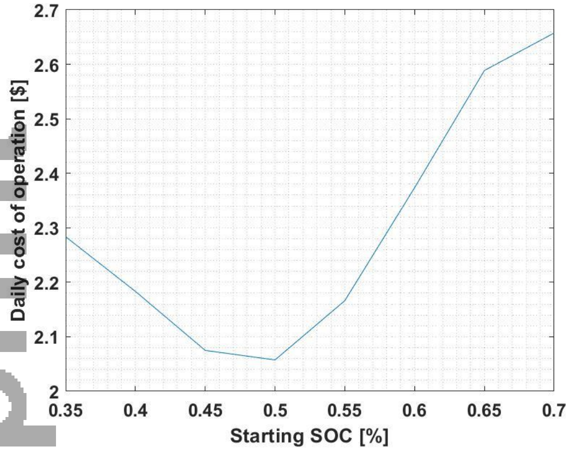

Figure 5: Daily operation cost vs. initial SOC of EV

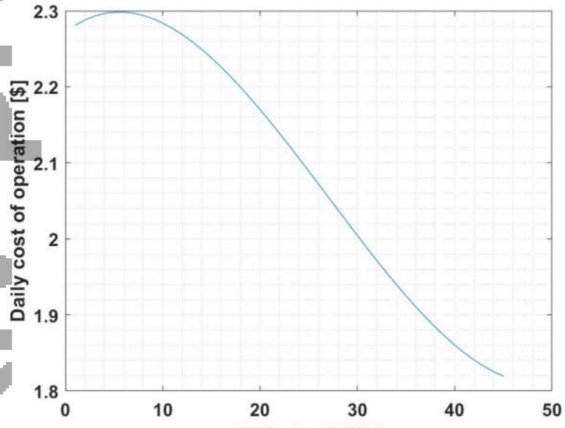

Figure 6: Daily operation cost with varying HES size

The size of HES battery also has a significant impact to the daily operational cost. The daily operation cost is very high for extremely small HES sizes, see Fig. 6. However, it is usually difficult for residential homes to procure large size batteries due to the high capital cost.

4. CONCLUSIONS

This paper focuses on the impact of different battery chemistries on residential V2G. Three types of Li-ion battery chemistries and one new Li-S battery with double SEI layers are investigated, and it is concluded that this new Li-S battery has the lowest daily operation cost for V2G, while $LiFePO_4$ has the lowest operation cost within Li-ion batteries. Operating cost of $LiMn_2O_4$ is close to $LiFePO_4$, while $Li(NiMnCo)O_2$ has the highest cost for V2G.

ACKNOWLEDGMENT

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