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Multi-objective optimization of combined peak shaving and frequency regulation in Vehicle-to-Building/Grid

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Summary

The energy stored in electric vehicles (EVs) would be made available to commercial buildings to actively manage energy consumption and costs in the near future. These concepts known as vehicle-to-building (V2B) and vehicle-to-grid (V2G) technologies have the potential to provide storage capacity to benefit both EVs and buildings owners respectively, by reducing some of the highest cost of EVs, buildings' energy cost, and providing reliable emergency backup services. In this study, we considered a vehicle-to-building/grid (V2B/V2G) storage system simultaneously for peak shaving and frequency regulation via a combined optimization strategy which captures battery state of charge (SOC), EV battery degradation, EV driving scenarios, operational constraints and uncertainties in building load, V2B/V2G patterns and regulation signals. Under these assumptions, we showed that the electricity usage/bill can be reduced. A multi-objective control policy is described and shown to achieve a considerable performance. Comparative analysis with previous works that used battery storage systems for either peak shaving or frequency regulation showed that EV batteries can also achieve superior economic benefits under controlled SOC limits.

Keywords: multi-objective optimization, vehicle-to-building/grid, electric vehicles, peak shaving, frequency regulation

1 Introduction

It is expected that 3% and 54% of new car sales and 1% and 33% of the global car fleet will be electric by 2020 and 2040, respectively [1]. The energy stored in electric vehicles (EVs) would be made available to commercial buildings to actively manage energy consumption and costs in the near future. These concepts known as vehicle-to-X (V2X) (where X = home (H), building (B), or grid (G)) technologies have the potential to provide storage capacity to benefit EVs owners, grid companies, and buildings owners by reducing some of the highest cost of EVs, reducing buildings' energy cost, and providing reliable emergency backup services [2]. For example, Tesla S70 has 90 kWh battery capacity, and its daily consumption for trips is about 12.5% of this capacity (average daily distance for light vehicles is 53 Km [3]). Hence of, 60 kWh can be used as an energy storage system after reduction of 20% depletion ratio.

Our goal in this study is to use these energies for peak shaving and frequency regulation in a vehicle-to-building/grid (V2B/V2G) technology. Studies in this direction have already been done and published in the literature. The studies presented in [4] and [5] showed the economic benefit of using stationary batteries and plug-in electric vehicles batteries, respectively for energy arbitrage and frequency regulation. These early works showed that using batteries for peak shaving and frequency regulation simultaneously yields beneficial results in comparison to single application. However, their approaches did not account for the stochastic nature of the problem. In order to deal with potential uncertainties from energy and ancillary service markets such as price and frequency regulation signals, the studies published in [6], [7], [8] formulate the battery usage for peak shaving and frequency regulation as a stochastic problem.

The current study is similar to [8]. That is, both the future market uncertainties and timescale difference between peak shaving and frequency regulation are captured. But, in comparison to [8], our work contributes in significantly different ways. We propose a multi-objective optimization framework for EV batteries to perform load management (building load and driving), peak shaving and frequency regulation services. This framework accounts for battery degradation, operational constraints, and uncertainties in customer loads, driving profiles and regulation signals. Since EV batteries cycle multiple times a day when used for frequency regulation, peak shaving and load management, the battery degradation plays an important role in determining their operations. One major observation in our work is that EV batteries can achieve much larger economic benefits if they jointly provide multiple services under controlled SOC limits.

This paper presents potential economic benefits of V2B/V2G based on multi-objective optimization of combined peak shaving and frequency regulation for EV and building owners. Section 2 describes models used and the problem formulated in this study. Section 3 presents multi-objective scheme and its control strategy. Matlab/Simulink results are presented and discussed in Section 4, followed by conclusions in Section 5.

2 Model and Problem Formulation

The electricity bills were calculated with the goal to use the energy stored in EVs batteries to reduce the energy cost for EV and building owners. Models for electricity bill calculation, peak shaving, frequency regulation, and battery degradation used in this study are described below.

