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Study of Electric Vehicles for Grid Services – A Gender-based Approach

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Abstract—**This paper investigates the battery degradation and financial benefits of using an EV as a car only and as a revenue source as well when participating in the electric grid services. The study looks into behaviours of female and male drivers to investigate whether gender plays an important role in battery degradation of EVs. Firstly, a battery degradation model is developed using data provided by an EV maker. Then, a breakeven point study is presented to compare between an EV and an internal combustion engine (ICE) vehicle cost of ownership, differentiated by usage type and gender. It is shown that if the difference in price is above 5000 GBP and the milage is low, EVs are less attractive, unless used for grid support. The results show that a single weekly grid support event is not harmful for the EV battery life but has a great impact on the breakeven point and makes the EV a competitor to the ICE vehicle which facilities the future transition to a market full of EVs. Battery degradation considering published chemistry and performance data differs very slightly between male and female users.**

Keywords—battery degradation, breakeven point, electric vehicle, grid services

I. INTRODUCTION

Transport is one of Europe's biggest climate problems with 27% of total EU greenhouse gas emissions, from which passenger cars resulted in 41%, in 2016 [1]. With the current intention to achieve a net-zero carbon footprint, the electrification of the transport sector is in progress [2, 3]. Electrifying cars/vans is much easier than aviation and shipping [1]. In order to encourage and increase the electric vehicles (EVs) penetration, fast charging forecourts, which mimic traditional petrol stations, were built that can reduce the EV battery charging time to a few minutes [4]. Nevertheless, the recent study in [5] showed the need for a subsidy to accelerate the EV uptake in the UK market.

The high initial cost of EVs compared to ICE cars is a main reason for the slow EVs growth and made EVs not cost-effective. That is why a subsidy was necessary as reported in [5]. However, sale of petrol/diesel cars is banned in the near future [3]. Vehicle to grid (V2G) is one of the potential revenue sources that could encourage the EV uptake. Briefly, V2G is to use the EV battery to participate in grid balancing services such as frequency response, i.e., selling the energy stored in the EV battery to the grid when requested [6]. This leads to more charging/discharging for the EV battery which affects the battery life. V2G has been included in different research directions. In [6], a feasibility study for a company investing in V2G chargers to use its employees EVs for grid services was reported. The study considered paying for the EV battery degradation effect as well. In [7], the V2G operation is optimized to provide frequency and voltage regulation services by performing a day-ahead scheduling of EV charging/discharging. SoC pre-conditioning was suggested in [8] to allow V2G while reducing the battery degradation.

The previous few examples considered the V2G but not mainly from the EV owner point of view. From a car owner view, this paper studies the impact of the little participation in grid balancing services on the EV battery degradation and on the breakeven point if an EV is compared to an ICE vehicle. This impact is introduced for both male and female car owners using statistics from the National Travel Survey (NTS) in the UK to see how it varies from a gender perspective.

II. EV BATTERY DEGRADATION MODEL

Current EVs use Lithium-ion batteries due to their favourable properties including high energy and power densities, and low self-discharge rate [9]. The EV battery degrades due to charging/discharging processes which is known as cycling ageing and degrades over time even if unused which is known as calendar ageing [10]. In this section, a degradation model, based on the empirical model reported in [11], is developed to estimate the capacity loss of the EV battery. It is worth noting that an accurate model can only be developed when the experimental data for the battery of interest is available. In other words, batteries of different parameters such as different chemistry or different manufacturer or even different size may exhibit different degradation characteristics [12]. Degradation data for real-world EV batteries, currently in operation, can hardly be found. In this paper, the data provided by Tesla [13] is used to estimate the model parameters when possible. Model parameters that require further data which cannot be obtained have been assigned values from the literature.

