Applied Energy xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

# Influence analysis of driver behavior and building category on economic performance of electric vehicle to grid and building integration

Yanqing Kuang [a,b], Yang Chen [a], Mengqi Hu [a,*], Dong Yang [b]

[a] Department of Mechanical and Industrial Engineering, University of Illinois at Chicago, 842 W Taylor St., Chicago, IL 60607, USA
[b] Department of Information Management, School of Management, Donghua University, 1882 West Yanan Road, Shanghai 200051, China

## HIGHLIGHTS

- A collaborative decision model aiming to maximize cost savings of V2G/V2B integration is proposed.
- A set of parameters is introduced to model the driver behaviors.
- The impacts of driver behaviors and building categories on V2G/V2B integration are characterized.
- This study can provide a valuable insight for smart community design.

## ARTICLE INFO

*Article history:*
Received 7 January 2017
Received in revised form 5 June 2017
Accepted 10 July 2017
Available online xxxx

*Keywords:*
Electric vehicle
Vehicle to grid
Vehicle to building
Driver behavior
Building category

## ABSTRACT

The electric vehicle (EV) can be utilized as a dynamically configurable dispersed energy storage in the vehicle-to-grid (V2G) and vehicle-to-building (V2B) operation mode to balance the energy demand between buildings and EVs. This paper proposes a mixed integer linear programming based collaborative decision model to study the energy sharing between a building and an EV charging station (CS). The building has its distributed generator, and electric and thermal energy storage, and the CS has its own renewable energy source. To model the V2G/V2B integration, we introduce three sets of decision variables to represent the energy exchange among building, CS and power grid. A set of parameters are introduced to model the driver behaviors, such as initial and desired state of charge level of EV battery, and available hours of EV, and sixteen different building categories (e.g., office, restaurant, hotel, warehouse, etc.) are studied. The impacts of driver behaviors and building categories on the economic performance of V2G/V2B integration are characterized and analyzed. The results from this research can recommend best V2G/V2B integration considering various driver behaviors and building categories which can provide valuable insight for smart community design.



## 1. Introduction

Among all the consumption units, the proportions of energy use in building and transportation are 37% and 32% of the total energy use in the U.S. respectively [1]. With the concerns of energy efficiency and environmental sustainability, the smart buildings and electric vehicles (EVs) have attracted increasing attention in recent years. To stimulate consumers to purchase EVs, various incentive policies have been proposed by governments [2]. It is expected that there will be 2.7 million EVs on the road in the U.S. by 2020 [3]. A large adoption of EVs will bring both challenges and opportunities for the power grid. For example, the peak electric demand and voltage fluctuation of power grid will be increased if the EV charging is not well scheduled [4].

In the smart grid operation, the economic performance and environmental sustainability can be significantly improved by introducing the bidirectional communication and power flow between EV and power grid, which is termed as "vehicle-to-grid" (V2G) operation [5,6]. V2G operation can provide benefits to the power grid through actively using the EVs as energy storage [7–9]. For example, EVs can be used as dispersed energy storages to shift energy demand from peak hours to off-peak hours to reduce energy cost and $CO_2$ emissions [10]. The benefits of V2G technology in terms of greenhouse gas emission reduction and peak demand reduction can be significantly improved through integrating with renewable energy resources [11,12]. The performance of V2G technology for peak-shaving and valley-filling of power grid is evaluated in [13,14]. The economic and environmental analysis

* Corresponding author.
*E-mail address:* mhu@uic.edu (M. Hu).

http://dx.doi.org/10.1016/j.apenergy.2017.07.006
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**Nomenclature**

*Abbreviations*

| | |
|---|---|
| B | building |
| BO | boiler |
| BS | battery storage |
| CC | cooling component |
| CCHP | combined cooling, heating & power |
| CS | charging station |
| EV | electric vehicle |
| G | power grid |
| HC | heating component |
| PGU | power generation unit |
| PV | photovoltaic |
| SOC | state of charge |
| TE | thermal energy |
| TES | thermal energy storage |