2.1 Electricity Bill Calculation

We consider an industrial building or a commercial unit, whose electricity bill H is the summation of energy charge and peak demand charge.

$$H = H^{elec} + H^{peak} = \alpha_{elec} \int_{T_0}^{T} r(t)dt + \alpha_{peak} \max_{t=T_0 \ldots T} [r(t)] = \alpha_{elec} \int_{T_0}^{T} r(t)dt + \alpha_{peak} r_{peak}(t) \quad (1)$$

where, α_{elec} (\$/MWh): energy price, r(t): power consumed at time t,

α_{peak} (\$/MW): peak demand price, r_{peak}(t): power consumed at t over 15 or 30 minutes [8, 9]

2.2 Peak Shaving

Peak demand charges can significantly increase the electricity bill. Smoothing these peak demands represents one of the best ways for reducing electricity cost. Several techniques have been developed and proposed in the literature for peak shaving: using energy storage [10], load shifting and balancing [11]. In this study, we consider a set of N EVs, each having one mobile battery energy storage system (MBESS), which can be connected to the grid via fast bidirectional chargers installed in the parking lot of a commercial building. The MBESS can discharge energy to the grid when it is connected and electrical demand is high and charge in other times to smooth building's consumption profiles.

Let's define $b_n(t)$ as the power injected from the n^{th} MBESS at a given time t when it is connected to the grid. Note that $b_n(t) > 0$ for discharging, $b_n(t) < 0$ for charging. The total adjusted electricity bill H^a is given by Equation 2.

$$H^a = \alpha_{elec} \int_{T_0}^{T} [r(t) - \sum_{n=1}^{N} b_n(t)]dt + \alpha_{peak} \max_{t=T_0 \dots T} [r(t) - \sum_{n=1}^{N} \overline{b}_n(t)] + \sum_{n=1}^{N} f(b_n) \quad (2)$$

where, r(t): power consumed at time t, $r_a(t) = r(t) - \sum_{n=1}^{N} b(t)$: actual power recorded when the N EVs are connected to the grid, $\overline{b}_n(t)$: average power injected from the n^{th} battery, and $f(b_n)$: operating cost of the n^{th} battery

2.3 Frequency Regulation

In addition to peak shaving, we also consider using MBESS for frequency regulation market. We use a simplified version of the Pennsylvania, New Jersey, and Maryland (PJM) frequency regulation market [12]. The revenue for providing frequency regulation service over time T is:

$$S = \alpha_c CT - \alpha_{\min} \int_{T_0}^{T} | \sum_{n=1}^{N} b_n(t) - Cs(t) | dt - \sum_{n=1}^{N} f(b_n) \quad (3)$$

In Equation 3, $f(b_n)$ is the operating cost of the MBESS and s(t) is the normalized frequency regulation signal. Compared with traditional frequency regulation signals, it has a much faster ramping rate and is designed to have a zero-mean within a certain time interval, which is well aligned with the characteristics of MBESS. Note that, for providing frequency regulation service, the grid operator pays a per-MW option fee α to a resource withstand-by power capacity C for each hour. While during the frequency regulation procurement period, the resource is subjected to a per-MWh regulation mismatch penalty (α) for the absolute error between the instructed dispatch and the resource's actual response [12].

2.4 MBESS Cell Degradation

A vital element in the operational planning of MBESS is their operating cost, a majority of which comes from the degradation of MBESS cells subjected to repeated charge and discharge cycles:

$$f(b_n) = \frac{\lambda_{cell}^{n} .10^6}{2K_n (SoC_{\max}^{n} - SoC_{\min}^{n})} | b_n(t) | \quad (4)$$

In this study, as in [8] and [13], the degradation of the n^{th} MBESS is modelled using Equation 4. In Equation 4, λ_{cell}^{n} is the n^{th} MBESS cell price (\$/Wh) and K_n is the number of cycles that the n^{th} MBESS could be operated within.

2.5 Problem Formulation

Our goals in this study are to reduce the total energy cost H for EV and building owners through the optimized control strategy and to find the SoC optimal range of EV batteries under which the battery degradation rate will be slow, while providing building load supply when necessary, powertrain for the EV, peak shaving and frequency regulation services simultaneously.

3 Multi-objective Optimization and Control Strategy

The optimization scheme and element of the control algorithm are described below.

3.1 Multi-objective Optimization

We considered using the EV batteries for load management (house load, building load and powertrain) but also to provide frequency regulation (building/grid) service and peak shaving. The total energy cost (electricity bill) for an EV owner can be minimized by using multi-objective optimization and control strategy to minimize the EV battery degradation and maximize the gain from EV battery energy sold to building owners. The battery degradation also has significant correlation with the level of State of Charge (SoC) during battery cycling, requiring the careful control of SoC in the range between SoC_{min} and SOC_{max} preferable for long cycle life of EV batteries.