In [11], the degradation is represented as a nonlinear process and the battery life is estimated using (1).

$$L = 1 - A_{sei} e^{-B_{sei} f_d} - (1 - A_{sei}) e^{-f_d} \qquad (1)$$

where, L refers to life loss with $L = 0$ indicating a new battery, f_d is the linearized degradation rate, and A_{sei} and B_{sei} reflects the degradation due to Solid Electrolyte Interphase (SEI) film formation which accelerates the degradation at the beginning of life. This will be clear later when looking at the data from Tesla [13] that shows higher degradation at start of life (first few thousand miles) compared to the later operation.

Considering cycling ageing and assuming N identical charge/discharge cycles, the capacity loss is given by (2), where f_{d1} is the degradation rate per cycle.

$$L = 1 - A_{sei} e^{-N B_{sei} f_{d1}} - (1 - A_{sei}) e^{-N f_{d1}} \qquad (2)$$

In [13], the capacity retention per travelled distance is given (Fig. 1). Assuming a full cycle corresponds to 275 miles, the capacity retention versus cycles can be obtained. The model given by (2) was fitted to the data extracted from [13] using the least squares fitting method. The estimated model parameters are given in Table I. The actual data versus the estimated model output is shown in Fig. 2.

III. IRREGULAR BATTERY CYCLING

The previous model assumes identical charge/discharge cycles which is not realistic. The model is updated in this section to account for irregular battery cycling. The previously estimated degradation rate f_{d1} is replaced by a cycle-based degradation rate. The degradation rate is a function of the individual cycle depth of discharge (DoD), state of charge (SoC), and temperature [11]. For simplicity, it is assumed that the temperature can be maintained around the required level by the battery management system and its effect on the degradation is negligible. For a cycle number "*i*", the cycling degradation rate f_{ci} is defined by (3) where DoD_i and SoC_i are the DoD and SoC respectively of the cycle number "*i*", and SoC_{ref} is the reference SoC at which the model parameters were initially estimated. The total cycling degradation rate f_d in (1) is represented by (4) where n_i is either 1 or 0.5 based on the identified cycle and will be illustrated later.

$$f_{ci} = \left(k_1 DoD_i^{\,k_2} + k_3\right)^{-1} \times e^{k_4\left(SoC_i - SoC_{ref}\right)} \tag{3}$$

$$f_d = \sum_{i=1}^{N} n_i f_{ci} \tag{4}$$

Four other parameters (k_1, k_2, k_3, and k_4) are required. Due to lack of data, the three parameters (k_1, k_2, and k_4) were assigned to the values specified in [11]. The value of k_3 is calculated such that the model provides the value of f_{d1} as given in Table I when assuming identical cycles.

The EV will not always be in use, instead there will be long periods of parking. The EV battery exhibits calendar ageing during the parking periods. The calendar degradation rate can be estimated by (5) (ignoring the temperature effect), where t and SoC_t are the period in seconds when the EV battery was not charging/discharging and the average SoC during this period, respectively. According to [13], the EV battery technology is improving to ensure a long lasting battery. Therefore, k_5 is assumed to be half the value reported in [11]. All the model parameters are given in Table I.

$$f_t = k_5 t \times e^{k_4\left(SoC_t - SoC_{ref}\right)} \tag{5}$$

To apply the model, it is necessary to identify the battery cycles and the corresponding DoD and SoC. The rainflow cycle-counting algorithm was implemented for cycles analysis [14, 15]. The EV battery SoC profile is the input for the rainflow algorithm in [15]. The algorithm identifies the cycles and their amplitude and mean values as shown in Fig. 3.

IV. BREAKEVEN POINT

EVs are commonly more expensive than ICE vehicles. However, there may be no chance in the future to buy new gasoline car aligning with different countries plans to achieve a net-zero carbon footprint [3, 16]. In this section, the breakeven point—the point at which the cost of owning an EV equals the cost of owning a petrol car—is studied. EVs have the potential to be a source of income if participated in grid services. This activity has also been considered when studying the breakeven point. The EV owner would presumably receive payment for the energy used during grid activity. The following assumptions are used:

- Maintenance cost is excluded from the calculation as there is insufficient data relating to EVs.
- Fixed petrol and electricity prices are assumed over the study period.
- Taxes, subsidies, and cost of CO_2 emissions are not included.

