INVITED PAPER

Electric Vehicles for Smart Buildings: A Survey on Applications, Energy Management Methods, and Battery Degradation

This article focuses on different vehicle-to-building (V2B) application ideas and reviews energy management methods in smart buildings with V2B integration.

By Shima Nazari, Francesco Borrelli, *Fellow IEEE*, and Anna Stefanopoulou, *Fellow IEEE*

ABSTRACT | Plug-in electric vehicles (PEVs) have the highest promise for dramatically reducing transportation emissions. No other option has comparable emission reduction potential or as a promising pathway. Still, PEVs can offer more than green transportation. In particular, their onboard storage can further serve the society by providing an energy buffer to increase the reliability, affordability, and sustainability of electric services. These benefits are only achievable by fully exploiting the multifaceted flexibility provided by PEVs' mobility, charging adaptability, and bidirectional flow of power, as well as adopting effective decision-making and control algorithms, while minding the likely unfavorable side effects, such as shortened battery life span. This work takes a closer look at different elements of this puzzle. The main subject of this survey is behind the meter energy management with vehicle to building (V2B). We focus on different V2B application ideas and review energy management methods in smart buildings with V2B integration. Recent findings on battery capacity fade resulting from the bidirectional flow of power and extra discharging cycles with V2B are reviewed, and the methods for integrating the battery degradation in energy management formulation are discussed. Finally, the main findings of this review and research gaps are summarized and clarified.

KEYWORDS | Battery degradation; building energy management; electric vehicle; vehicle to building (V2B).

I. INTRODUCTION

Electric vehicles are a promising solution to meet the growing environmental concerns and the increasing energy challenge [1]. They allow the integration of green and renewable energy resources into the transportation sector, which is traditionally powered by fossil fuels. However, the rapid development of electric vehicles can impose a significant challenge on the power grid [2], [3]. Intelligent charging algorithms and bidirectional flow of power from/to the vehicles can transform this challenge to new opportunities to further benefit the society and environment by decreasing the total cost of ownership of electric vehicles and increasing the stability and sustainability of the power grid [4], [5]. Plug-in electric vehicles (PEVs) can play a pivotal role as dispersed energy storage units in the emerging concepts of smart grid and smart homes.

Manuscript received August 14, 2020; revised October 23, 2020; accepted November 10, 2020. Date of publication December 9, 2020; date of current version May 20, 2021. *(Corresponding author: Shima Nazari.)*

Shima Nazari is with the Department of Mechanical and Aerospace Engineering, University of California at Davis (UC Davis), Davis, CA 95616 USA (e-mail: snazari@ucdavis.edu).
Francesco Borrelli is with the Department of Mechanical Engineering, University of California at Berkeley (UC Berkeley), Berkeley, CA 94720 USA (e-mail: fborrelli@berkeley.edu).
Anna Stefanopoulou is with the Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48105 USA (e-mail: annastef@umich.edu).

Digital Object Identifier 10.1109/JPROC.2020.3038585

The benefits of the bidirectional flow of power from PEVs' battery to the grid, known as V2G, are comprehensively discussed in the literature [6]–[10]. Andersen *et al.* [11] compared different aspects of three V2G integration projects, and a summary of 50 most recent V2G implementation projects around the world can be found in [12]. The most studied applications are peak power supply [13], [14], frequency regulation [15]–[18], contingency reserves [14], [19], and utility-scale renewable integration [20], [21]. It is found that V2G is economically profitable particularly for applications such as frequency regulation that requires fast response time or spinning reserve that demands standby power supply capacity [14], [17], [19]. Yet, a large number of PEVs have to be deployed and coordinated for V2G in order to have any meaningful impact on the grid, given that the utility-scale electricity generation capacity was 1.1 TW in the United States in 2019 [22], while the average rated power of a light-duty vehicle (LDV) is only 180 kW [23]. The above studies are all based on the premise of considerable electrification of the LDV fleet, which has a size of around 250 million vehicles in the United States [24], for example. This assumption is far from the reality of 1.2 million on-road PEVs in the United States in 2019 [25]. Furthermore, implementing V2G requires significant modification to the grid infrastructure and communication, as well as control and aggregation algorithms [26].

Vehicle to building, called V2B, enables using the PEV battery for behind the meter energy management of a smart building with minimum complexity. The practicality of V2B from hardware and low-level control point of view is demonstrated in the literature [27], and bidirectional chargers are commercially available and compatible with some Nissan and Mitsubishi vehicle models [28]. V2B does not need any grid infrastructure or large-scale communication upgrade, and the PEV user can enable it by simply plugging in the vehicle. V2B is practical even with a single PEV and can be more energy efficient due to no transmission loss [26], [29]. Vehicle to home (V2H) is a subcategory of V2B, in which one or more PEVs are used to facilitate the energy management of a residential building. Large-scale adoption of V2H and V2B allows improved utilization of generating capacity and increases the stability and reliability of the grid by reducing the peak load and enabling distributed generation and self-consumption of the buildings [4], [30].

The application of battery storage systems for behind the meter energy management of buildings has been investigated in the literature [31]–[36]. However, there are some fundamental differences between using stationary batteries for energy storage versus using PEV batteries. While the cost-effectiveness of stationary batteries for distributed and residential electricity services continues to improve [37], V2B reduces the battery capital cost by adopting the existing batteries in PEVs and, thus, can be more economically appealing. V2B couples the energy management of the building to the transportation of its occupants, managing the inherent conflict since the vehicle is not available all day for energy storage and has to maintain enough charge for transportation. On the other hand, the vehicle mobility permits transporting the stored energy in the battery, possibly from green sources, or a more stable grid. The building energy management system (BEMS) has to account for these constraints and the extra flexibility to fully exploit the V2B capacity to improve the building power service efficiency and reliability. Finally, battery degradation is a primary concern for the V2B application because the capacity fade from the degradation reduces the vehicle driving range and can escalate the charge anxiety of drivers.

This work focuses on the vehicle to building and vehicle to home (both addressed as V2B here) for behind the meter energy management of homes and buildings. There are some conceptual similarities in energy management of smart buildings and hybrid electric vehicles (HEVs), which is broadly explored in the literature [38], because they both deal with optimal resource allocation with more than one energy source. However, smart buildings usually have very diverse components, and the generation of renewables is usually uncontrolled with uncertain predictions. Moreover, flexible appliances, such as HVAC and washer, and intricate electricity tariffs, such as demand charge or time of use energy tariffs, further increase the complexity of BEMS. V2B has to deal with the additional uncertainty in vehicle mobility and accessibility and keeping enough charge in the battery for the transportation needs of the driver, which again complicates the BEMS.

Unlike V2G, V2B is less studied in the literature. Hence, first, a survey on applications and novel ideas for V2B is presented. The second part of this study briefly reviews energy management algorithms for V2B, with an emphasis on vehicle mobility. Both optimization-based methods and rule-based methods are covered. The last part of the work reviews the most recent findings on V2B influence on battery capacity fade, and the methods for including capacity loss concerns in energy management are discussed.

II. VEHICLE-TO-BUILDING APPLICATIONS

Electric vehicles are operated as a traditional load, and their interaction with buildings is limited to simple charging or delayed/overnight charging. However, as the market penetration of these vehicles grows, the high power necessary for dc fast charging (DCFC) outlets (as high as 1+ MW [39]) can impose substantial challenges on the power grid and jeopardize its stability and reliability by voltage deviation and saturation of transformers and lines [2], [3]. Smart charging algorithms and bidirectional flow of power between the building and the vehicle battery can transform this challenge to new opportunities for a more efficient, resilient, and cheaper power service. Fig. 1 shows a schematic of the V2B layout in a smart home. In this figure, we highlight new smart building elements, including battery storage and local renewable energy generation.

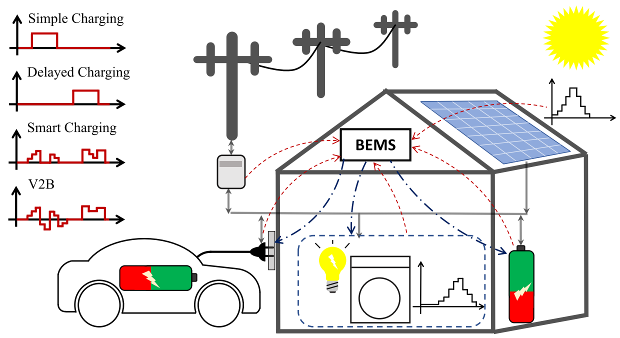

Fig. 1. ***Smart building microgrid with V2B, PV generation, and BESS. BEMS receives data from the smart meter and other system elements and schedules the controllable building loads and V2B and BESS power.***

This section briefly reviews the opportunities provided by smart control of PEV power during plug-in times. In this work, PEV is used to refer to both plug-in HEVs (PHEVs) and electric vehicles, and when differentiation is necessary, the sentence is clarified.

A. Unidirectional Charging

Smart charging algorithms modify the timing and power of charging to minimize the charging cost or the entire building electricity expense. A broad review of smart charging algorithms is presented in the literature [10], [40]. Passive smart charging methods charge the vehicle during off-peak price hours, overnight for example, without considering the building demand. Active charging approaches, on the other hand, treat the vehicle as a flexible load and systematically control both the charging power and timing to fulfill different operational objectives. Active charging can reduce both the energy and demand charges by monitoring the electricity prices and the building demand and adjusting the PEV charging power accordingly. Smart charging strategies can extend the battery life too [41], resulting in more savings for the owners. Furthermore, these algorithms can be used to increase the self-consumption of distributed energy resources (DERs), such as photovoltaic (PV) generation and enhance the sustainability of buildings [42]–[44].

Smart charging algorithms are especially important for DCFC stations, in which high power demand can increase the costs significantly. In [45]–[47], it is found that colocation with buildings and stationary battery storage can significantly reduce demand charges, while PV generation in areas with expensive energy is recommended. Smart charging methods can integrate all these elements in a DCFC station and further reduce costs.

B. Bidirectional Charging

Bidirectional charging, or V2B, allows discharging the vehicle battery while plugged in to feed the building loads or even selling energy back to the grid. In the literature, V2B is usually deployed within a building microgrid in coordination with stationary battery energy storage systems (BESSs), flexible building loads, and one or more DERs, such as PV, wind, combined heat and power (CHP) system, and combined cooling heat and power (CCHP) system. Table 1 presents a summary of smart building components that are integrated with V2B in the literature. Flexible loads in Table 1 include shiftable loads, such as dishwasher, controllable loads, such as HVAC, and thermal storage systems, such as hot and chilled water tanks. The majority of literature studies V2B along with PV generation and BESS. V2B provides valuable flexibility for improving different aspects of a smart building performance [64]. The most relevant ones are explained in the following.

1) Electricity Cost Reduction: The electricity bill usually consists of three parts: energy cost, demand cost, and fixed costs. The energy tariffs vary by time of use, and the cost is higher during on-peak hours (4:00–9:00 P.M. of each day for example). PEVs can decrease the energy cost of a building by discharging the energy stored in their batteries to the building and, hence, limiting the energy purchase during on-peak hours [48], [73]. This process is also known as peak shifting.

The demand charge is proportional to the maximum load power over the billing cycle. The maximum power is usually the average value over some time interval (often 15 or 30 min). The demand charge can be substantial for commercial buildings because it is tied to the grid infrastructure capacity. V2B can curtail the demand charge by discharging its battery when the building has high power consumption to restrict the peak load from the grid. Peak load reduction, known as peak shaving, is addressed for both residential and commercial buildings in [49], [51], [77], [94], and [95].

Both peak shifting and peak shaving can be easily implemented with a simple control structure for homes [77]; however, it has been shown that long daily commutes that utilize the majority of the vehicle range undermine the V2B effectiveness [49], [96]. Commercial buildings, on the other hand, might need aggregated services and financial incentives to encourage the vehicles parked in their parking or a nearby smart garage to participate in V2B [48], [97]. In this case, a real-time capacity projection might also be necessary to ensure that the optimal amount of energy from PEVs is used without influencing the requirements of the drivers [98].