The electricity bill for a building owner can be reduced by increasing ancillary service revenue obtained from connected electric vehicles, but it is required to consider reimbursement to EV owners and electricity cost fluctuation from utilities or grid operator. Equation 5 mathematically describes a multi-objective optimization problem with the goal to find a middle ground where all the involved parties can agree.

$$H^{multi} = \min_{c_n, b_n^{ch}(t), b_n^{dc}(t), y(t), N} H^a - \lambda_c T \sum_{n=1}^{N} c_n - \lambda_{\min} \int_{t=T_0}^{T} |-r(t) + \sum_{n=1}^{N} b_n(t) + y(t) - \sum_{n=1}^{N} c_n s(t)| \, dt \tag{5}$$

Such that:

$$b_n(t) = b_n^{dc}(t) - b_n^{ch}(t), \tag{6}$$

$$\sum_{n=1}^{N} c_n \geq 0 \tag{7}$$

$$SoC_{\min}^n \leq \frac{SoC_{ini}^n + \int_{\tau}^{t} [b_n^{ch}(\tau)\eta_c - \frac{b_n^{dc}}{\eta_d}] d\tau}{E} \leq SoC_{\max}^n \tag{8}$$

$$0 \leq b_n^{ch}(t) \leq P_{\max}^n \tag{9}$$

$$0 \leq b_n^{dc}(t) \leq P_{\max}^n \tag{10}$$

Most of the constraints are on the EV owner side. On the building owner side, as in [8], the multi-objective optimization model should capture both the uncertainties of future demand r(t) and future frequency regulation signals s(t). The objective function (5) minimizes the total electricity cost of a commercial user for the next day, including the energy cost, peak demand charge, and EV battery degradation cost and frequency regulation service revenue. Unlike [8], optimization variables considered at the EV level are frequency regulation capacity c_n of each EV, battery charging/discharging power $b_n^{dc}(t), b_n^{ch}(t)$ of each EV, number of EVs N connected at a given time t, and frequency regulation load baseline $y(t)$. Participants in frequency regulation market should report a baseline y(t) to the grid operator ahead of their service time [12]. For a commercial user, the baseline y(t) is its load forecasting including the projected driving patterns of the EV owners.

3.2 Control Strategy

For simulation purposes, several scenarios/hypotheses are considered in our control strategy: EV connection to the grid, EV driver's behavior and SoC operation limits. We assumed that when the EV is used as stationary, the EV is at a parking lot and connected to the grid for peak shaving and frequency regulation, and the multi-objective optimization framework is applied. When the EV is used as mobile, it is not connected to the grid and it is been driven by its owner to go to work, to come back home or to run some errands. We also assumed that when EV at home, they can be used for house load management, and that the batteries get charge overnight every day during off-peak period, and leave every morning fully charge to the maximum SoC defined. Furthermore, in this study, the SoCs of the batteries are kept within different operating limits. We considered 5 EV users working at the same building with different driving profiles and SoC limits for providing the same ancillary services. EV_1 = [10% -90 %], EV_2 = [20% -90%], EV_3 = [30% -90%], EV_4 = [40%-90%], and EV_5 = [50% -90%] = [SoC_{min} - SoC_{max}]. The main difference among the users is their driving profiles as shown by their SoC limits. The SoC limits are correlated to the driving distance to and from work for each EV user.

4 Results and Discussion

In order to verify the proposed control algorithm for V2B/V2G application, a small residential house with an electricity consumption of 26kWh/day, a commercial unit with an electricity consumption of 70kWh/day and 5 EVs having a battery storage capacity of 24 kWh per EV have been utilized for simulation on battery degradation and electricity bill estimation. The results are obtained using Matlab/Simulink and can be applicable to any larger buildings with a fleet of EVs by multiplication and additional detailed adjustment.

4.1 Electricity Bill for EV Owner and Household

For each EV user, we assumed a fixed driving profile over a period of 10+years. The MBESS of the n^{th} user can be used for household load, building load, and driving purposes. Figure 1 shows the Simulink schema of an EV with V2H, driving, V2B/V2G and charging, Figure 2 shows the daily simulation profile of EV4 = [40%-90%]. Simulated battery degradation for various driving patterns and SoC limits of EVs over the period is shown in Figure 3. The deeper the depth of battery discharge is used, the more the battery degradation is pronounced. Short commute driving habit, EV5 with a SoC range between 50% and 90% shows the lowest battery degradation.