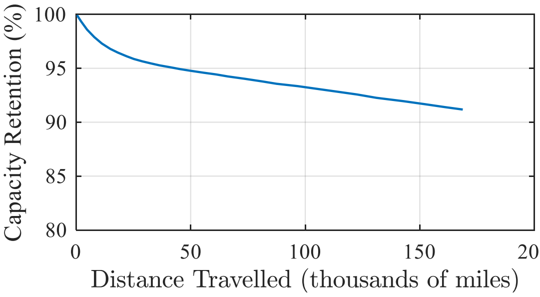

Fig. 1. Capacity retention per distance travelled [13].

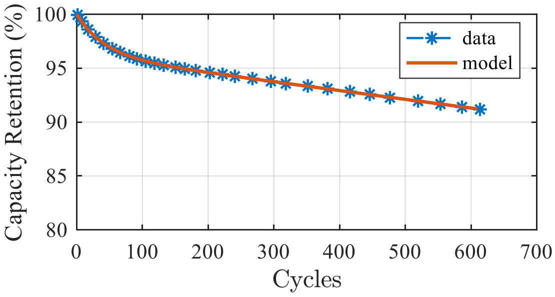

Fig. 2. Actual data versus the degradation model output.

TABLE I. DEGRADATION MODEL PARAMETERS

Parameter	A_{sei}		B_{sei}		f_{d1}
Value	3.75E-2		272.8		8.8E-5
Parameter	k_1	k_2	k_3	k_4	k_5
Value	1.4E5	-0.501	-1.286E5	1.04	2.07E-10

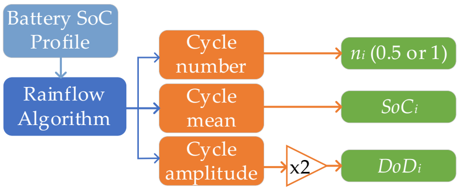

Fig. 3. Application of the rainflow counting algorithm.

The total ownership cost for both petrol and electric vehicles is calculated using (6) and (7), respectively. To estimate the breakeven point, the two costs are subtracted (8).

$$\mathrm{Cost_{IC}(y)} = \mathrm{IC0} + \sum_{1}^{y} \frac{Pc \times Mi \div mLitre}{(1+r)^y} \tag{6}$$

$$\mathrm{Cost_{EV}(y)} = \mathrm{EV0} + \sum_{1}^{y} \frac{TR1 \times Mi \div mkWh - TR2 \times E_G}{(1+r)^y} \tag{7}$$

$$\Delta\mathrm{Cost} = \mathrm{Cost_{IC}} - \mathrm{Cost_{EV}} \tag{8}$$

where, IC0, and EV0 are the petrol and EV purchase cost, Pc is the petrol price per liter, Mi is the annual mileage, $mLitre$, and $mkWh$ are the miles per liter and per kWh, $TR1$, and $TR2$

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are the electricity price per kWh for charging EV and for providing grid services, E_G is energy delivered to grid, r is the interest rate and y is the year number.

V. RESULTS

Numerical results are provided in this section showing the EV battery degradation with different driving patterns with and without supporting grid services. Then, a study showing the breakeven points for EVs is presented.

A. Driving patterns and the corresponding degradation

The study presented in this paper uses as realistic data as possible. The National Travel Survey (NTS) statistics for 2021 were used to derive two possible driving patterns [17]. The two patterns reflect the average yearly driving for males and females. The average number of trips per week as a car driver was extracted from Table NTS0601 [17] where it was approximately 6 trips per week. The trip length changes according to the trip purpose. Potential trip purposes that may require a car have been extracted from Table NTS0611 [17] and their normalized values are shown in Fig. 4. Table II shows the average trip length by purpose as obtained from Table NTS9912 [17]. The distance in Table II is used for males and the females trip length is scaled according to the annual average distance travelled by females with respect to males.

