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Author(s)	Iacobucci, Riccardo; McLellan, Benjamin; Tezuka, Tetsuo
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# Costs and carbon emissions of shared autonomous electric vehicles in a Virtual Power Plant and Microgrid with renewable energy

Riccardo Iacobucci<sup>a,\*</sup>, Benjamin McLellan<sup>a</sup>, Tetsuo Tezuka<sup>a</sup>

<sup>a</sup>Graduate School of Energy Science, Kyoto University, Yoshida Honmachi, Kyoto, Japan

## Abstract

Shared autonomous electric vehicles (SAEVs) are expected to become commercially available within the next decade. This technology could transform transport paradigms and alter the availability of controllable storage from electrified transportation. This work describes a novel simulation methodology for investigating the potential for SAEVs to act as storage in the framework of a Virtual Power Plant or a microgrid with intermittent renewable energy. The model simulates aggregate storage availability from vehicles based on transport patterns and optimizes charging. We study the case of a grid-connected VPP with rooftop solar and the case of a isolated microgrid with solar, wind, and dispatchable generation. The results show that SAEVs offer significantly lower costs compared to private vehicles. SAEVs can also substantially increase renewable energy utilization in a microgrid.

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Keywords: shared transportation; electric vehicles; demand response; vehicle-to-grid; charge scheduling

# 1. Introduction

Shared autonomous electric vehicles (SAEVs) offer the flexibility of private vehicles without the need for car ownership, similar to one-way car sharing services already popular in large cities in Europe [1], but more convenient. The advent of SAEVs could facilitate electrification and coordinated vehicle charging. It is therefore important to study the impact of this system on the electricity grid, especially their potential to provide grid services such as storage. In particular, the grid synergies offered by SAEVs can be realized in the framework of a Virtual Power Plant (VPP) or microgrid. This allows users that sign in the transport service to renounce their private vehicle and use SAEVs instead, and to acquire electricity from the same provider (VPP/microgrid and SAEV operator). This may lower the total costs of the system and allowing a larger penetration of renewable energy.

\* Corresponding author. Tel.: 075-753-4739

E-mail address: iacobucci.riccardo.38e@kyoto-u.jp

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CPESE 2018, 19–21 September 2018, Nagoya, Japan. 10.1016/j.egypro.2018.11.104 Most studies on the charging of electric vehicles and their interaction with renewable energy have focused on private vehicles, mostly assuming that vehicles are used once or twice a day and charged at night [2]. On the other hand, research on SAEVs have mostly dealt with transport optimization, without considering charging optimization or renewable energy integration [3]. In this work we aim to evaluate the synergies of SAEVs with renewable energy by investigating the cost savings for users, CO2 emissions changes, and the renewable energy integration potential. To our knowledge, this is the first attempt to evaluate the renewable energy integration potential of SAEVs. We present a methodology to optimize the charging and discharging of SAEVs with distributed dispatchable generators (DG), renewable energy generators, grid electricity with variable price, and taking into account variable transport and rebalancing requirements. We investigate the costs and carbon emissions of a SAEV system in the case of a grid-connected VPP and an isolated microgrid by comparing it with alternative storage and transport options.

# 2. Methods

The model optimizes the aggregate charging and discharging of SAEVs considering transport demand, nontransport load, and renewable energy generation in a VPP or microgrid. Passenger requests are generated stochastically from trip frequency distribution taken from transport surveys through a Poisson process. Generally, passenger origin and destination distributions are not symmetric during any period of time shorter than a day. Redistribution of vehicles is needed to ensure service to all passengers. It has been shown that the minimum amount of redistribution distance is the Earths Mover Distance (EMD) between the origin and destination distributions during a certain period of time [4]. This is a theoretical minimum rebalancing distance which can however be reached in practice with an efficient routing strategy [4]. In this work the EMD is calculated for each time interval from the trip distributions, and this extra relocation travel distance is added to the total distance traveled for trips with passengers to account for the energy needed for rebalancing. The evolution of the energy stored in the vehicles and the electricity flow balance are:

$$e(t+1) = e(t) - d(t) + c(t) - q(t)/\eta$$
(1)

$$G_{re}(t) - L(t) + i(t) - k(t) - c(t) + q(t) + \sum_{j} g_{j}(t) \ge 0$$
<sup>(2)</sup>

where *e* is the total stored energy in the vehicles, *d*, *c*, and *q* are respectively transport energy demand, charge, and V2G discharge, all non-negative,  $\eta$  is the efficiency of V2G, set at 0.9,  $G_{re}$  is the renewable energy generation, *L* is all other electric load in the system, *i* is the grid import, *k* is the grid export, and  $g_j$  is the generation from unit *j*. Three binary decision variables are introduced to control the dispatchable distributed generation (DG) units:  $v_j(t)$ ,  $w_j(t)$ ,  $o_j(t)$ , all  $\in \{0, 1\}$ , to account respectively for startup, shutdown and operation of unit *j* at time *t*. The constraints are:

$$g_{j,min} \cdot o_j(t) \le g_j(t) \le g_{j,max} \cdot o_j(t) \quad , \quad o_j(t) - o_j(t-1) = v_j(t) - w_j(t)$$
(3)

with  $g_{j,min}$  and  $g_{j,max}$  respectively the minimum and maximum generation for generator *j* when operational. The grid import/export capacity is also constrained by the maximum capacity  $i_{max}$ . The energy stored is subject to the constraints of the battery capacity of vehicles. The amount of energy that can be exchanged with the grid at any time interval is constrained by the number of vehicles connected to the grid during the interval. Assuming a uniform distribution of passenger trip requests, the average number of vehicles connected  $m_{av}$  is:

$$m_{av}(t) = m - (f_{pass}(t) + f_{rel}(t)) / (u(t) \cdot t_{len})$$
(4)

where *u* is the average speed of vehicles and  $t_{len}$  is the length of the time step interval. The maximum energy exchangeable is therefore  $e_{max}(t) = m_{av}(t) \cdot e_{v,max}$ , where  $e_{v,max}$  is the maximum energy that can be exchanged by each vehicle during a time interval. As the actual instantaneous power during the period may vary depending on the specific position of vehicles, it is assumed that actual maximum vehicle power connections are higher so that extra power can be temporarily drawn by or from available vehicles if required. The model objective is the minimization of the total

	ICEV	CAEV	DG unit	min.	max.	cost	$CO_2$
· 1 /		SAEV		kW	kW	yen/kWh	kg/kWł
capital cost	$2 \min \text{yen}$	5 min yen	gas turbine	1000	5000	20	0.6
consumption	4.5 I/100km	0.15 KW n/Km	diesel engine	100	1000	25	0.65
expected life	12 years	5 years	biomass	500	500 2000	15	0.4

Table 1: Transport mode characteristics

Table 2: Summary of distributed generation characteristics

costs from the grid, the total cost from generators, and the cost of battery cycling:

$$\min\sum_{t} \left( i(t) \cdot y(t) - k(t) \cdot y(t) \cdot \eta_{grid} + \sum_{j} \left( i_j(t) \cdot C_{op,j} + v_j(t) \cdot C_{start,j} \right) + \frac{\gamma_{cycles} \cdot c(t) \cdot C_{bat}}{L_{bat}} \right)$$
(5)

with y(t) the wholesale price of electricity at time t.  $\eta_{grid}$  is an efficiency parameter representing the cost of selling to the grid and to avoid simultaneous import and export. This was chosen at 0.99.  $\gamma_{cycles}$  is the fraction of the battery costs amortized by cycling as opposed to aging, which was chosen as 0.5. The model can be solved with mixed integer linear programming methods. The renewable energy (wind and solar) generation g was generated stochastically based on historical data. Wind power profiles were generated with a Markov model, which have been used extensively to generate wind speed profiles based on historical data [5]. Solar irradiance profiles were generated by multiplying hourly extraterrestrial solar irradiation profiles for the simulation days and location by a stochastically generated average daily clearness index K. The probability distribution of K was determined by comparing computed values for the average daily extraterrestrial solar irradiation over actual measured historical irradiation values for each day.