Table 1 Summary of Smart Home Components That Are Integrated With V2B in the Literature

Microgrid components	Article
No integration	[48]–[54]
Flexible loads	[55]–[71]
Stationary battery	[56], [57], [62]–[64], [68]–[86]
PV	[55]–[66], [68]–[91]
Wind	[56], [64], [75], [91]–[93]
CHP/CCHP/PGU	[55], [56], [60], [63], [65], [66], [70], [71]

Electricity services occasionally can be very expensive when there is no fixed price contract. The price spikes, which can be up to 100 times of regular price [99], occur when the grid is not balanced. These price spikes are different from on-peak/off-peak pricing and only take place a few times per year. Zhang and Li [100] proposed using V2B to reduce the energy cost during these spikes. Prediction of price spikes timing is critical to effectively curtail the cost. Zhang and Li [100] assert that the price spikes happen repeatedly over several hours and use a hidden Markov model for price regime identification. They also exploit a risk management strategy to keep a certain amount of energy stored in the PEV batteries and reduce the loss due to the following spikes.

Another novel idea in this area is using electrified cars in ride-sharing services, such as Uber and Lyft, to provide electricity services in addition to transportation services [101], [102]. Commercial and residential buildings can request electricity services when they anticipate a high demand, and the drivers can choose whether to provide transportation or electricity service based on the offered incentives. Both these works deal with the pricing problem, and it is shown that these dual-function benefits transportation services too by reducing their spatial imbalance. The mobile battery storage system, in which batteries are stacked on the back of a truck and can move between buildings to provide electricity services, follows the same idea [103].

2) Self-Sufficient Buildings: Decreasing the electricity cost does not directly translate into the reduction of consumed energy or emissions. In fact, the energy loss from charging and discharging of the battery will increase both [30], [104] if V2B is not coupled with renewable energy sources. V2B can provide an energy buffer necessary for integrating intermittent renewable sources. As seen in Table 1, many articles studied the integration of V2B with PV and wind. CHP/CCHP can also reduce energy consumption and emissions, despite being less efficient in electricity production compared with large power generation units, because they use the exhaust heat of their small gas turbines. All DERs obtain grid energy reduction, even when electricity cost reduction was the main objective in the literature [50], [57]–[59], [61], [63], [73], [75], [77]. Reducing carbon emissions of the microgrid, as an objective of BEMS, is an alternative indirect way to increase the self-consumption of local DERs pursued by some researchers [60], [65], [79], [105].

Net or nearly zero-energy building (ZEB) refers to high-energy-performance buildings that need no or little energy from the grid. This objective is achieved by efficient and sustainable design, as well as integrating renewable DERs [106], [107]. V2B can have a central role in future ZEBs by reducing their grid dependence and increasing DERs self-consumption [72], [78].

Barone *et al.* [72] investigated the energy consumption of a microgrid comprised of single-family housing, an office, and a PEV. This work assumes that the PEV travels 13 km each way between the house and the office and is plugged in at the office during work hours. Otherwise, the car is either commuting or plugged in at home. It is shown that, with PV panels on the house roof, BESS, and V2B, the microgrid energy consumption from the grid reduces by 47.9%, and even without energy storage and with PV panels on the office building (instead of the house), the grid-supplied energy to the microgrid reduces by 44.5%. In both these cases, the PEV acts as an energy vector, carrying the renewable energy produced by PV between the two buildings. Battery swapping is also considered in this work. It is shown that the capability to swap the stationary and the PEV battery reduces the energy input from the grid from 47.9% to 77.0% for the case with PV panels on the house. In this work, the cooperation between the two buildings (house and office) plays a major role in increasing the effectiveness of V2B and self-consumption of PV; however, Salpakari *et al.* [58] showed that this benefit declines for a larger number of houses and saturates at around three to five collaborating houses.

3) Backup Power: The bidirectional flow of power from PEVs can also improve the reliability of building electricity service by providing emergency backup power and uninterruptible power services [4], [48], [52], [80]. The backup power services will be prolonged if the building is equipped with PV panels [87] or if the PEV includes an internal combustion engine as in PHEVs [89]. In the latter case, an optimal energy management system (EMS) is necessary to find the right power split ratio between the engine and the battery and maximize the backup power duration.

III. ENERGY MANAGEMENT ALGORITHMS

Building energy management methods can be categorized in different ways. In this article, we classify them based on the approach that they use to make decisions, which can be heuristics or by solving an optimization problem. The decision can be made for the day-ahead horizon or in real time, and optimization-based schemes can have a deterministic or stochastic formulation. Furthermore, the decisions can be made in a centralized or a decentralized way if more than one agent (i.e., building, charging station, PEV, and so on) are included in decision-making. In the next sections, first, rule-based methods are introduced, followed by optimization-based approaches. Both deterministic and stochastic optimization methods are reviewed, and the constraints that couple the vehicle mobility to building energy management are elaborated in detail.

A. Rule-Based Energy Management Systems

Rule-based EMSs are real time and based on simple heuristics. These rules are usually designed for a specific objective and a specific system, for example, for maximizing the self-consumption of local DERs [72] or peak shaving [77]. Therefore, a different system or a different

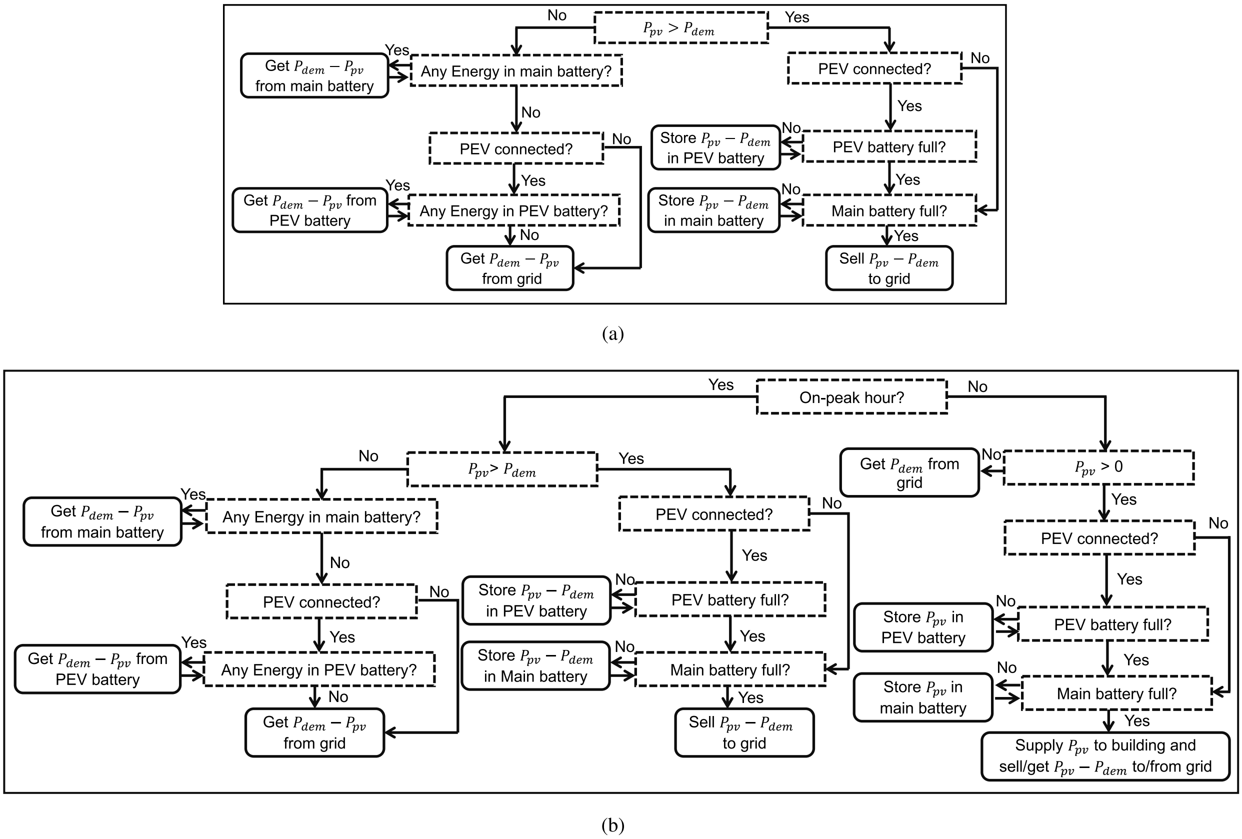

Fig. 2. ***Examples of rule-based BEMS (a) from [78] and (b) from [64].***

objective requires the redesign of the rules. In general, rule-based EMSs do not fully exploit the system flexibility to produce an optimal solution. However, for a simple electricity tariff structure, an optimal energy management strategy can be estimated heuristically. For example, if the ratio of off-peak energy price, C^{OFF}, to on-peak energy price, C^{ON}, is less than the battery and charger round-trip efficiency, η_r $((C^{\mathrm{OFF}}/C^{\mathrm{ON}}) < \eta_r)$, then it is profitable to charge the battery during off-peak hours and discharge it during on-peak hours. Similarly, if it is possible to sell the energy back to the grid and the ratio of off-peak energy price to the energy selling price during on-peak hours, C^{sell}, is less than the battery and charger round-trip efficiency $((C^{\mathrm{OFF}}/C^{\mathrm{sell}}) < \eta_r)$, then the grid customers can make a profit by charging the battery during off-peak hours and selling electricity to the grid during peak hours. Starting from this principle, Turker and Bacha [108] proposed an energy management algorithm for V2B that closes time slots with a high price at the lowest state-of-charge (SOC) level and closes the cheap time slots with the highest SOC. This strategy might not be optimal in the presence of demand charge, for example, because the increased demand during off-peak hours can increase the operating cost.

Another example of rule-based algorithms for energy management of a net ZEB with PV, BESS, and V2B is proposed by Alirezaei *et al.* [78] to maximize the self-consumption of the PV. Fig. 2(a) sketches the algorithm. When the vehicle is plugged in, if the PV generation, P_{pv}, is larger than the building energy consumption, P_{dem}, the BEMS stores the excess energy in the vehicle battery. If the PEV battery is fully charged, then it stores the extra generated energy in the BESS (main battery), and it eventually sells the surplus energy to the grid when both batteries are full. At any moment, if the PV power generation drops to less than the building power consumption, the extra power is supplied from the battery first, and if the BESS is fully depleted, then the PEV battery will be discharged. When both batteries are fully discharged, the required extra power is supplied by the grid.

The aforementioned algorithm maximizes the self-consumption of the PV at each time instant, its main deficiency is that it does not take into account the electricity tariffs variations during on-peak versus off-peak hours, and thus, it is not an effective algorithm for energy cost reduction. Zhou and Cao [64] proposed two alternative strategies to account for higher on-peak electricity price, one of which is shown in Fig. 2(b) [with small modifications compared with the original work for better comparison to Fig. 2(a)]. This algorithm stores all produced renewable electricity in the EV battery first and then in the stationary battery during off-peak hours and only uses the surplus energy to meet the building demand. The second alternative strategy, which is not shown here, uses the grid power in addition to PV generation to charge the batteries. During the on-peak hours, the strategies work exactly the same as the algorithm in Fig. 2(a).

Rule-based strategies are a group of "*if* ... *then* ... *else*" statements; hence, including all possible scenarios for transportation needs of the driver (neglected in both algorithms in Fig. 2), complex electricity tariffs, such as demand charge, and operational concerns, such as battery degradation, will make the algorithm very complicated. The increased complexity for a small adjustment in off-peak tariffs is clear in the algorithm shown in Fig. 2(b) compared with Fig. 2(a) as an example. Also, with the exception of very simple cases, the designer cannot guarantee whether the rule-based strategy produces the best possible outcome even with the most complex algorithms. Finally, the optimal energy management of a building is an acausal problem, meaning that the solution depends on the future user demand and future DERs generation. Although there are few rule-based algorithms that use preview information [92], exploiting forecasts is not usually adopted in these methods, and hence, they are less effective than optimization-based approaches. The recent advances in learning heuristics and control rules from optimization solutions can be used in the future to produce more effective rule-based strategies for complex systems [109], [110]. Despite these deficiencies, rule-based methods are deployable in cases where no preview data, advanced modeling, control, and communication infrastructures are available; therefore, they could be more cost-effective compare to optimization-based approaches discussed in the next section.