The first step to create the travel pattern is to select the trip purpose. The normalized values in Fig. 4 are used to create a probability distribution that has been used to randomly select the trip purpose for different trips along the year. The trip length is then selected from Table II for each selected trip. It has been assumed that the battery SoC linearly decreases while travelling according to (9):

$$\mathrm{SoC}(\mathrm{m}+) = \mathrm{SoC}(\mathrm{m}-) - \mathrm{D}(\mathrm{m})/\mathrm{Dmax} \tag{9}$$

where $\mathrm{SoC}(\mathrm{m}+)$, $\mathrm{SoC}(\mathrm{m}-)$, $\mathrm{D}(\mathrm{m})$, and Dmax are the battery SoC after and before the trip number “m”, trip length, and total mileage range of the EV, respectively.

The battery is recharged only once per week and the annual SoC profile is shown in Fig. 5. Other than using the EV for driving, the EV can participate in different grid balancing services such as frequency response. For simplicity, a single grid support event per week that extends for 30 minutes is assumed which is an emulation for the maximum secondary frequency response requirement [18] (assuming an aggregator would be operational). The created patterns in Fig. 5 were repeated including a weekly grid support event but are not shown due to space limitation.

Two other patterns simulating a daily commuting for 20 miles and a three five-miles short trips (Escourt and Shopping) during the weekdays were constructed. In the commuting pattern, daily charging at the workplace was assumed while the short trip pattern assumed charging at home once a week. The two patterns were built without and with the grid support. Fig. 6 shows the patterns with the weekly grid support event. The annual SoC profiles were repeated five times to create five years utilization profiles.

The developed degradation model was applied to different five years SoC profiles to estimate the capacity retention after five years of utilization. The periods where the EV was not in use were used to calculate the calendar ageing. The cycle and calendar ageing were added to estimate the total degradation.

TABLE II. AVERAGE TRIP LENGTH

Purpose	Commuting	Business	Escort	Shopping
Miles	8.2	15.2	1.9	3.5
Purpose	Visiting friends at home	Visiting friends elsewhere	Day trip	
Miles	10.3	7.4	16.3	

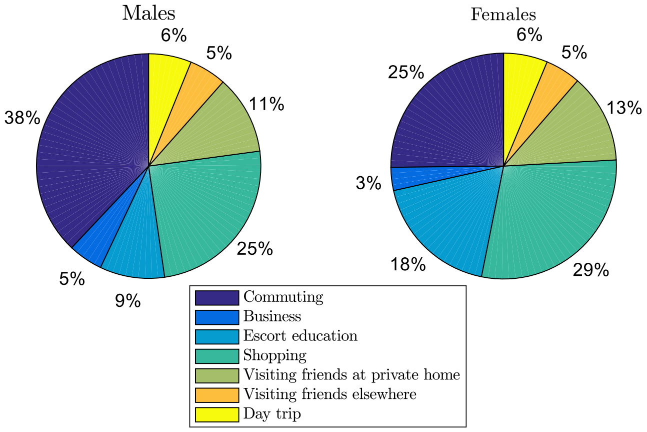
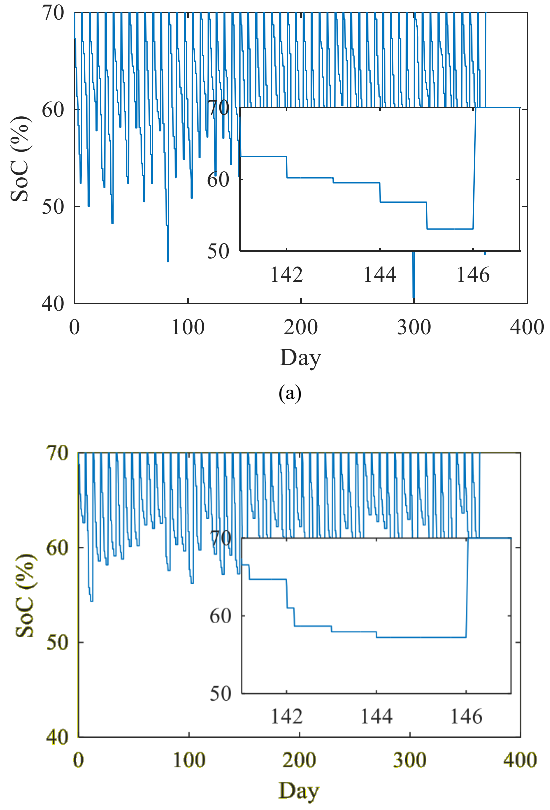