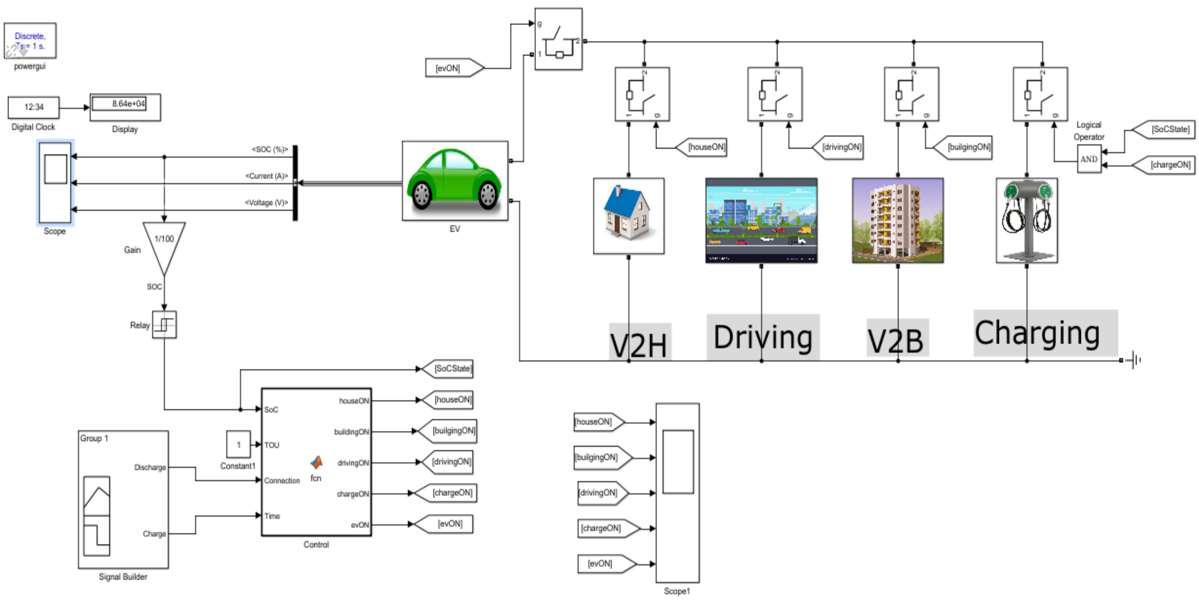

Figure 1: Simulink schema of an EV with V2H, driving, V2B/V2G and charging.