B. Optimization-Based Energy Management Systems

Optimization-based methods for behind the meter energy management exploit electricity resources most efficiently. However, optimization is only effective when there is some flexibility in the system. Little effort is reported in the literature to define and quantify the energy flexibility of buildings. Zhou and Cao [64] provided some methods to quantify the energy flexibility of a building. These definitions relate the flexibility to the amount of energy (either from the grid or DERs) stored during off-peak hours. In addition to storage devices, flexible loads, such as HVAC, or uncontrollable loads that can be shifted in time, such as dishwasher, can also add some elasticity to the system and, hence, provide optimization opportunity.

Generally, the components of a smart building model used in an optimization algorithm include the following.

1) *Local generation:* Local DERs, such as PV, wind, and CHP/CCHP produce electricity, to feed either the building or sell to the grid. The output power of CHP/CCHP can be controlled as an optimization variable, but PV and wind generation are not usually controllable and depend on weather conditions.
2) *Energy storage devices:* These usually include the stationary battery, PEV battery, and thermal storage, such as chilled and hot water tanks and building thermal mass. All these devices provide a bidirectional flow of energy.
3) *Loads:* Building loads include all kinds of devices that consume electricity. Loads can be uncontrollable, meaning that they have to be met immediately upon the user request, such as lighting, or controllable, meaning that either they can be shifting in time, such as dishwasher, or their power can be adjusted, such as HVAC and heating.

Table 2 Summary of Cost Functions With V2B in the Literature

Cost Function	Article
Energy cost	[50], [52], [53], [55]–[60], [62], [63], [74]–[76] [61], [65]–[71], [81]–[83], [86], [90]
Demand cost	[51], [53], [86]
Maintenance/installation cost	[56], [59], [61], [62], [75], [76], [81], [86]
Emissions	[60], [63], [65], [66], [71]
PEV battery degradation	[50], [53], [56], [58], [61], [62], [75], [86]
User disturbance/comfort	[52], [61], [67], [76], [86], [91]

In addition to modeling the above components, the BEMS depends on sensors and communication to provide feedback from the system state, such as indoor temperature, devices energy usage, DERs production, and batteries SOC. To familiarize the reader with optimal energy management of a smart building, next, we formulate an optimization problem for a house with PV, battery storage, and V2B, which is the most common architecture in the literature.

1) Objective Function: The objective function defines the optimization goal to be minimized

$$\min_{u} \Sigma_{k=1}^{K=N} L(u, x, w, k) \tag{1}$$

where u represents the optimization variables, x is the system state, w represents the exogenous inputs, N is the problem horizon, and L is the stage cost. L can include different terms, such as the net energy cost, the demand cost, emissions, user disturbance, and maintenance cost for different components, such as PV or battery degradation cost. Table 2 summarizes different costs adopted in the literature. PEV battery degradation is shown separately from other maintenance costs. For more complex cases that include more than one entity, such as connecting a charging station with a smart building, the energy transaction cost between different individuals has to be included [63]. Furthermore, when aggregation services are required to encourage the drivers to participle in V2B, the battery degradation cost is replaced by the incentives for PEV drivers [63], [76]. Finally, if some electricity is produced by a PHEV internal combustion engine or CHP/CCHP, the fuel cost has to be included as well.

2) Power Balance Constraint in the Microgrid: The electric power has to be in balance at all times on the microgrid, meaning that the supply and the demand must match. Next, we consider a simple energy balance model

$$P_{\text{dem}}(k) + S(k)P_{\text{pev}}(k) + P_{\text{grid}}(k) + P_{\text{pv}}(k) + P_{\text{bess}}(k) = 0, \quad k = 1, 2, \ldots, N \quad (2)$$

where P_{dem} is the power demand of the building, P_{pev} is the PEV power, P_{grid} is the grid power, P_{pv} is the PV generated power, P_{bess} is the power from stationary battery energy storage, and k refers to the k^{th} step time in the optimization horizon. The binary variable $S(k)$ is the PEV state and is equal to 1 only when plugged in

$$S(k) = \begin{cases} 1, & \text{if } t_{\text{in}} \le k \le t_{\text{out}} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where t_{in} is the PEV plug-in time and t_{out} is its plug-out time.

The PV generation forecast, P_{pv}, is an exogenous input to the optimization problem. However, an accurate prediction is not possible due to the uncertainty in weather conditions. The simplest method for predicting the PV output is to use the predicted solar radiance level, PV panels surface area, and generation efficiency, usually around 20% [65], [75]. Other methods include semiempirical models based on temperature and solar radiation [60], [70], [74], neural networks [79], [90], and available tools and applications, such as NREL's PVWatts [105], [111]. The uncertainty in the PV generation is modeled with different methods in the literature, such as bimodal distribution [65], two-point estimation method [55], or Gaussian distribution [56].

The building demand, P_{dem} in (2), includes energy usage from all sources except the PEV. It is possible to exploit the flexibility of building loads to improve energy management efficiency. Loads, such as HVAC and heating, can be controlled actively, while other loads, such as dishwasher and dryer, can be shifted over time. In both cases, detailed modeling of different loads is necessary, and in the former case, the building thermal model and its coupling to the electricity consumption have to be modeled too [56], [59]–[61], [67], [68], [105]. Nevertheless, this approach requires a massive amount of data and modeling and increases the BEMS complexity enormously [112]. Another approach, which does not take advantage of flexible loads, is to lump all loads together and use historical data and machine learning methods, such as neural networks to predict the building load demand [79], [90], while some probability distribution can be included to account for uncertainties [56], [59], [65].

3) Grid Constraints: At each time instance, the power received from or supplied to the grid is restricted by the building wiring and power electronics, as well as the contract with the electricity provider company

$$P_{\text{grid}}^{\min} \le P_{\text{grid}}(k) \le P_{\text{grid}}^{\max} \quad (4)$$

in which $P_{\text{grid}}^{\min}$ and $P_{\text{grid}}^{\max}$ are the minimum and maximum grid powers. For example, some grids might not allow supplying power to the grid; in that case, $P_{\text{grid}}^{\min} = 0$.

4) V2B Constraints: The V2B model comprises of four parts: 1) the state of energy (or charge) dynamics; 2) operation constraints; 3) PEV mobility model; and 4) battery degradation model, which will be discussed in detail in the last part of this work.

1) *SOC/energy dynamics:* The literature on smart buildings usually models the state of energy in the battery and not the SOC, or often the SOC and the state of energy are used interchangeably. The state of energy is modeled by adopting a simple efficiency value for charge/discharge of the PEV battery along with integration of power to track the stored energy in the battery

$$E_{\text{pev}}(k+1) = E_{\text{pev}}(k) + P_{\text{pev}}(k)\eta_{\text{pev}}^{-\text{sgn}(P_{\text{pev}})}\Delta t, \quad k = t_{\text{in}}, t_{\text{in}}+1, \ldots, t_{\text{out}}-1 \quad (5)$$

$$E_{\text{pev}}(t_{\text{in}}) = E_{\text{pev},i} \quad (6)$$

in which E_{pev} is the energy stored in the PEV battery, η_{pev} is the battery and charger efficiency, Δt is the problem step time, and $E_{\text{pev},i}$ is the battery energy at plug-in time. Sometimes different numbers are assumed for charging and discharging efficiencies [67], [84]. Unlike the equivalent circuit models [113] used for modeling the SOC evolution in energy management of hybrid and electric vehicles, this simplistic method does not compute the battery current and voltage that are necessary for precise battery internal loss estimation and more accurate battery degradation models. However, equivalent circuit models add nonlinearity to the optimization problem.

2) *Operation constraints:* The PEV power is restricted by its charger and power electronics, and the battery energy has to remain between its minimum and maximum energy capacities

$$P_{\text{pev}}^{\min} \le P_{\text{pev}}(k) \le P_{\text{pev}}^{\max}, \quad k = t_{\text{in}}, t_{\text{in}}+1, \ldots, t_{\text{out}}-1 \quad (7)$$

$$E_{\text{pev}}^{\min} \le E_{\text{pev}}(k) \le E_{\text{pev}}^{\max}, \quad k = t_{\text{in}}, t_{\text{in}}+1, \ldots, t_{\text{out}}. \quad (8)$$

The above equations assume that the vehicle only plugs in and out once a day. This implies that there has to be an additional constraint to ensure that there is sufficient energy left in the battery for transportation when the vehicle is unplugged

$$E_{\text{pev}}(t_{\text{out}}) \geq E_{\text{pev}}^{\text{out}}. \tag{9}$$

In some works, the desired stored energy at the departure time is added to the optimization cost function instead of including it as a constraint [85].

3) *PEV mobility model:* The PEV plug-in and plug-out times along with (6) and (9) couple the building energy management to the PEV mobility. Some studies simply assume that these parameters are known or specified by the user [55], [57], [61], [65], [67], [81], [83], [86]. However, such an assumption is naive, and expecting the PEV drivers to program such information into the BEMS every day is not reasonable. An alternative solution is to use stochastic approaches and historical data to model the vehicle mobility. For example, Wu *et al.* [90] used the Markov chains with temporal transition probability distributions to model the transition from plug-in to plug-out, and vice versa. The transition probabilities were built from historical data. This work modeled the battery energy at the plug-in time as a conditional distribution of the battery energy at unplugging time. Another work, which formulates optimal energy management for an office building [59], used uniform distribution for PEVs state of energy at home departure along with normal distributions for traveled distance and plug-in/plug-out time to model the PEVs' mobility. Lognormal distribution [79], [92] and truncated normal distribution [50] are among other methods used to model the uncertainty in PEV driving distance, the initial state of energy, and arrival and departure time.

In some studies, when the only flexible component of the system is the PEV battery, the energy management problem is only solved for the duration that the PEV is plugged in [52]. In this case, it is not necessary to model the vehicle arrival time and the initial battery energy; however, the departure time and the desired SOC level at departure have to be still modeled from historical data or specified by the user.

In addition to the PEV mobility and charging models in the V2B literature, as discussed earlier, a wide variety of models for PEV charging behavior are found across energy, transportation, and power sector literature. These modeling approaches are diverse in terms of both time scale and level of details. A comprehensive survey on PEV use and charging patterns is given by Daina *et al.* [114], where the authors classified the PEV mobility models to vehicle ownership and annual mileage models and short-period models. The latter in turn is categorized into summary travel statistics models [115], activity-based approaches [116], and the Markov chain models [117], [118]. Summary travel statistics models provide less spatial and temporal details; hence, they are not suitable for V2B planning. Both the activity-based models and the Markov chain models are applicable to V2B energy management problems because they model the PEV daily use and charging patterns. Most of the models discussed above, which use probability distributions for modeling the PEV mobility, are examples of activity-based models. Another example is presented in [119], which finds the probability distributions for electric taxis charging frequency, charging start time, and charging duration.

State-of-the-art PEV charging behavior models integrate social and economic parameters in addition to technical aspects for accurate results. For example, Chaudhari *et al.* [120] introduced an agent-based model (ABM) to get qualitative and quantitative insights into the charging behavior of PEV users, which can be used for infrastructure planning, such as optimal charging station placement. The ABM accounts for a vast variety of factors, such as initial and final SOC, PEV type, charging time, parking duration, range anxiety, and driver experience. A similar work [121] introduced a Markov-based probabilistic model that accounts for the driver's habits and behavioral characteristics in addition to the battery specifications and charge level to model PEV charging. These models that take into account a variety of factors, especially human behavior factors, can be adopted in future V2B developments for maximizing the effectiveness of energy management algorithms and minimizing the interference with the transportation needs of the driver.