Fig. 4. Normalized number of trips by trip purpose and gender.



(a)

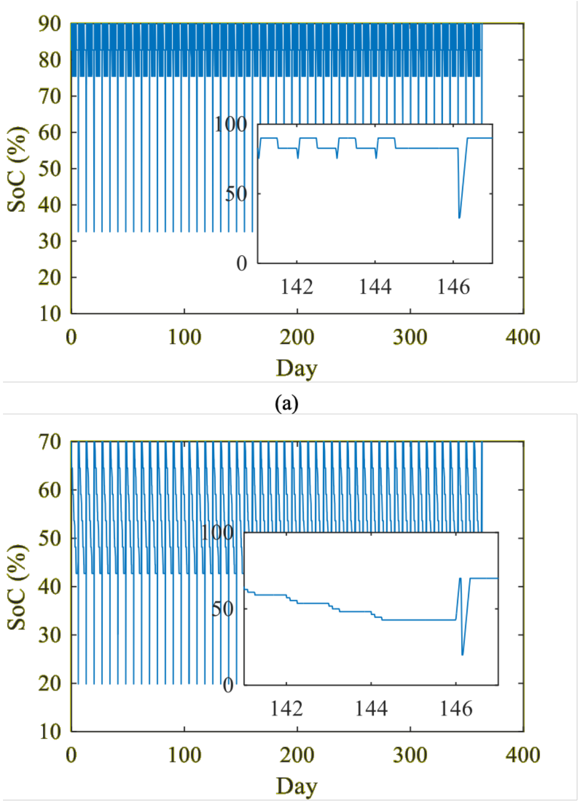
(b)

Fig. 5. Annual SoC profile without grid support for (a) males and (b) females.

Table III and Table IV show the percentage degradation for different cases and the following points can be derived:

1. The calendar ageing is dominant because the EV stays unused for long periods.
2. Females show lower degradation than males because they move shorter distances according to the NTS.
3. Adding a weekly grid event increases the cycle ageing which is expected.
4. Battery degradation differs very slightly between male and female users as illustrated in Table III.

5. The impact of participation in grid balancing services on the battery degradation decreases when the EV is driven over longer distances. This can be seen from comparing **ΔTotal** in Table IV. Commuting for medium distance shows lower effect of the grid support (**ΔTotal** is 0.58%) compared to the short trips (**ΔTotal** is 1.6%).



(a)

(b)

Fig. 6. Annual SoC profile with grid support for repeated (a) commuting and (b) short trips.