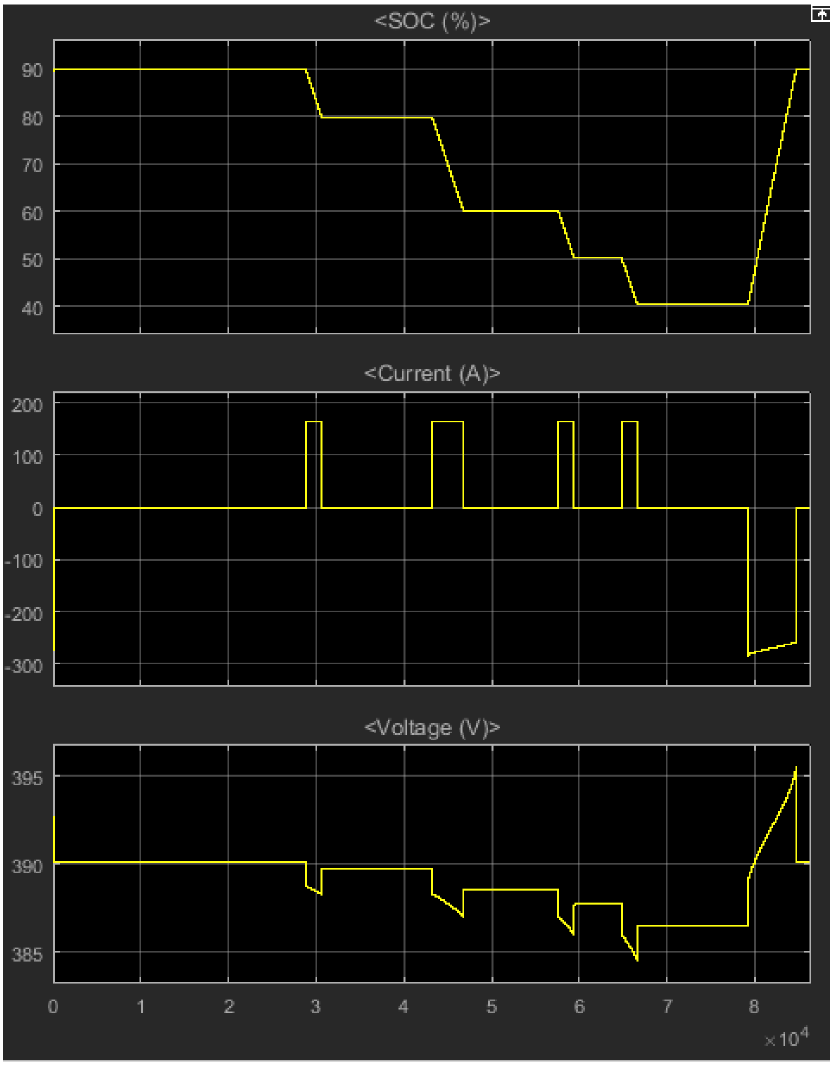

Figure 2: Daily SoC simulation profile of EV4 = [40%-90%].

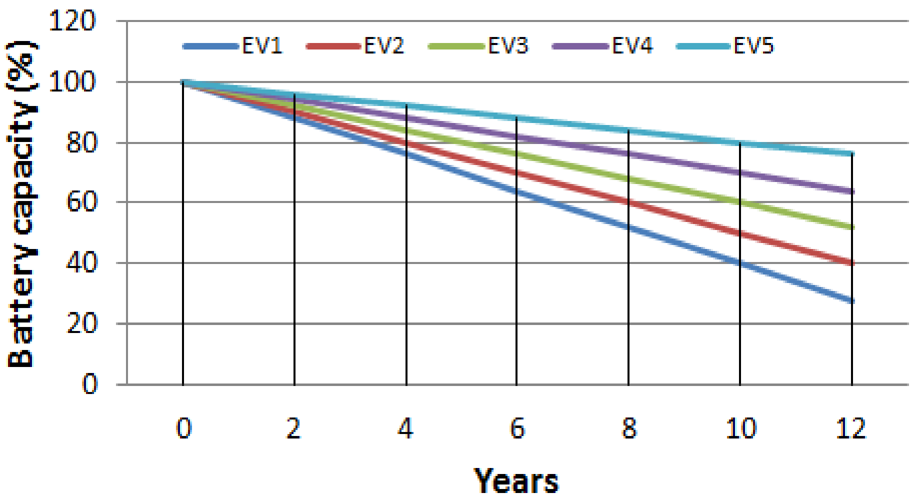

Figure 3: Battery degradation for various driving patterns and SoC limits: EV1 = [10% -90 %], EV2 = [20% -90%], EV3 = [30% -90%], EV4 = [40%-90%], and EV5 = [50% -90%].

Figure 4 shows the comparison of the original bill normalized to 1 with simulated bills after frequency regulation only, peak shaving only and combined peak shaving and frequency regulation, for each of the SoC operation range considered above. Electricity bills to be paid by EV owners after reflecting reimbursement for ancillary services were compared.