5) *Stationary Battery Constraints:* Similar to the PEV battery constraints, the BESS has to maintain its power and energy within some limits, and its energy state is computed by including an efficiency number and integrating its power. Unlike the PEV battery, the stationary battery is available all day and does not have to keep enough charge for transportation purpose. A simple set of constraints is described next

$$P_{\text{bess}}^{\min} \leq P_{\text{bess}}(k) \leq P_{\text{bess}}^{\max}, \quad k = 1, 2, \ldots, N-1 \tag{10}$$

$$E_{\text{bess}}(k+1) = E_{\text{bess}}(k) + P_{\text{bess}}(k)\eta_{\text{bess}}^{-\text{sgn}(P_{\text{bess}})}\Delta t, \quad k = 1, 2, \ldots, N-1 \tag{11}$$

$$E(0) = E_{\text{bess},\, i} \tag{12}$$

$$E_{\text{bess}}^{\min} \leq E_{\text{bess}}(k) \leq E_{\text{bess}}^{\max}, \quad k = 1, 2, \ldots, N \tag{13}$$

in which $P_{\text{bess}}^{\max}$ and $P_{\text{bess}}^{\min}$ are the maximum and minimum battery powers, E_{bess} is the store energy in the battery, η_{bess} is the battery and its charger efficiency, $E_{\text{bess},\, i}$ is the initial battery energy, and $E_{\text{bess}}^{\max}$ and $E_{\text{bess}}^{\min}$ are the maximum and minimum battery energies.

6) *Energy Management Solution:* For the example presented in this part, the problem states are the state of

energy in the PEV and the stationary battery, the decision variables are the PEV and the BESS power, and the building load and PV generation are exogenous inputs. However, if the building flexible loads, such as HVAC, were included in the formulation, new states and decision variables have to be included. Constraints (2)–(13) are linear, and with a linear cost function, which can include the energy cost, maintenance cost, or some emission parameters, the above optimization problem converts to a mixed-integer linear program (MILP), which is the most common formulation in the literature [56], [57], [60], [63], [68]–[70], [75], [83], [86]. Nevertheless, nonlinear cost or constraints may appear if nonlinear models are used, for instance, by including a detailed battery degradation model [58], [62].

If uncertainties are included in the control problem design, then the optimization problem is affected by random variables. The choice of cost, constraints, and optimization space greatly varies in the literature, and it affects problem complexity and conservativeness. Average cost or min–max cost formulations are often used. Optimization of linear policies instead of over constant input sequences is also preferred. Finally, stochastic or robust programming approaches are often used to transform the chance constraints into deterministic constraints. For example, Dubarry *et al.* [93] used robust optimization for energy management of a small electrical system with electric vehicles and wind turbines, where only the bound on PEVs charge/discharge power is known.

After selecting the cost function and defining the constraints, the next steps would be to select the problem horizon and pick a solver. In the literature, the building energy management problem is often solved for a day-ahead horizon (next 24 h) [60], [63], [81], [83], [85], [90]. This method can plan the buying/selling of the microgrid for the next day, but, in reality, there is always some mismatch between the predicted and actual PV generation, load demand, and PEV mobility. Hence, these algorithms have to be integrated with real-time strategies that compensate for forecast errors, often by exploiting the energy storage flexibility. Jin *et al.* [59] proposes using the building thermal mass as virtual energy storage and the PEV battery in two different time scales, 15 min for the building and 1 min for the PEV, to smooth the microgrid power and compensate for the mismatch between the day-ahead planning and real-time optimization. Yan *et al.* [76] proposed a four-stage algorithm for energy management of a smart charging station. In addition to the day-head and real-time planning steps, the algorithm includes two intermediate steps for maximized the PEV drivers' incentives to encourage them to participate in V2B and another hour-ahead energy management optimization step to maximize the cost savings.

Another approach is to solve the optimal control problem in a receding horizon manner. In this method, the optimization problem is solved over some horizon at each step time, but only the first computed control law is implemented, and the rest is discarded. In the next step time, the problem information, such as batteries SOC and PV and load demand forecasts, is updated, and the optimization is solved again to find the next control law. This method is also known as model predictive control (MPC) [122]. This feedback structure in the receding horizon method provides some robustness to uncertainties and forecast error, which can be really useful for energy management of buildings with V2B, because PEV mobility uncertainty plays a major role in this problem. Zhang *et al.* [56] used MPC, with a prediction horizon of 24 h and a 30-min step time, for energy management of a house with V2B and different DERs. Wu *et al.* [74] used a two-step approach, in which the first step solves energy scheduling for the day-ahead power market and the second step uses MPC with the horizon of rest of the day for real-time energy scheduling. In this algorithm, the first step is only necessary to determine the amount of power to be purchased for each time slot. De Angelis *et al.* [123] suggested to repeat the optimization any time a change in the scenario happens, for example, whenever the vehicle plugs in or out or a device switches ON.

EMSs with V2B often have a centralized structure because the problem usually involves only a few players, such as a house and a PEV. A centralized approach is the formulation presented in (1)–(13). An example of the centralized formulation for a large number of PEVs at a university campus is presented in [53], and another example for collaboration between a building and a smart charging station is given in [71]. Nevertheless, when the number of PEVs or connected buildings increases, a large amount of data have to be exchanged between the system elements and the central controller, which might not be practical. Furthermore, exposing PEVs' information, such as the battery SOC or arrival and departure times, might sabotage the drivers' privacy. The centralized problem also has a higher dimensionality, and hence, it is hard to solve; the solution might not be fair for all players [69]. Decentralized control methods reduce data communication between elements of the system and break down the energy management problem into smaller optimizations. Decentralized approaches are especially useful for V2G applications, where an enormous number of PEVs are interacting with the grid. Game-theoretical approaches that are capable of modeling PEVs as independent self-interested decision-makers are used to model the interaction with grid aggregators [124], [125]. Decentralized approaches are applied to V2B too. Nguyen and Song [51] used a game-theoretical framework to model-independent decision-making of PEVs for V2B operation. A cost-sharing model was designed such that the Nash equilibrium of the problem reduces the peak demand and energy cost of the building.

Among the optimization tools and solvers adopted by the literature, Cplex, which can handle linear, quadratic, and linear mixed-integer programming problems, is the most widely used solver. Chance-constrained optimization

Table 3 Summary of Optimization Tools/Solvers Used in the Literature

Solver	Article
Cplex	[56], [58]–[60], [63], [65] [57], [68], [70], [71], [83], [86]
Gurobi	[82]
CVX	[50], [67], [81]
Stochastic dynamic programming	[54], [90]
Stochastic dual dynamic programming	[85]
Chance-constrained optimization	[76]
Particle swarm optimization	[79], [91]
Natural aggregation algorithm	[61]
Genetic algorithm	[62]

and stochastic dynamic programming are among the methods used for handing stochastic formulation. Although dynamic programming has a relatively higher computational cost compared with linear and quadratic programming approaches, dynamic programming produces a control policy that can be implemented with a lookup table for online implementation with the minimum computational burden. Metaheuristic methods, such as genetic algorithm (GA) and particle swarm optimization (PSO), are also used for energy management of buildings. These methods are especially useful for cases that gradient-based methods fail to produce a globally optimal solution, such as for nonlinear mixed-integer problems. Table 3 summarizes the solvers that are used in the literature for energy management of buildings with V2B.

IV. BATTERY DEGRADATION CONCERNS FOR V2B

The practicality of V2G and V2B has been challenged from the beginning due to battery life concerns. Battery capacity fade for V2B is a major concern compared with stationary batteries because it directly influences the vehicle range and, thus, its mobility. While there is no doubt that extra discharging cycles can reduce the effective battery life, the benefits of V2B with battery life considerations have been the subject of a continuous debate. Although some measures, such as restricting the current to limit the premature degradation of the battery, have been proposed in the literature [126], there are not sufficient studies to refute or substantiate such concerns, and the limited available studies, sometimes, produced conflicting results. Some studies found V2G and V2B extremely damaging to the battery life [127], [128] or claimed no financial benefit from V2B [58], while others alleged that this bidirectional flow of power can actually extend the battery life [129] or has a limited effect on the battery capacity fade [130]. This section takes a closer look into these studies, trying to unravel the mystery of the lithium-ion battery wear for secondary uses. The studies on battery life investigation for both V2B and V2G, called V2X here when referred to both, are considered due to the similarity in concept and the limited number of studies on V2B.

A. Capacity Loss From V2X

Lithium-ion batteries age when used and even when they are just stored. A reduction in capacity and an increase in resistance, which causes battery energy and power loss, respectively, are the observable effects of aging. Different irreversible chemical side reactions are involved in battery aging, such as degradation of electrode material, permanent loss of cycling lithium, and growth of film layers at electrodes. These mechanisms take place at a slow rate within a battery even when it is not in use. Battery life is often quantified by two interdependent measures: calendar life and cycling life. The end of battery life for automotive application is usually marked by 20%–30% decrease in the capacity, or some[1] increase in the battery internal resistance. In simple words, the calendar life determines how many years the battery is expected to last and cycling life is the number of charge-discharge cycles that a battery is predicted to go through before reaching the threshold for capacity loss or resistance increase. Yet, battery degradation is very complex in practice and depends on many factors including temperature, SOC, Depth of Discharge (DOD), C-rate, voltage exposure, and current profile, among others [93], [131]. Generally speaking, calendar aging is mostly influenced by temperature and SOC, while cycling aging additionally depends on C-rate and DOD [132]. Few good semiempirical battery degradation models are available in the literature, which captures both calendar aging and cycling aging [131], [133].

Some studies completely neglected calendar aging in their technoeconomical analysis and consequently concluded that V2G and V2B are extremely detrimental to the battery life and would produce no or little economical revenue [58], [127]. However, calendar aging can be a significant part of battery capacity fade. For example, Wang *et al.* [134] showed that, with simple charging (no V2G), PEVs on average lose 15% of their capacity due to calendar aging, and they lose another 15% to cycling aging in the San Francisco weather condition. This work randomly selected travel itineraries of 100 vehicles from the NHTS data set and assumed that all PEVs repeat the same daily travel itineraries for ten years. The semiempirical battery degradation model used in this work was developed in [133].

The key factor to comprehend V2X influence on battery wear and, thus, its practicality is the relative significance of calendar aging and cycling aging in a battery. Generally, batteries with higher calendar aging and lower cycling aging are more suitable for V2X applications. Chemistry is one of the fundamental drivers of this balance; however, the results on the sensitivity of different chemistries to calendar aging versus cycling aging for V2G and V2B applications are not always consistent. For example, Petit *et al.* [135] showed that lithium nickel cobalt aluminum oxide (NCA) batteries, despite lower overall capacity fade, are more vulnerable to cycling compared with lithium iron phosphate (LFP) batteries and concluded

[1]The values between 20% [131] and 100% [132] increase in the battery internal resistance are reported by the literature to mark the end of life for a lithium-ion battery.

that LFP cells are a better choice for V2G. A conflicting study [129] found that NCA cells are sensitive to calendar aging and, hence, can benefit from V2G. In a third study, Marongiu *et al.* [136] showed that LFP batteries degrade more with cycling compare to lithium nickel manganese cobalt oxide (NMC) chemistry and suggested that NMC batteries should be used for V2G. This work also proposed that PEVs should be selected for V2G operation based on the impact on battery health. In summary, some studies found that a chemistry is favorable for V2X and others did not. The reason might lie within other driving factors that were not the same for all these studies. Furthermore, these studies used different semiempirical battery degradation models; hence, these contradictory results call for developing more accurate and chemistry-specific battery aging models for future investigations.