*Subscripts*

| | |
|---|---|
| $t$ | index for time period |
| $v$ | index for EV |

*Parameters*

| | |
|---|---|
| $\alpha_{cmax}$ | maximum charging limit |
| $\alpha_{cmin}$ | minimum charging limit |
| $\alpha_{dmax}$ | maximum discharging limit |
| $\alpha_{dmin}$ | minimum discharging limit |
| $\Delta t$ | decision time interval |
| $\eta$ | system efficiency |
| $\eta_c$ | charging efficiency |
| $\eta_d$ | discharging efficiency |
| $\eta_{etoc}$ | electricity-to-carbon conversion factor |
| $\eta_{ftoc}$ | fuel-to-carbon conversion factor |
| $a_{PGU}$,$b_{PGU}$ | PGU electric efficiency |
| $C$ | cost function |
| $C_{tax}$ | carbon emission tax |
| $EC$ | cost for EV to enter CS |
| $EL$ | building electric load |
| $N$ | number of charging slots in CS |
| $PF$ | fuel price |
| $PP$ | electricity purchasing price |
| $PS$ | electricity selling price |
| $PT$ | electricity local transaction price |
| $QCL$ | building cooling load |
| $QHL$ | building heating load |
| $S$ | system size or capacity |
| $SOC_0$ | initial SOC |
| $SOC_d$ | desired EV electricity level |
| $SOC_{max}$ | maximum SOC |
| $SOC_{min}$ | minimum SOC |
| $SR$ | solar radiation |
| $T$ | decision time horizon |
| $T_a$ | EV available time |
| $T_{ua}$ | EV unavailable time |

*Decision variables*

| | |
|---|---|
| $e$ | stored or generated electricity |
| $ec$ | electricity charging rate |
| $ed$ | electricity discharging rate |
| $ef_{A,B}$ | electricity flow from A to B |
| $f$ | fuel consumption |
| $q$ | stored TE |
| $qc$ | TE charging rate |
| $qd$ | TE discharging rate |
| $qf_{A,B}$ | TE flow from A to B |
| $x$ | system ON/OFF state |
| $xA$ | entering state of EV |
| $xc$ | charging state |
| $xd$ | discharging state |
| $xL$ | leaving state of EV |
| $xS$ | connecting state of EV |

of V2G technology for current electricity markets has been widely studied in [15–19]. A spatial-temporal model is developed in [20] to study the impact of large penetrations of EVs on power distribution networks. An optimized fuzzy controller is adopted to control the charging and discharging state of EV batteries with respect to grid frequency [21]. A multi-objective optimization model using weighted sum and fuzzy control approaches is proposed in [22] to minimize the load variance and energy cost for V2G operation.

To significantly reduce the energy consumption from the two main sectors, building and transportation, the vehicle-to-building (V2B) technology has attracted greater attention recently. It is demonstrated that the V2B integration can achieve cost savings [23] and $CO_2$ emissions reductions [24] using appropriate operation decision strategy. Instead of installing stationary energy storage system, the EVs can help buildings reduce peak energy demand and energy cost [25,26]. By using the V2B technologies, the benefits for demand side management and outage management can be significantly improved [5]. The potential benefits for V2B integration together with additional revenue through providing ancillary service can be amplified [27]. A distributed scheduling algorithm based on game theory for charging and discharging EVs in V2B operation mode is developed in [28]. The benefits of optimizing EV and home energy scheduling considering user preferences in a residential community are discussed in [29,30]. In order to improve the self-consumption of energy generated by photovoltaic (PV) panel and reduce the impact on power grid, a heuristic operation strategy for commercial building level microgrid including EVs and PV system is studied [31]. The economic impacts of EVs under various demand response strategies for smart households are studied in [32].

Other than V2G/V2B integrations, the energy performance of EVs can be highly influenced by driver patterns and behaviors, such as when to charge/discharge, duration time for charging/discharging, initial energy level when connecting to the EV charging station (CS) and desired energy level when leaving the CS [33]. The unpredictable mobility behaviors of drivers are simulated using a dynamic model [34]. A framework is developed to comprehensively evaluate the viability and efficiency of V2G considering driver behaviors [35]. A stochastic distributed energy resources customer adoption model considering driver schedules is developed to obtain optimal distributed energy resource investment and scheduling decisions to reduce energy cost [36]. A Markov decision process model is developed in [37] to optimally charge the EVs considering the randomness of driving patterns. The driver patterns, behaviors and types are considered in a data-driven approach to estimate the benefits of EVs at non-residential locations [38]. The drivers' battery swapping behaviors are optimized to balance the daily load for power grid in [39]. The values for EVs to provide regulation and reserve services by considering EV user's charging and driving characteristics are studied in [40].

While promising, we notice that most of the existing V2G/V2B studies have been focused on efficiently operating the EVs and