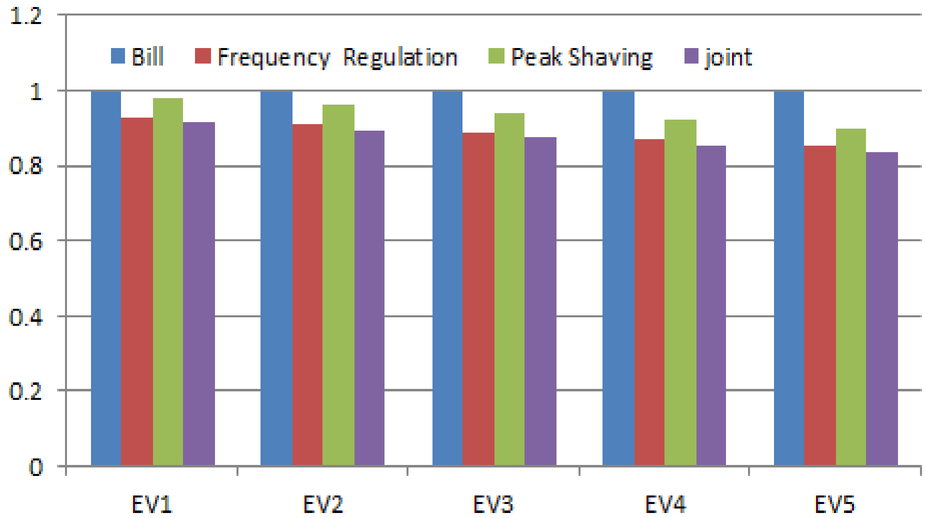

Figure 4: Comparative analysis of the original bill normalized to 1 with electricity bills to be paid by EV owner after frequency regulation, peak shaving, and combination of peak shaving and frequency regulation under different SoC limits.

4.2 Electricity Bill for Building Owner

On the Building owner side, we assumed that 5 EVs are connected during working hours to provide a fixed amount of power or energy in each day to a building owner for peak shaving and frequency regulation service. Figure 5 shows the Simulink model for the building owner. Figure 6 shows the simulated electricity bills under different scenarios.