In addition to chemistry, factors such as temperature, SOC, DOD, and C-rate can also affect the proportion of calendar versus cycling aging. It is understood that high SOCs can increase calendar aging significantly [131]. It is also shown that this capacity fade aggravates at higher environmental temperatures, even for chemistries that do not have substantial high-SOC-related calendar aging at room temperature [93]. Petit *et al.* [135] showed that battery life can extend by "just-in-time" (delayed) charging, which is to store the battery at a lower SOC overnight and recharge the battery early in the morning before leaving home instead of charging the battery right after arrival and keeping the battery fully charge. Due to the charge anxiety caused by long charging time and a smaller range of PEVs, it is more likely that PEV drivers leave the battery fully charged for long durations that cars are parked and not in use. Smart building energy management algorithms can take advantage of preview information and smart control to reduce the average battery SOC while parked. Uddin *et al.* [129] showed that V2G can extend an NCA battery life by 6% over a three-month period by discharging the battery when arriving home and storing the battery overnight at SOCs of around 40%.

The C-rate and DOD of the battery can be controlled and tailored during V2X to reduce the adverse effects on the capacity fade. The C-rate is always restricted by the charger and its power electronics rated power, which is less than 2 kW for a level 1 charger and less than 8 kW for a level 2 charger. There is a subtle difference between V2G and V2B in this regard. Typical three-phase house wiring can carry around 15 kW of power, and a house power consumption is usually less than 3–4 kW, which is much smaller than a vehicle power during driving. However, the requested power for V2G can be really high if high-power bidirectional chargers, in public parkings and charging stations, for example, are used, resulting in high C-rates. Therefore, necessary measures have to be in place to avoid premature degradation of the battery during V2G operation [126]. It is also shown that restricting the duration of V2X can reduce DOD and energy throughput and minimize battery wear. Wang *et al.* [134] showed that limited utilization of a vehicle's battery for grid services, such as frequency regulation and peak load shaving, does not significantly increase the battery capacity loss compared with the wear from driving and natural calendar aging. As an example, employing the vehicle for frequency regulation and peak load shaving for 2 h each day with a level 1 charger over ten years reduces the battery capacity by 3.6% and 5.6%, respectively. In an extreme case, the vehicle battery was used for net load shaping for all day over ten years, resulting in 22.6% capacity loss. In another study, Darcovich *et al.* [130] compared battery capacity fade from driving to capacity loss from V2B. This work showed that a 16-year PEV battery calendar life reduces to 10.6 years with 50-km daily mixed-cycle driving, and this life further reduces to 10.2 years with 1-h daily V2B services. In the case of intensive use of the PEV battery for V2B, i.e., 8 h per day, the predicted battery life was reduced to 8.5 years. This work also showed that if larger batteries are used, the battery degradation from both driving and V2B reduces, most likely due to smaller DODs. Englberger *et al.* [82] also compared the wear from driving to V2B services. This work showed that a supplementary car is more effective in reducing the operating expense of a building compared with a commuter car; however, the battery degradation will be slightly higher. An open-source simulation tool, SimSES [137], was used in this investigation to estimate the capacity loss. It was shown that V2B reduces the battery capacity by 12% compared with smart unidirectional charging when the vehicle is plugged in whenever at home.

A major shortcoming of the literature is the lack of experimental studies. One of the very few experimental results on V2X influence on battery aging is presented by Dubarry *et al.* [128]. This work showed that the cycling capacity loss increases from 5% to 9% after 18 months if NCA batteries are additionally discharged twice daily with a level 2 charger, each time for 1 h. However, one of the deficiencies of this work is that it quantified cycling aging and calendar aging separately, and the results are not accumulated to estimate the effect of V2G on the total capacity loss. For cycling aging, the 24-h daily operation is condensed into 11 h for testing, and calendar aging is quantified by storing the battery with different SOCs and at various temperatures. Furthermore, these experiments assumed that PEV battery discharges at a constant power during V2G service, which is the worst case scenario, resulting in the highest DOD and maximum energy throughput and capacity loss. The energy throughput for the vehicle to home will most likely be lower. To date, there has been no real-world experimental study on battery degradation resulting from V2X, which takes into account the interplay of all influential factors, such as time, current profile shape, environment temperature, chemistry, SOC, DOD, C-rate, and human factors. The semiempirical correlations used in the literature do not model all these factors, and it is difficult if not impossible to include all the factors and uncertainties around vehicle usage and environment conditions in simulations. On the other hand, experimental investigation has to be carried out over the scope of several years, but the rapidly evolving battery technology makes it pointless.

As seen in this section, the literature reported a range of battery capacity loss values for V2X services, from insignificant to extremely high values, depending on the chemistry, duration, and other factors. However, the feasibility of V2B relies on the battery cost in addition to the degradation rate. The question is not whether V2B is economic, but at what battery cost and at what degradation rate V2B would be practical. A study in nature climate change [138] showed that lithium-ion battery cost is reduced from over 1000$/kWh in 2007 to around 410$/kWh in 2014. Reports from the Department of Energy (DOE) also confirm this substantial decline in lithium-ion battery price with a goal of 81$/kWh within the next decade [139]. Therefore, the economical analyses that are only a few years old might not be valid anymore due to this sharp drop in the battery cost. The technoeconomical analysis has to be constantly updated with new battery cost numbers, especially since extremely high (compared with today) battery prices are assumed in some of the older studies [18], [41].

B. Battery Degradation Role in Energy Management

Including a battery life model that can accurately predict both calendar and cycling aging in the energy management algorithm is necessary to maximize the V2B benefits and minimize the negative effects on battery life. Most studies in the literature either did not consider battery aging in energy management formulation, per survey shown in Table 2, or they dealt with battery aging by including some general maintenance/wear cost [53], [75]. Others took into account the battery life in more detail but mainly for battery cycling aging only [50], [58], [74], [79]. This is usually done by integrating ampere-hour or power throughput. For example, Wu *et al.* [74] assumed that the battery has to be retired when its capacity falls to 80% of its nominal capacity and, hence, computed the battery degradation cost, C^{deg}, as follows:

$$C^{\text{deg}} = \frac{C^r}{100-80} \cdot \frac{\Sigma_{k=1}^{N}(|p_{\text{pev}}(k)|.\Delta t}{E_{\text{pev}}^{\max}} \cdot G \tag{14}$$

where C^r is the battery replacement cost and G is the degradation factor, computed from the expected cycling life of the battery. This simple method neglects calendar aging and other shaping factors, such as temperature, C-rate, and DOD on cycling aging, but it is a convenient approach for optimization purposes because it keeps the linear format of the cost function and allows using popular solvers, such as Cplex.

The nonlinearity of battery life models is the main obstacle prohibiting the researchers from including them in the energy management because the standard optimization tools, which are mostly based on the calculus of variations, are not effective in finding the global optimum solution of an arbitrary mixed-integer nonlinear problem. There are only a few studies that included a nonlinear aging model in energy management formulation. Salpakari *et al.* [58] used a nonlinear model that captures temperature and minimum SOC effects on cycling aging [140]. To deal with this nonlinearity, the authors had to solve the energy management problem iteratively. Other studies, such as [62], used metaheuristic solvers, such as GA, to find the nonlinear program solution. However, these methods do not guarantee the optimality of the solution in general. Given the large step time of building energy management algorithms, which is often 30 min or 1 h, dynamic programming can also be an effective method to find the global optimum solution if the problem dimension is limited to only a few inputs and states.

Aging-aware or health-conscious optimal EMSs for HEVs, which have conceptual similarities to BEMS, are also addressed in the literature [141]–[146]. Aging-aware EMS reduces battery operation severity factors to improve the battery health. The experience in aging-aware EMS for HEVs can be used for designing more effective V2B strategies. It is shown that, although there is a tradeoff between the battery capacity loss and the vehicle fuel consumption [141], [144], aging-aware EMS can effectively preserve the battery with a minimum fuel penalty [146]. Semiempirical aging models are usually used in these studies, but the adoption of equivalent circuit models allows accessing the battery voltage and current and, hence, using higher fidelity physics-based electrochemical aging models. However, these models usually describe only a single aging mechanism inside the cell and often require long computation time. Still, some researchers used simplified physics-based models in their optimal EMS design. For example, Moura *et al.* [144] fit a nonlinear static function to the anode-side resistive film formation model, or De Pascali *et al.* [146] used a fast running reduced-order electrochemical cell model developed in [147] to include the battery degradation cost in energy management of an HEV. Active battery thermal management, which is neglected in the V2X literature, is used to reduce the battery temperature and, thus, capacity loss in HEVs [145]. Finally, an alternative method used for curbing HEV battery capacity loss is modeling the battery state of health (SOH) and restricting the SOH in the optimal control problem formulation [142]. These techniques and methods from HEV EMS design can be pursued in BEMS design to ensure limited PEV battery wear from the secondary use.

V. CONCLUSION

Electric vehicles have an indispensable role in future smart buildings. PEVs offer a multidimensional elasticity as local energy storage systems, energy carriers, and flexible loads.

Many different concepts and configurations for the bidirectional flow of power between PEVs and buildings are investigated in the literature and reviewed here. It is shown that V2B can reduce the electricity service cost by curbing the peak power and limiting the energy purchase from the grid during on-peak pricing hours. It can supply backup power during outages and reduce the carbon footprint of buildings by enabling the integration of distributed renewable energy sources. In addition to personal cars for home energy management, PEV fleets, such as ride-sharing services, and nearby smart parkings and charging stations can be deployed for V2B applications. In cases when the peak demand, electricity price spikes, or power outage happen only during a few days per year, PEV fleets are a cost-effective choice to decrease the expenses or provide backup. However, for daily applications, such as integrating renewable energies, the long-term presence of PEVs is necessary.

Methods for behind the meter energy management of buildings fall into categories of rule-based approaches and optimization-based approaches. Rule-based methods are online solutions based on heuristics and simple conditions, such as the availability of the PEV or relative value of generation versus consumption. These algorithms are usually developed for a specific target, for example, for maximizing self-consumption of renewables or peak shaving, and are not reusable if the system, objective, or electricity tariffs structure change. Furthermore, these methods are only effective for simple cases and generally cannot guarantee the optimality of their outcome. Optimization-based methods solve an optimal control problem to determine control laws. Different terms, such as energy cost, user comfort, or emissions, can be included in the optimization cost function. The methods for modeling the PEV mobility, which couples the driver's transportation to the building energy management, were reviewed here. In addition to the centralized approaches, noncooperative decentralized methods that deploy game theory were covered, and the most common solvers used for building energy management were surveyed. BEMSs usually solve the optimal control problem for a day-ahead horizon, but it is shown that MPC formulation deals with uncertainties better.

Premature battery degradation is the primary concern for V2B implementation. The literature on battery capacity loss with V2B and V2G is very limited, and almost all studies are based on semiempirical battery aging models and, thus, are restricted by the model accuracy and limitations. Generally, batteries with high calendar aging and low cycling aging are more suitable for V2B. Battery chemistry and operational factors, such as temperature, SOC, DOD, and C-rate, influence the balance between calendar aging and cycling aging. There is not a unique resolution in the literature on which chemistry is the best option for V2B, but it is shown that careful control of other driving factors can reduce the battery capacity loss or even extend it in some rare cases. A more thorough evaluation of V2B influence on PEV battery requires developing more accurate and chemistry-specific aging models or realistic long-term experiments. Battery wear is usually neglected in designing the BEMS; however, given the high cost of batteries and capacity loss effect on the vehicle range, it is necessary to include the battery life in the energy management. The nonlinearity and complexity of battery aging models are the main factors preventing researchers from involving them in energy management formulation.