	solar	wind	ref	scenario	transport	storage	charge schedul.	VPP
capital cost [m yen/kW]	0.25	0.20	[ <mark>6</mark> ]	Baseline	ICEV	×	Х	×
O&M cost [yen/kW/year]	0	7600	[ <mark>6</mark> ]	VPP	ICEV	×	×	0
payback [years]	10	10	-	Battery	ICEV	0	0	0
capacity factor [%]	13	21	-	SAEV1	SAEV	0	×	0
emissions [kg CO2/kWh]	0.041	0.011	[7]	SAEV2	SAEV	0	0	$\bigcirc$
				SAEV2+V2G	SAEV	$\cap$	$\cap$	$\cap$

Table 3: Summary of renewable energy characteristics

Table 4: Summary of scenarios for VPP case

The model was developed in MATLAB and tested in a variety of scenarios to evaluate costs and emissions. We used a model predictive control (MPC) approach with an optimization period (horizon) of 3 days. At each step of the MPC, the first day of the 3-days optimization is implemented, and the optimization is rerun with an updated prediction horizon for the next day. The transport request probability is based on the Tokyo Person Trip Survey 2008 [8], a survey of around 2 million trips in the Tokyo metropolitan area. The electricity load profile was taken from TEPCO for 2017. The electricity price was taken from the Japan Electric Power Exchange (JEPX) historical price data for the corresponding electricity load period. We assume that the VPP has access to the wholesale electricity market as a price-taker. Solar irradiation data was taken from the Japan Meteorological Agency and wind data from NOAA. The generation capacity was sized to generate the total non-transport electricity consumption over a year. For simulation with only solar power, this is equivalent to about 2 kW of solar PV per person. A summary of the transport and renewables cost assumptions can be found in tables 1 and 3. Grid emissions was set at 0.534 kg CO2/kWh, the value in the Japanese electricity supply in 2015. For the microgrid case, we used hypothetical DG units with characteristics summarized in table 2 taken from [9]. Start-up costs for each unit were chosen as the cost of running the unit at full power for one hour.

The time interval length was set to 1 hour. The fleet size was selected at 1.4 vehicles per average trip per hour (TPH). This ratio was found in previous work to be a good compromise between minimizing waiting times and operating costs of the system [10]. Assuming an average of 2 trips per private vehicle per day, this suggests that autonomous vehicles would replace traditional vehicles with a proportion of about 1:10, in accordance with previous studies [11], [3]. The total population assumed in these simulation was chosen as 12,000 people, resulting in a total of 24,000 trips per day.

#### 3. Results and discussion

We considered first the case of the grid-connected VPP without DG, and then the case of the isolated microgrid. Simulations were run over one week (Monday to Sunday), with a total of 100 iterations for each data point. We considered 6 scenarios (table 4) to compare the cost and emissions performance of SAEV. The total costs and  $CO_2$  emissions for each scenario considered are reported in table 5. SAEV cases (scenarios 4 to 6) are the lowest total cost options. The cost savings are dominated by capital costs, as vehicles are shared among all participants in the VPP. Cost of electricity becomes significantly higher in the case of SAEV, although it is still lower than the fuel costs it replaces. Compared to the unscheduled charging, the proposed algorithm decreases electricity costs by 38% and 76%, respectively for the scenario with no V2G and with V2G. Further electricity savings (and possibly profits) could be attained in a grid with a more variable electricity price profile that favors storage services, characteristic of a grid with high penetration of renewable energy. With all other things equal, carbon emissions increase significantly with the adoption of SAEV, due to the high carbon intensity of the Japanese grid and the high efficiency of hybrid cars. The total distance to travel for SAEV is also higher than that for private vehicles due to the need to rebalance empty, as discussed previously.