TABLE III. DEGRADATION VALUE FOR DIFFERENT PATTERNS

% degradation	**Males**		**Females**	
	Drive	***Drive+Grid***	***Drive***	***Drive+Grid***
Cycle	1.31	3.25	0.97	3.10
Calendar	7.15	7.04	7.25	7.14
Total	8.46	10.29	8.22	10.24
ΔTotal	1.83		2.02	

TABLE IV. DEGRADATION VALUE FOR REPEATED COMMUTING AND SHORT TRIPS

% degradation	**Commuting**		**Short Trips**	
	Drive	***Drive+Grid***	***Drive***	***Drive+Grid***
Cycle	4.10	4.95	1.76	3.46
Calendar	7.85	7.74	6.89	6.79
Total	11.95	12.53	8.65	10.25
ΔTotal	0.58		1.60	

B. *Breakeven point study*

The results in the previous subsection showed how participation in the grid balancing services once a week affects the EV battery degradation. In this subsection the influence of this participation on the breakeven point is determined. The parameters values are given in Table V. The EV initial cost and the annual mileage are variables. In addition to the paid charging, free charging is also considered as a possible option.

TABLE V. PARAMETERS FOR THE BREAKEVEN POINT STUDY

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
Petrol price (*Pc*)	1.5 £/litre	Miles/kWh (*mkWh*)	4	Interest rate (*r*)	5%
Miles/litre (*mLitre*)	10	Electricity price (*TR*1)	0.35 £/kWh	IC0	£20k
EV battery	57 kWh	Electricity price (*TR*2)	1.05 £/kWh	EV0	£20k: £60k

The analysis is carried out for a period of 15 years which reflects a reasonable lifetime of a vehicle. The breakeven point is obtained from monitoring (8) at different study scenarios.

With an initial cost difference of £10,000 between the petrol car and the EV, Fig. 7 shows the accumulated cost difference for 4,000 and 8,000 annual mileages when the EV is used for driving only or for grid support as well. Using an EV for driving only will not be cost effective over its entire life. Noting that the EV owner pays for the battery charging in this case. On the other hand, when participating in grid balancing service once a week, the EV tends to provide positive cash flow after a few years. With larger annual mileage, the breakeven point comes earlier which can remove anxiety for drivers used to travel for long distances. This test scenario has been repeated for initial EV prices of £20k, £30k, £40k, £50k, and £60k. Fig. 8 shows the breakeven year when the EV supports the grid for different prices and different annual mileage. Only three initial prices (£20k, £30k, and £40k) can bring breakeven point within 15 years depending on the mileage. The other high prices cannot provide breakeven points. The larger the mileage the earlier the breakeven point.

Some facilities (work) allow free EV charging to increase the EV acceptance level. As the EV owners do not need to pay for charging, they may choose not to support the grid. Breakeven point is still achievable as shown in Fig. 9 depending on the EV price and annual mileage. Not all prices can have a breakeven point. On the other hand, if the EV participated in grid support, the breakeven is achievable for all prices used in the study as depicted in Fig. 10.

To sum up, using an EV as an ordinary car is not a cost-effective option if compared to a petrol car. However, purchasing a petrol car will not be allowed in the near future. To solve this dilemma, little participation in the grid balancing services to provide a sort of revenue while slightly affecting the EV battery degradation is recommended as shown from the results obtained in this section.

VI. CONCLUSION

A battery degradation model was developed using data available from one of the EV makers. Driving patterns for both males and females were created using the UK's NTS statistics. The developed degradation model and the generated patterns were used to estimate the capacity retention for an EV battery after five years of utilization. The study included participation in the grid balancing services only once a week. The findings indicated that the battery life is only marginally impacted by a single 30-minute weekly grid support event. Additionally, the effect was lessened as the EV travelled farther. For instance, the increase in degradation was 0.58% and 1.6% for medium distance commuting and short trips, respectively. For both male and female users, the aggregate end degradation was extremely near. A simplified study for the breakeven point between owing an EV or ICE vehicle was presented. The small amount of grid service usage resulted in an early breakeven point that would not have been possible without this usage. The breakeven point model will be expanded in future work to include other costs like taxes, subsidies, and the cost of CO2 emissions into account while doing the analysis.