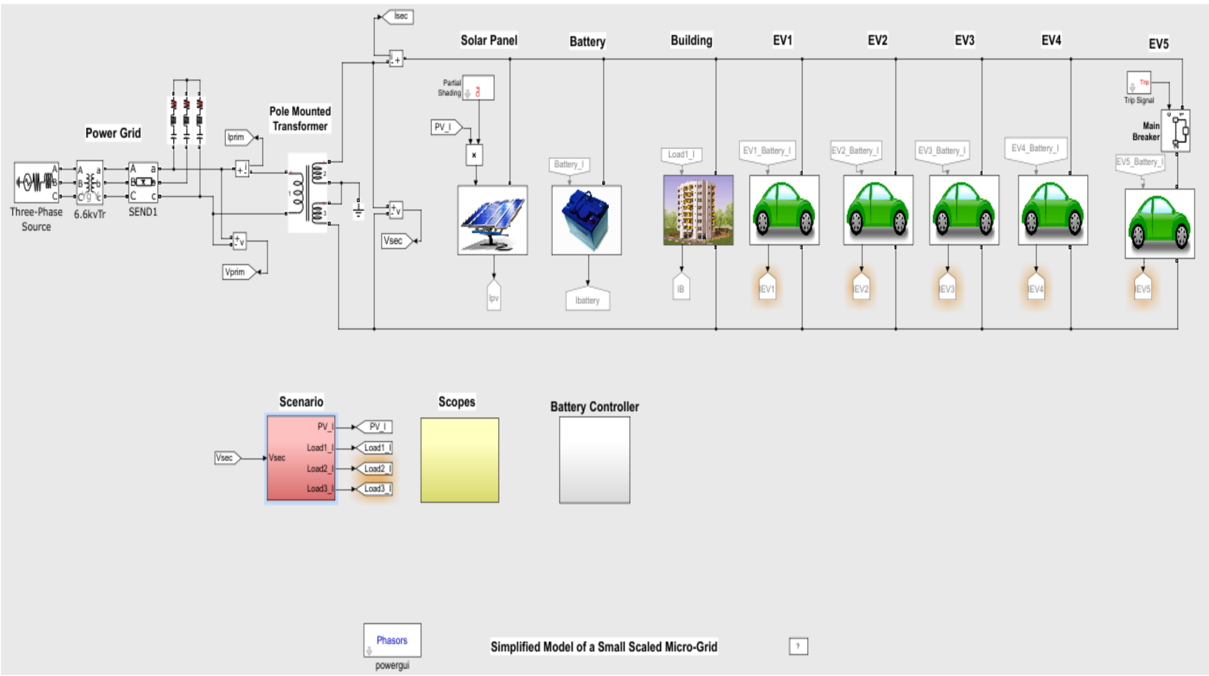

Figure 5: Simulink model for building owner

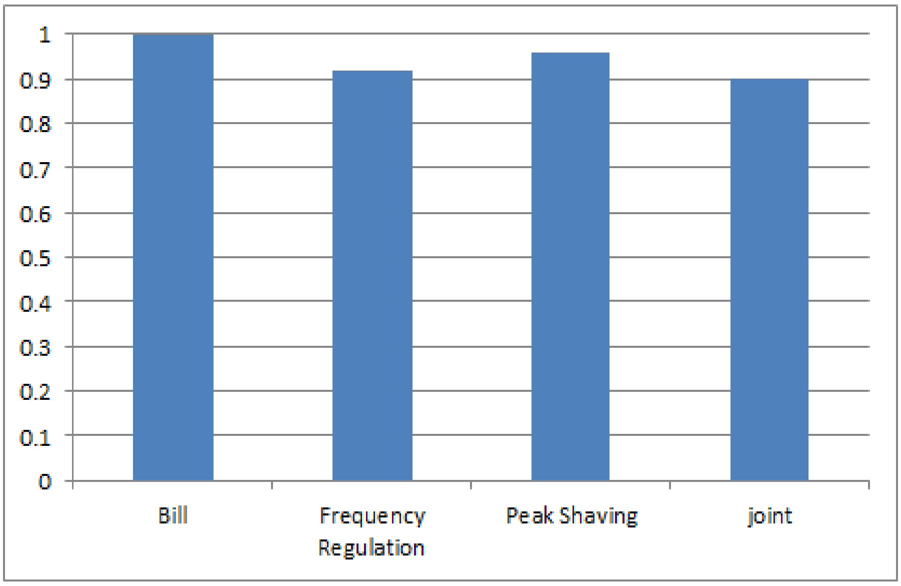

Figure 6: Comparative analysis of the original bill normalized to 1 with electricity bills for the building owner after frequency regulation, peak shaving, and combination of peak shaving and frequency regulation

5 Conclusions

In this paper, we present a multi-objective strategy using EV batteries not only for V2B (building load and powertrain) application, but also for reducing the peak demand charge and gaining revenue from participating in frequency regulation market as V2G. We formulated a multi-objective optimization framework for battery usage for the above applications. Comparative analysis with previous works that used battery storage systems for either peak shaving or frequency regulation showed that EV batteries can also achieve superior economic benefits under controlled SOC limits.

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References

[1] "Electric Vehicle Outlook 2017", Bloomberg New Energy Finance, July 2017.
[2] Pike Research a Part of Navigan. Report on Vehicle to Building Technology, 2012.
[3] Tesla Motors, "Tesla Model S Specifications". [Online]. Available:https://www.teslamotors.com/en_CA/support/model-s-specifications, (last access: 30 September 2015).
[4] R. Walawalkar, J. Apt, and R. Mancini, "Economics of electric energy storage for energy arbitrage and regulation in new york," *Energy Policy*, vol. 35, no. 4, pp. 2558–2568, 2007.
[5] C. D. White and K. M. Zhang, "Using vehicle-to-grid technology for frequency regulation and peak-load reduction," *Journal of Power Sources*, vol. 196, no. 8, pp. 3972–3980, 2011.
[6] X. Xi, R. Sioshansi, and V. Marano, "A stochastic dynamic programming model for co-optimization of distributed energy storage," *Energy Systems*, vol. 5, no. 3, pp. 475–505, 2014.
[7] B. Cheng and W. Powell, "Co-optimizing battery storage for the frequency regulation and energy arbitrage using multi-scale dynamic programming," *IEEE Transactions on Smart Grid*, 2016.
[8] S. Yuanyuan, X. Bolun, W. Di, Z. Baosen."Using battery storage for peak shaving and frequency regulation: joint optimization for superlinear gains," arXiv: 1702.08065v3, 2017.
[9] Intro to demand charge management [https://www.civicsolar.com]
[10] S. Lukas, E. Lobato, and L. Rouco, "Energy storage systems providing primary reserve and peak shaving in small isolated power systems: an economic assessment," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 675–683, December 2013.

[11] D. Caprino, M. L. D. Vedova, and T. Facchinetti, “Peak shaving through real-time scheduling of household appliances,” *Energy and Buildings*, vol. 75, pp. 133–148, June 2014.
[12] B. Xu, Y. Dvorkin, D. S. Kirschen, C. A. Silva-Monroy, and J. P. Watson, “A comparison of policies on the participation of storage in us frequency regulation markets,” in *In Power and Energy Society General Meeting (PESGM)*, 2016.
[13] Y. Guo and Y. Fang, “Electricity cost saving strategy in data centers by using energy storage,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, pp. 1149–1160, June 2013.

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