	VPP costs (million yen)				$CO_2$ (t)	Microgrid costs (million yen)				<i>CO</i> <sub>2</sub> (t)		
	ele.	fuel	batt.	cap.	total		ele.	fuel	batt.	cap.	total	
Baseline	0.19	3.29	0.00	50.01	53.49	55.73	4.78	3.29	0.00	48.16	56.23	180.26
VPP	-0.10	3.29	0.00	50.01	53.20	55.73	-	-	-	-	-	-
Battery	-1.30	3.29	3.31	50.01	55.31	60.20	1.84	3.29	3.55	48.16	56.84	118.88
SAEV1	1.91	0.00	3.96	38.50	44.37	113.99	6.46	0.00	3.96	40.20	50.63	184.37
SAEV2	1.19	0.00	3.88	38.50	43.57	106.53	4.46	0.00	3.82	40.20	48.49	127.25
SAEV2+V2G	0.46	0.00	4.24	38.50	43.19	108.14	2.75	0.00	4.39	40.20	47.34	95.86

Table 5: Electricity, fuel, battery, capital and total costs and emissions for VPP and microgrid scenarios



Fig. 1: Microgrid case: sensitivity to total renewable energy generation (as a share of total consumption in a year) of (a) total costs (b) carbon emissions. SAEV+V2G with high renewable penetration have lower costs and emissions than the case with no renewables and private vehicles.

To test the microgrid case, we used the same transport, load and weather data used for the VPP. We assume an isolated microgrid with no grid connection. We tested the same scenarios in table 4 with the exception of the second, as it does not apply to the microgrid case. In all cases, renewable generation was sized to cover all electrical loads over a year with a 50/50% share of wind and solar power. Fig. 2 shows an example of the results for one week with and without V2G. Costs and  $CO_2$  emissions for each scenario are listed in table 5. The sensitivity to renewable energy capacity is shown in Fig. 1. It can be noted that the total costs of SAEV+V2G with high renewable energy penetration level, costs are almost flat. This shows the potential for SAEV to effectively integrate intermittent power generation. The synergies of SAEV and renewable energy are also evident in Fig. 1b, with emissions decreasing much faster in the case with charge-scheduled SAEVs than for the baseline.



Fig. 2: Example of SOC, charge [C], load [L] and generation from gas [GT], diesel [DE], biomass [B], solar [S] and wind [W] (a) without V2G (b) with V2G. V2G discharge (negative charge) allows to avoid the gas turbine start-up.

## 4. Conclusions

An optimization methodology was developed for the charge and discharge of Shared Autonomous Electric Vehicles (SAEV) to minimize costs in the context of a Virtual Power Plant (VPP) or microgrid. The model was tested with several scenarios using weather data and transport patterns for the Tokyo region. The results show that total costs are about 20% lower for households with rooftop solar power shifting from utility power and hybrid private vehicles to the VPP with SAEV. However, the system would increase carbon emissions due to the high emission intensity of the Japanese grid and the high fuel efficiency of new hybrid vehicles. A carbon pricing mechanism could be included to maximize use of energy at times of low carbon intensity.

In the case of the isolated microgrid, SAEVs with V2G decrease cost by 16% and cut carbon emissions by half, helping to integrate intermittent renewable energy while costing a fraction of the equivalent stationary battery storage. In conclusion, SAEVs have significant potential to integrate renewable energy, especially when their storage potential is adequately compensated as in the case of the microgrid. This could guide policy decisions for the deployment of distributed renewable energy with storage through VPP with SAEVs, which would benefit both households and the grid, making deployment of intermittent generation more sustainable.

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