VI. FUTURE RESEARCH OUTLOOK

1) Integrating state-of-the-art cross-disciplinary PEV mobility models that are customized to drivers' behavioral factors in addition to the vehicle technical specifications can improve the effectiveness of V2B schemes and facilitate their adoption by providing more accurate predictions for energy management and reducing the charge anxiety of drivers. Therefore, one possible future research direction would be to take advantage of new PEV mobility and charging behavior models, often originally developed for infrastructure planning, to produce more practical V2B designs.
2) Developing effective rule-based strategies that produce near-optimal solutions for the cases that limited computational power, sensing, and communication capacity that restricts the application of optimization-based methods is necessary for future BEMSs with V2B integration. Such rules have to be robust to changes in the system structure or electricity tariffs. Recent advances in methods that learn control rules from optimization solutions can be used in the future to develop more effective rule-based algorithms.
3) A building energy management is usually on a daily basis; therefore, it is a repetitive task. This quality makes the building energy management problem a suitable candidate for data-driven and learning-based control methods. Some limited use of machine learning tools, mostly for predicting a building load and PV generation, is found in the literature. However, the learning schemes can be further incorporated into the control task to produce faster and efficient energy management algorithms.
4) Battery wear concern has to be addressed more thoroughly in the future to make the V2B ideas operational. One aspect of this problem is developing accurate semiempirical aging models or fast running physics-based aging models to better estimate the battery wear from V2B. Another aspect is implementing new methods to curb the battery capacity fade during V2B, such as active thermal management of the battery or adding battery SOH as a constraint to the optimization problem. ■

REFERENCES

[1] A. Elgowainy *et al.*, "Cradle-to-grave lifecycle analysis of us light duty vehicle-fuel pathways: A greenhouse gas emissions and economic assessment of current (2015) and future (2025–2030) technologies," Argonne Nat. Lab., Argonne, IL, USA, Tech. Rep. ANL/ESD-16/7, 2016.

[2] K. J. Dyke, N. Schofield, and M. Barnes, "The impact of transport electrification on electrical networks," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 3917–3926, Dec. 2010.

[3] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of vehicle-to-grid on the distribution grid," *Electr. Power Syst. Res.*, vol. 81, no. 1, pp. 185–192, Jan. 2011.

[4] N. Z. Xu and C. Y. Chung, "Reliability evaluation of distribution systems including vehicle-to-home and vehicle-to-grid," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 759–768, Jan. 2016.

[5] R. Loisel, G. Pasaoglu, and C. Thiel, "Large-scale deployment of electric vehicles in Germany by 2030: An analysis of grid-to-vehicle and vehicle-to-grid concepts," *Energy Policy*, vol. 65, pp. 432–443, Feb. 2014.

[6] B. K. Sovacool and R. F. Hirsh, "Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition," *Energy Policy*, vol. 37, no. 3, pp. 1095–1103, Mar. 2009.

[7] L. Noel, G. Zarazua de Rubens, J. Kester, and B. K. Sovacool, "Beyond emissions and economics: Rethinking the co-benefits of electric vehicles (EVs) and vehicle-to-grid (V2G)," *Transp. Policy*, vol. 71, pp. 130–137, Nov. 2018.

[8] S. Habib, M. Kamran, and U. Rashid, "Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks—A review," *J. Power Sources*, vol. 277, pp. 205–214, Mar. 2015.

[9] M. Noori, Y. Zhao, N. C. Onat, S. Gardner, and O. Tatari, "Light-duty electric vehicles to improve the integrity of the electricity grid through vehicle-to-grid technology: Analysis of regional net revenue and emissions savings," *Appl. Energy*, vol. 168, pp. 146–158, Apr. 2016.

[10] J. Hu, H. Morais, T. Sousa, and M. Lind, "Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1207–1226, Apr. 2016.

[11] P. Bach Andersen, R. Garcia-Valle, and W. Kempton, "A comparison of electric vehicle integration projects," in *Proc. 3rd IEEE PES Innov. Smart Grid Technol. Eur. (ISGT Eur.)*, Oct. 2012, pp. 1–7.

[12] *V2G Global Roadtrip: Around the World in 50 Projects*. Accessed: Jul. 1, 2020. [Online]. Available: http://everoze.com/app/uploads/2019/02/UKPN001-S-01-J-V2G-global-review.pdf

[13] W. Kempton and T. Kubo, "Electric-drive vehicles for peak power in Japan," *Energy Policy*, vol. 28, no. 1, pp. 9–18, Jan. 2000.

[14] W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, Jun. 2005.

[15] N. Neofytou, K. Blazakis, Y. Katsigiannis, and G. Stavrakakis, "Modeling vehicles to grid as a source of distributed frequency regulation in isolated grids with significant RES penetration," *Energies*, vol. 12, no. 4, p. 720, Feb. 2019.

[16] J. Tomić and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *J. Power Sources*, vol. 168, no. 2, pp. 459–468, Jun. 2007.

[17] C. D. White and K. M. Zhang, "Using vehicle-to-grid technology for frequency regulation and peak-load reduction," *J. Power Sources*, vol. 196, no. 8, pp. 3972–3980, Apr. 2011.

[18] S. Han and S. Han, "Economic feasibility of V2G frequency regulation in consideration of battery wear," *Energies*, vol. 6, no. 2, pp. 748–765, Feb. 2013.

[19] W. Kempton, J. Tomic, S. Letendre, A. Brooks, and T. Lipman, "Vehicle-to-grid power: Battery, hybrid, and fuel cell vehicles as resources for distributed electric power in California," UC Davis, Inst. Transp. Stud., Davis, CA, USA, Tech. Rep., 2001. [Online]. Available: https://escholarship.org/uc/item/0qp6s4mb

[20] J. R. Pillai and B. Bak-Jensen, "Vehicle-to-grid systems for frequency regulation in an islanded Danish distribution network," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2010, pp. 1–6.

[21] W. Kempton and J. Tomić, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *J. Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005.

[22] *U.S. Energy Information Administration*. Accessed: Jun. 9, 2020. [Online]. Available: https://www.eia.gov/energyexplained/electricity/electricity-in-the-us-generation-capacity-and-sales.php

[23] *The 2019 EPA Automotive Trends Report Greenhouse Gas Emissions, Fuel Economy, and Technology Since 1975*. Accessed: Jun. 10, 2020. [Online]. Available: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100YVFS.pdf

[24] *Bureau of Transportation Statistics*. Accessed: Jun. 10, 2020. [Online]. Available: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances

[25] *Edison Electric Institute*. Accessed: Jul. 8, 2020. [Online]. Available: https://www.eei.org/issuesandpolicy/electrictransportation/Documents/FINAL_EV_Sales_Update_April2019.pdf

[26] C. Liu, K. T. Chau, D. Wu, and S. Gao, "Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies," *Proc. IEEE*, vol. 101, no. 11, pp. 2409–2427, Nov. 2013.

[27] V. Monteiro, J. G. Pinto, and J. L. Afonso, "Operation modes for the electric vehicle in smart grids and smart homes: Present and proposed modes," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1007–1020, Mar. 2016.

[28] *NUVVE*. Accessed: Jul. 21, 2020. [Online]. Available: https://nuvve.com/v2g-chargers/

[29] D. Guo and C. Zhou, "Potential performance analysis and future trend prediction of electric vehicle with V2G/V2H/V2B capability," *AIMS Energy*, vol. 4, no. 2, pp. 331–346, 2016.

[30] A. Colmenar-Santos, C. de Palacio-Rodriguez, E. Rosales-Asensio, and D. Borge-Diez, "Estimating the benefits of vehicle-to-home in islands: The case of the Canary Islands," *Energy*, vol. 134, pp. 311–322, Sep. 2017.

[31] G. S. Georgiou, P. Christodoulides, and S. A. Kalogirou, "Real-time energy convex optimization, via electrical storage, in buildings—A review," *Renew. Energy*, vol. 139, pp. 1355–1365, 2019.

[32] I. S. Bayram and T. S. Ustun, "A survey on behind the meter energy management systems in smart grid," *Renew. Sustain. Energy Rev.*, vol. 72, pp. 1208–1232, May 2017.

[33] A. Barbato and A. Capone, "Optimization models and methods for demand-side management of residential users: A survey," *Energies*, vol. 7, no. 9, pp. 5787–5824, Sep. 2014.

[34] J. Neubauer and M. Simpson, "Deployment of behind-the-meter energy storage for demand charge reduction," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5400-63162, 2015.

[35] G. Liu, M. Starke, X. Zhang, and K. Tomsovic, "A MILP-based distribution optimal power flow model for microgrid operation," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2016, pp. 1–5.

[36] K. Anderson *et al.*, "REopt Lite," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep., 2019.

[37] A. Breckel, "Residential electricity bill savings opportunities from distributed electric storage," in *Proc. Grid Future Symp. Next Gener. Netw. (NGN) Paper Competition*, 2015.

[38] C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao, and M. Wellers, "Energy management in plug-in hybrid electric vehicles: Recent progress and a connected vehicles perspective," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 4534–4549, Jun. 2017.

[39] T. Bohn. (2020). *Multi-Port, 1+MW Charging System for Medium- and Heavy-Duty EVs: What We Know and What is on the Horizon?* [Online]. Available: https://cleancities.energy.gov/files/u/news_events/document/document_url/525/ANL_CleanCities_MW_plus_WhatsAhead_Jan7_2020.pdf

[40] J. García-Villalobos, I. Zamora, J. I. San Martín, F. J. Asensio, and V. Aperribay, "Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches," *Renew. Sustain. Energy Rev.*, vol. 38, pp. 717–731, Oct. 2014.

[41] B. Lunz, Z. Yan, J. B. Gerschler, and D. U. Sauer, "Influence of plug-in hybrid electric vehicle charging strategies on charging and battery degradation costs," *Energy Policy*, vol. 46, pp. 511–519, Jul. 2012.

[42] J. Van Roy, N. Leemput, F. Geth, J. Büscher, R. Salenbien, and J. Driesen, "Electric vehicle charging in an office building microgrid with distributed energy resources," *IEEE Trans. Sustain. Energy*, vol. 5, no. 4, pp. 1389–1396, Oct. 2014.

[43] D. Mazzeo, "Nocturnal electric vehicle charging interacting with a residential photovoltaic-battery system: A 3E (energy, economic and environmental) analysis," *Energy*, vol. 168, pp. 310–331, Feb. 2019.

[44] P. Huang *et al.*, "Transforming a residential building cluster into electricity prosumers in Sweden: Optimal design of a coupled PV-heat pump-thermal storage-electric vehicle system," *Appl. Energy*, vol. 255, Dec. 2019, Art. no. 113864.

[45] M. Muratori *et al.*, "Technology solutions to mitigate electricity cost for electric vehicle DC fast charging," *Appl. Energy*, vol. 242, pp. 415–423, May 2019.

[46] L. Yang and H. Ribberink, "Investigation of the potential to improve DC fast charging station economics by integrating photovoltaic power generation and/or local battery energy storage system," *Energy*, vol. 167, pp. 246–259, Jan. 2019.

[47] A. Burrell and S. Gillard. *Behind-The-Meter Storage*. Accessed: Aug. 13, 2020. [Online]. Available: https://www.nrel.gov/transportation/assets/pdfs/behind-the-meter-storage-fy20-q2-progress-report.pdf

[48] C. Pang, P. Dutta, and M. Kezunovic, "BEVs/PHEVs as dispersed energy storage for V2B uses in the smart grid," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 473–482, Mar. 2012.

[49] G. Haines, A. McGordon, P. Jennings, and N. Butcher, "The simulation of vehicle-to-home systems–using electric vehicle battery storage to smooth domestic electricity demand," in *Proc. EVER Monaco*, 2009.

[50] T. Mao, X. Zhang, and B. Zhou, "Modeling and solving method for supporting 'vehicle-to-anything' EV charging mode," *Appl. Sci.*, vol. 8, no. 7, p. 1048, 2018.

[51] H. K. Nguyen and J. B. Song, "Optimal charging and discharging for multiple PHEVs with demand side management in vehicle-to-building," *J. Commun. Netw.*, vol. 14, no. 6, pp. 662–671, Dec. 2012.

[52] A. Alahyari, M. Fotuhi-Firuzabad, and M. Rastegar, "Incorporating customer reliability cost in PEV charge scheduling schemes considering vehicle-to-home capability," *IEEE Trans. Veh. Technol.*, vol. 64, no. 7, pp. 2783–2791, Jul. 2015.