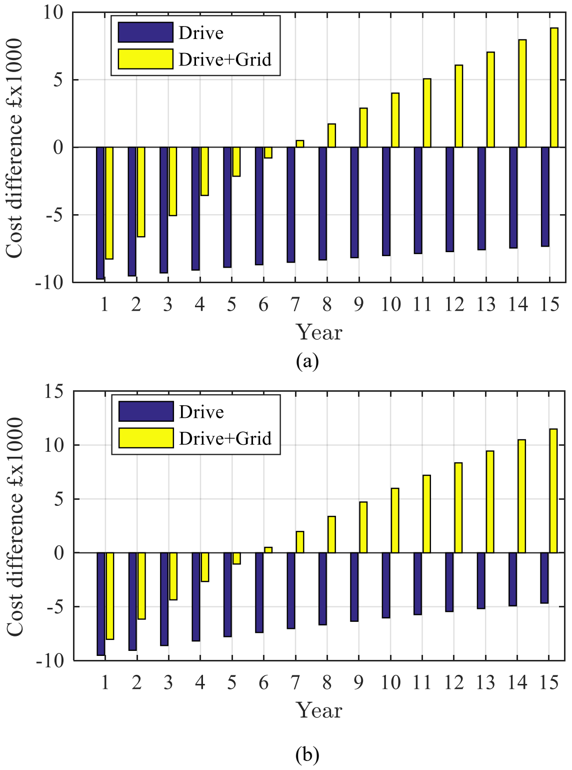


Fig. 7. Cost difference between using petrol car and EV for annual mileage of (a) 4000 miles and (b) 8000 miles.

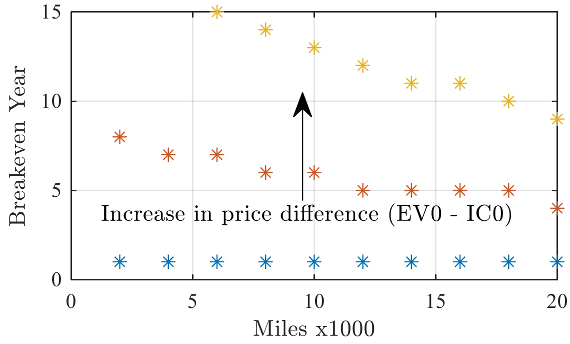


Fig. 8. Breakeven year when the EV supports the grid for different initial cost difference and annual mileage.

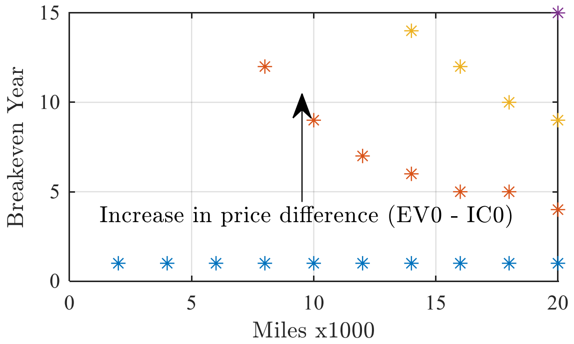


Fig. 9. Breakeven year when using a free charging facility while the EV is used for driving only.

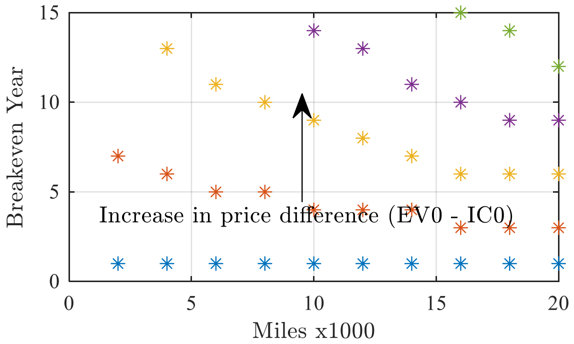


Fig. 10. Breakeven year when using a free charging facility while the EV is used for driving and grid support.

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