[53] K. Tanguy, M. R. Dubois, K. L. Lopez, and C. Gagné, "Optimization model and economic assessment of collaborative charging using vehicle-to-building," *Sustain. Cities Soc.*, vol. 26, pp. 496–506, Oct. 2016.

[54] E. B. Iversen, J. M. Morales, and H. Madsen, "Optimal charging of an electric vehicle using a Markov decision process," *Appl. Energy*, vol. 123, pp. 1–12, Jun. 2014.

[55] M. Rastegar, M. Fotuhi-Firuzabad, H. Zareipour, and M. Moeini-Aghtaieh, "A probabilistic energy management scheme for renewable-based residential energy hubs," *IEEE Trans. Smart Grid*,

vol. 8, no. 5, pp. 2217–2227, Sep. 2017.

[56] Y. Zhang, T. Zhang, R. Wang, Y. Liu, and B. Guo, "Optimal operation of a smart residential microgrid based on model predictive control by considering uncertainties and storage impacts," *Sol. Energy*, vol. 122, pp. 1052–1065, Dec. 2015.

[57] O. Erdinc, "Economic impacts of small-scale own generating and storage units, and electric vehicles under different demand response strategies for smart households," *Appl. Energy*, vol. 126, pp. 142–150, Aug. 2014.

[58] J. Salpakari, T. Rasku, J. Lindgren, and P. D. Lund, "Flexibility of electric vehicles and space heating in net zero energy houses: An optimal control model with thermal dynamics and battery degradation," *Appl. Energy*, vol. 190, pp. 800–812, Mar. 2017.

[59] X. Jin, J. Wu, Y. Mu, M. Wang, X. Xu, and H. Jia, "Hierarchical microgrid energy management in an office building," *Appl. Energy*, vol. 208, pp. 480–494, Dec. 2017.

[60] F. Brahman, M. Honarmand, and S. Jadid, "Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system," *Energy Buildings*, vol. 90, pp. 65–75, Mar. 2015.

[61] F. Luo, G. Ranzi, W. Kong, Z. Y. Dong, and F. Wang, "Coordinated residential energy resource scheduling with vehicle-to-home and high photovoltaic penetrations," *IET Renew. Power Gener.*, vol. 12, no. 6, pp. 625–632, Apr. 2018.

[62] Y. Sun, H. Yue, J. Zhang, and C. Booth, "Minimization of residential energy cost considering energy storage system and EV with driving usage probabilities," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 1752–1763, Oct. 2019.

[63] Y. Kuang, Y. Chen, M. Hu, and D. Yang, "Influence analysis of driver behavior and building category on economic performance of electric vehicle to grid and building integration," *Appl. Energy*, vol. 207, pp. 427–437, Dec. 2017.

[64] Y. Zhou and S. Cao, "Energy flexibility investigation of advanced grid-responsive energy control strategies with the static battery and electric vehicles: A case study of a high-rise office building in Hong Kong," *Energy Convers. Manage.*, vol. 199, Nov. 2019, Art. no. 111888.

[65] M. Sedighizadeh, M. Esmaili, and N. Mohammadkhani, "Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles," *J. Cleaner Prod.*, vol. 195, pp. 301–317, Sep. 2018.

[66] B. Brendle *et al.*, "Model-predictive energy management for the integration of plug-in-hybrid electric vehicles into building energy systems," SAE Tech. Paper 2013-01-1443, 2013.

[67] D. T. Nguyen and L. B. Le, "Joint optimization of electric vehicle and home energy scheduling considering user comfort preference," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 188–199, Jan. 2014.

[68] N. G. Paterakis, O. Erdinc, A. G. Bakirtzis, and J. P. S. Catalão, "Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1509–1519, Dec. 2015.

[69] N. G. Paterakis, O. Erdinç, I. N. Pappi, A. G. Bakirtzis, and J. P. S. Catalão, "Coordinated operation of a neighborhood of smart households comprising electric vehicles, energy storage and distributed generation," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2736–2747, Nov. 2016.

[70] X. Wu, Y. Li, Y. Tan, Y. Cao, and C. Rehtanz, "Optimal energy management for the residential MES," *IET Gener., Transmiss. Distribution*, vol. 13, no. 10, pp. 1786–1793, May 2019.

[71] M. A. Quddus, O. Shahvari, M. Marufuzzaman, J. M. Usher, and R. Jaradat, "A collaborative energy sharing optimization model among electric vehicle charging stations, commercial buildings, and power grid," *Appl. Energy*, vol. 229, pp. 841–857, Nov. 2018.

[72] G. Barone, A. Buonomano, F. Calise, C. Forzano, and A. Palombo, "Building to vehicle to building concept toward a novel zero energy paradigm: Modelling and case studies," *Renew. Sustain. Energy Rev.*, vol. 101, pp. 625–648, Mar. 2019.

[73] M. Aziz, T. Oda, and T. Kashiwagi, "Extended utilization of electric vehicles and their re-used batteries to support the building energy management system," *Energy Procedia*, vol. 75, pp. 1938–1943, Aug. 2015.

[74] D. Wu, H. Zeng, C. Lu, and B. Boulet, "Two-stage energy management for office buildings with workplace EV charging and renewable energy," *IEEE Trans. Transport. Electrific.*, vol. 3, no. 1, pp. 225–237, Mar. 2017.

[75] F. Y. Melhem, O. Grunder, Z. Hammoudan, and N. Moubayed, "Optimization and energy management in smart home considering photovoltaic, wind, and battery storage system with integration of electric vehicles," *Can. J. Electr. Comput. Eng.*, vol. 40, no. 2, pp. 128–138, 2017.

[76] Q. Yan, B. Zhang, and M. Kezunovic, "Optimized operational cost reduction for an EV charging station integrated with battery energy storage and PV generation," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2096–2106, Mar. 2019.

[77] K. Mahmud, M. J. Hossain, and G. E. Town, "Peak-load reduction by coordinated response of photovoltaics, battery storage, and electric vehicles," *IEEE Access*, vol. 6, p. 29 353–29 365, 2018.

[78] M. Alirezaei, M. Noori, and O. Tatari, "Getting to net zero energy building: Investigating the role of vehicle to home technology," *Energy Buildings*, vol. 130, pp. 465–476, Oct. 2016.

[79] L. Wen, K. Zhou, S. Yang, and X. Lu, "Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting," *Energy*, vol. 171, pp. 1053–1065, Mar. 2019.

[80] M. S. Shemami, M. S. Alam, and M. S. J. Asghar, "Load shedding mitigation through plug-in electric vehicle-to-home (V2H) system," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Jun. 2017, pp. 799–804.

[81] X. Wu, X. Hu, Y. Teng, S. Qian, and R. Cheng, "Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle," *J. Power Sources*, vol. 363, pp. 277–283, Sep. 2017.

[82] S. Englberger, H. Hesse, D. Kucevic, and A. Jossen, "A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging," *Energies*, vol. 12, no. 5, p. 955, Mar. 2019.

[83] O. Erdinc, N. G. Paterakis, T. D. P. Mendes, A. G. Bakirtzis, and J. P. S. Catalao, "Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1281–1291, May 2015.

[84] H. Dagdougui, A. Ouammi, and L. A. Dessaint, "Peak load reduction in a smart building integrating microgrid and V2B-based demand response scheme," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3274–3282, Sep. 2019.

[85] F. Hafiz, A. R. de Queiroz, and I. Husain, "Coordinated control of PEV and PV-based storages in residential systems under generation and load uncertainties," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 5524–5532, Nov. 2019.

[86] A. T. Eseye, M. Lehtonen, T. Tukia, S. Uimonen, and R. J. Millar, "Optimal energy trading for renewable energy integrated building microgrids containing electric vehicles and energy storage batteries," *IEEE Access*, vol. 7, pp. 106092–106101, 2019.

[87] I. Cvetkovic *et al.*, "Future home uninterruptible renewable energy system with vehicle-to-grid technology," in *Proc. IEEE Energy Convers. Congr. Expo.*, Sep. 2009, pp. 2675–2681.

[88] A. Nagarajan and W. Shireen, "Grid connected residential photovoltaic energy systems with plug-in hybrid electric vehicles (PHEV) as energy storage," in *Proc. IEEE PES Gen. Meeting*, Jul. 2010, pp. 1–5.

[89] H. Shin and R. Baldick, "Plug-in electric vehicle to home (V2H) operation under a grid outage," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 2032–2041, Jul. 2017.

[90] X. Wu, X. Hu, S. Moura, X. Yin, and V. Pickert, "Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array," *J. Power Sources*, vol. 333, pp. 203–212, Nov. 2016.

[91] Z. Wang, L. Wang, A. I. Dounis, and R. Yang, "Integration of plug-in hybrid electric vehicles into building energy management system," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2011, pp. 1–8.

[92] T. Wu, Q. Yang, Z. Bao, and W. Yan, "Coordinated energy dispatching in microgrid with wind power generation and plug-in electric vehicles," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1453–1463, Sep. 2013.

[93] M. Dubarry, G. Baure, and A. Devie, "Durability and reliability of EV batteries under electric utility grid operations: Path dependence of battery degradation," *J. Electrochem. Soc.*, vol. 165, no. 5, pp. A773–A783, 2018.

[94] A. D. Clarke *et al.*, "A comprehensive analysis of plug in hybrid electric vehicles to commercial campus (V2C)," *J. Power Energy Eng.*, vol. 3, no. 1, p. 24, 2015.

[95] C. S. Ioakimidis, D. Thomas, P. Rycerski, and K. N. Genikomsakis, "Peak shaving and valley filling of power consumption profile in non-residential buildings using an electric vehicle parking lot," *Energy*, vol. 148, pp. 148–158, Apr. 2018.

[96] F. Berthold, A. Ravey, B. Blunier, D. Bouquain, S. Williamson, and A. Miraoui, "Design and development of a smart control strategy for plug-in hybrid vehicles including vehicle-to-home functionality," *IEEE Trans. Transport. Electrific.*, vol. 1, no. 2, pp. 168–177, Aug. 2015.

[97] M. H. Amirioun and A. Kazemi, "A new model based on optimal scheduling of combined energy exchange modes for aggregation of electric vehicles in a residential complex," *Energy*, vol. 69, pp. 186–198, May 2014.

[98] K. N. Kumar, B. Sivaneasan, P. H. Cheah, P. L. So, and D. Z. W. Wang, "V2G capacity estimation using dynamic EV scheduling," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1051–1060, Mar. 2014.

[99] *Electric Reliability Council of Texas (ERCOT)*. Accessed: May 30, 2020. [Online]. Available: http://www.ercot.com/mktinfo/prices

[100] L. Zhang and Y. Li, "Regime-switching based vehicle-to-building operation against electricity price spikes," *Energy Econ.*, vol. 66, pp. 1–8, Aug. 2017.

[101] J. Qin, J. Porter, K. Poolla, and P. Varaiya, "Piggyback on TNCs for electricity services: Spatial pricing and synergetic value," in *Proc. Amer. Control Conf. (ACC)*, Jul. 2020, pp. 500–507.

[102] T. Mamalis, S. Bose, and L. R. Varshney, "Ridesharing systems with electric vehicles," in *Proc. Amer. Control Conf. (ACC)*, Jul. 2019, pp. 3329–3334.

[103] T. D. Atmaja and Amin, "Energy storage system using battery and ultracapacitor on mobile charging station for electric vehicle," *Energy Procedia*, vol. 68, pp. 429–437, Apr. 2015.

[104] M. J. Fisher and J. Apt, "Emissions and economics of behind-the-meter electricity storage," *Environ. Sci. Technol.*, vol. 51, no. 3, pp. 1094–1101, Feb. 2017.

[105] T. Terlouw, T. AlSkaif, C. Bauer, and W. van Sark, "Optimal energy management in all-electric residential energy systems with heat and electricity storage," *Appl. Energy*, vol. 254, Nov. 2019, Art. no. 113580.

[106] D. Kolokotsa, D. Rovas, E. Kosmatopoulos, and K. Kalaitzakis, "A roadmap towards intelligent net zero-and positive-energy buildings," *Sol. Energy*, vol. 85, no. 12, pp. 3067–3084, 2011.

[107] N. Soares *et al.*, "A review on current advances in the energy and environmental performance of buildings towards a more sustainable built environment," *Renew. Sustain. Energy Rev.*, vol. 77, pp. 845–860, Sep. 2017.

[108] H. Turker and S. Bacha, "Optimal minimization of plug-in electric vehicle charging cost with

vehicle-to-home and vehicle-to-grid concepts," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10281–10292, 2018.

[109] D. Bertsimas and B. Stellato, "The voice of optimization," *Mach. Learn.*, pp. 1–29, Jul. 2020, doi: 10.1007/s10994-020-05893-5.

[110] E. Khalil, H. Dai, Y. Zhang, B. Dilkina, and L. Song, "Learning combinatorial optimization algorithms over graphs," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 6348–6358.

[111] A. P. Dobos, "PVWatts version 5 manual," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A20-62641, 2014.

[112] H. Turker, S. Bacha, D. Chatroux, and A. Hably, "Modelling of system components for vehicle-to-grid (V2G) and vehicle-to-home (V2H) applications with plug-in hybrid electric vehicles (PHEVs)," in *Proc. IEEE PES Innov. Smart Grid Technol. (ISGT)*, Jan. 2012, pp. 1–8.

[113] L. Gao, S. Liu, and R. A. Dougal, "Dynamic lithium-ion battery model for system simulation," *IEEE Trans. Compon. Packag. Technol.*, vol. 25, no. 3, pp. 495–505, Sep. 2002.

[114] N. Daina, A. Sivakumar, and J. W. Polak, "Modelling electric vehicles use: A survey on the methods," *Renew. Sustain. Energy Rev.*, vol. 68, pp. 447–460, Feb. 2017.

[115] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.

[116] L. Knapen, B. Kochan, T. Bellemans, D. Janssens, and G. Wets, "Activity based models for countrywide electric vehicle power demand calculation," in *Proc. IEEE 1st Int. Workshop Smart Grid Modeling Simulation (SGMS)*, Oct. 2011, pp. 13–18.

[117] C. Moreira, J. P. Lopes, P. R. Almeida, L. Seca, and F. J. Soares, "A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid," in *Proc. Power Syst. Comput. Conf. (PSCC)*, Stockholm, Sweden, 2011.

[118] D. Tang and P. Wang, "Probabilistic modeling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 627–636, Mar. 2016.

[119] R. Rao, H. Cai, and M. Xu, "Modeling electric taxis' charging behavior using real-world data," *Int. J. Sustain. Transp.*, vol. 12, no. 6, pp. 452–460, Jul. 2018.

[120] K. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil, and H. B. Gooi, "Agent-based aggregated behavior modeling for electric vehicle charging load," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 856–868, Feb. 2019.

[121] Z. Fotouhi, M. R. Hashemi, H. Narimani, and I. S. Bayram, "A general model for ev drivers' charging behavior," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 7368–7382, 2019.

[122] F. Borrelli, A. Bemporad, and M. Morari, *Predictive Control for Linear and Hybrid Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2017.

[123] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints," *IEEE Trans. Ind. Informat.*, vol. 9, no. 3, pp. 1518–1527, Aug. 2013.

[124] C. Wu, H. Mohsenian-Rad, and J. Huang, "Vehicle-to-aggregator interaction game," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 434–442, Mar. 2012.

[125] W. Saad, Z. Han, H. V. Poor, and T. Başar, "A noncooperative game for double auction-based energy trading between PHEVs and distribution grids," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2011, pp. 267–272.

[126] M.-A. Rodríguez-Licea, F.-J. Perez-Pinal, A.-G. Soriano-Sánchez, and J.-A. Vázquez-López, "Noninvasive vehicle-to-load energy management strategy to prevent Li-ion batteries premature degradation," *Math. Problems Eng.*, vol. 2019, pp. 1–9, May 2019.

[127] J. D. K. Bishop, C. J. Axon, D. Bonilla, M. Tran, D. Banister, and M. D. McCulloch, "Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV," *Appl. Energy*, vol. 111, pp. 206–218, Nov. 2013.

[128] M. Dubarry, A. Devie, and K. McKenzie, "Durability and reliability of electric vehicle batteries under electric utility grid operations: Bidirectional charging impact analysis," *J. Power Sources*, vol. 358, pp. 39–49, Aug. 2017.

[129] K. Uddin, T. Jackson, W. D. Widanage, G. Chouchelamane, P. A. Jennings, and J. Marco, "On the possibility of extending the lifetime of lithium-ion batteries through optimal V2G facilitated by an integrated vehicle and smart-grid system," *Energy*, vol. 133, pp. 710–722, Aug. 2017.

[130] K. Darcovich, S. Recoskie, H. Ribberink, F. Pincet, and A. Foissac, "Effect on battery life of vehicle-to-home electric power provision under Canadian residential electrical demand," *Appl. Thermal Eng.*, vol. 114, pp. 1515–1522, Mar. 2017.

[131] K. Smith, M. Warleywine, E. Wood, J. Neubauer, and A. Pesaran, "Comparison of plug-in hybrid electric vehicle battery life across geographies and drive-cycles," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/CP-5400-53817, 2012.

[132] A. W. Thompson, "Economic implications of lithium ion battery degradation for vehicle-to-grid (V2X) services," *J. Power Sources*, vol. 396, pp. 691–709, Aug. 2018.

[133] J. Wang *et al.*, "Degradation of lithium ion batteries employing graphite negatives and nickel–cobalt–manganese oxide+ spinel manganese oxide positives: Part 1, aging mechanisms and life estimation," *J. Power Sources*, vol. 269, pp. 937–948, Dec. 2014.

[134] D. Wang, J. Coignard, T. Zeng, C. Zhang, and S. Saxena, "Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services," *J. Power Sources*, vol. 332, pp. 193–203, Nov. 2016.

[135] M. Petit, E. Prada, and V. Sauvant-Moynot, "Development of an empirical aging model for Li-ion batteries and application to assess the impact of vehicle-to-grid strategies on battery lifetime," *Appl. Energy*, vol. 172, pp. 398–407, Jun. 2016.

[136] A. Marongiu, M. Roscher, and D. U. Sauer, "Influence of the vehicle-to-grid strategy on the aging behavior of lithium battery electric vehicles," *Appl. Energy*, vol. 137, pp. 899–912, Jan. 2015.

[137] M. Naumann, C. N. Truong, M. Schimpe, D. Kucevic, A. Jossen, and H. C. Hesse, "SimSES: Software for techno-economic simulation of stationary energy storage systems," in *Proc. Int. ETG Congr. VDE*, 2017, pp. 1–6.

[138] B. Nykvist and M. Nilsson, "Rapidly falling costs of battery packs for electric vehicles," *Nature Climate Change*, vol. 5, no. 4, pp. 329–332, Apr. 2015.

[139] *Potential Benefits of High-Power, High-Capacity Batteries*, U.S. Dept. Energy, Washington, DC, USA, 2020.

[140] A. Cordoba-Arenas, S. Onori, Y. Guezennec, and G. Rizzoni, "Capacity and power fade cycle-life model for plug-in hybrid electric vehicle lithium-ion battery cells containing blended spinel and layered-oxide positive electrodes," *J. Power Sources*, vol. 278, pp. 473–483, Mar. 2015.

[141] L. Tang, G. Rizzoni, and S. Onori, "Energy management strategy for HEVs including battery life optimization," *IEEE Trans. Transport. Electrific.*, vol. 1, no. 3, pp. 211–222, Oct. 2015.

[142] X. Hu, C. Zou, X. Tang, T. Liu, and L. Hu, "Cost-optimal energy management of hybrid electric vehicles using fuel cell/battery health-aware predictive control," *IEEE Trans. Power Electron.*, vol. 35, no. 1, pp. 382–392, Jan. 2020.

[143] J. Wu, Z. Wei, W. Li, Y. Wang, Y. Li, and D. Sauer, "Battery thermal-and health-constrained energy management for hybrid electric bus based on soft actor-critic DRL algorithm," *IEEE Trans. Ind. Informat.*, early access, Aug. 6, 2020, doi: 10.1109/TII.2020.3014599.

[144] S. J. Moura, J. L. Stein, and H. K. Fathy, "Battery-health conscious power management in plug-in hybrid electric vehicles via electrochemical modeling and stochastic control," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 3, pp. 679–694, May 2013.

[145] T. M. Padovani, M. Debert, G. Colin, and Y. Chamaillard, "Optimal energy management strategy including battery health through thermal management for hybrid vehicles," *IFAC Proc. Volumes*, vol. 46, no. 21, pp. 384–389, 2013.

[146] L. De Pascali, F. Biral, and S. Onori, "Aging-aware optimal energy management control for a parallel hybrid vehicle based on electrochemical-degradation dynamics," *IEEE Trans. Veh. Technol.*, vol. 69, no. 10, pp. 10868–10878, Oct. 2020.

[147] X. Jin *et al.*, "Physically-based reduced-order capacity loss model for graphite anodes in Li-ion battery cells," *J. Power Sources*, vol. 342, pp. 750–761, Feb. 2017.

ABOUT THE AUTHORS

Shima Nazari received the B.S. and M.S. degrees from Sharif University of Technology, Tehran, Iran, in 2009 and 2012, respectively, and the Ph.D. degree in mechanical engineering from the University of Michigan, Ann Arbor, MI, USA, in 2019.

She was a Postdoctoral Researcher with the UC Berkeley Model Predictive Control Laboratory, Berkeley, CA, USA. She is currently an Assistant Professor with the University of California at Davis (UC Davis), Davis, CA, USA. Her research interests are in the areas of dynamics and controls with applications to vehicle electrification, transportation systems, and connected and automated vehicles.

Francesco Borrelli (Fellow, IEEE) received the Laurea degree in computer science engineering from the University of Naples Federico II, Naples, Italy, in 1998, and the Ph.D. degree from the Automatic Control Laboratory, ETH Zurich, Zürich, Switzerland, in 2002.

Since 2004, he has been serving as a consultant for major international corporations. He was the Founder and the CTO of BrightBox Technologies Inc., a company focused on cloud-computing optimization for autonomous systems. He is currently the Co-Director of the Hyundai Center of Excellence in Integrated Vehicle Safety Systems and Control, University of California at Berkeley (UC Berkeley),

Berkeley, CA, USA, where he is also a Professor with the Department of Mechanical Engineering. He is the author of more than 150 publications in the field of predictive control. He is the author of the book *Predictive Control* (Cambridge University Press). His research interests are in the area of model predictive control and its application to automated driving and energy systems.

Dr. Borrelli is the winner of the 2009 NSF CAREER Award and the 2012 IEEE Control System Technology Award. In 2017, he was awarded the Industrial Achievement Award by the International Federation of Automatic Control (IFAC) Council.

Anna Stefanopoulou (Fellow, IEEE) is currently the William Clay Ford Professor of Technology and the Director of the Energy Institute, University of Michigan, Ann Arbor, MI, USA, where she joined the Department of Mechanical Engineering in 2000 after working at the University of California at Santa Barbara, Santa Barbara, CA, USA, and in the automotive industry, where she developed algorithms and calibrations for highly efficient and advanced powertrains. She is also working with a multidisciplinary group to knit automotive and manufacturing expertise with battery and grid experts with the goal to realize clean electrified transportation. Her innovation in powertrain control technology has been recognized by multiple awards and has been documented in a book, 21 U.S. patents, and 340 publications (eight of which have received awards) on estimation and control of internal combustion engines and electrochemical processes, such as fuel cells and batteries. She has coauthored influential reports on the cost-effectiveness of fuel-efficient technologies for light-duty vehicles, sponsored by the National Academies, to help inform policymakers.

Dr. Stefanopoulou is a Fellow of SAE and ASME.