Electric and Conventional Vehicle Driving Patterns

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ABSTRACT

The electric vehicle (EV) is an interesting vehicle type that can reduce the dependence on fossil fuels, e.g., by using electricity from wind turbines. A significant disadvantage of EVs is a very limited range, typically less than 200 km. This paper compares EVs to conventional vehicles (CVs) for private transportation using two very large data sets. The EV data set is collected from 164 vehicles (126 million rows) and the CV data set from 447 vehicles (206 million rows). Both data sets are collected in Denmark throughout 2012, with a logging frequency of 1 Hz. By comparing the two data sets, we observe that EVs are significantly slower on motorways, faster in cities, and drive shorter distances compared to CVs.

Categories and Subject Descriptors

H.2.8 [**Database Applications**]: Spatial databases and GIS, performance measurements

General Terms

Algorithms, Measurement, Documentation, Experimentation

Keywords

Electric vehicles, EV, GPS, CAN bus, spatial analysis

1. INTRODUCTION

The electric vehicle (EV) is a vehicle type that is gaining traction as an alternative to the conventional vehicle (CV) with an internal combustion engine. The EV has potential for lowering the greenhouse gas emissions and reducing the dependence on fossil fuels. Furthermore, the EV is an interesting vehicle type because it has a set of new features, such as close to ideal speed-torque profile, engine simplicity [1], and energy recuperation, i.e., the ability to recharge the battery when going down-hill or braking.

Although the EV has a number of advantages over the CV, it also has drawbacks. The major drawback is the limited range of EVs compared to CVs. A CV typically has a range of 500-600 km [2]. In contrast, the range of an EV is typical between 150 and 200 km see, e.g., [3]. Furthermore, a CV can be refilled with gasoline in a few minutes whereas it may take more than an hour to recharge the battery in an EV [4]. These drawbacks naturally limit the flexibility of EVs. However, only research on a smaller scale has compared the usage of the two vehicle types for personnel transport. A large-scale comparison is required in order to examine how well the EV satisfy the transportation needs of families and how restrictive the range limitations in reality are.

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The main contributions of this paper are a detailed comparison of the driving patterns for EVs and CVs and an analysis of the energy consumption of EVs. The work is based on two high-resolution GPS data sets (1 Hz) for a fleet of 164 EVs and a fleet of 447 CVs, recorded throughout 2012. We study the effects of the limited range of EVs by analyzing and comparing the average length of trajectories and daily driven distance of both EVs and CVs. Further, we analyze the energy consumption of EVs with respect to vehicle speed and season.

2. DATA FOUNDATION

The EV data set used in this paper is from the project "Test en Elbil" ("Try an Electric Vehicle") [5] and is collected from January to December 2012. Families in Denmark could try an EV as the main household vehicle for a period of three to six months. 164 vehicles were used in the project, consisting of 33 Citroën C-Zero, 56 Mitsubishi i-MiEV, and 75 Peugeot iOn. These three vehicle types are practically identical, i.e., identical shape, manufacturer, motor, and 16 kWh battery.

126.5 million records were collected in total from the 164 EVs, with a total driven distance of 1.4 million km and 159 862 trajectories. An EV record include GPS information and parameters from the EV, i.e., location, altitude, direction, speed, time-stamp, State of Charge (SoC), charging status, and odometer speed.

We compare the EV data set to a large data set from CVs. 205.6 million records were collected from 447 vehicles, with a total driven distance of 3.4 million km and 187,303 trajectories. This data set is collected in the "ITS Platform" project [6]. Records are logged with a 1 Hz frequency, in the period January to December in 2012. The EV and CV data sets are thus similar, except that the CV data set includes only GPS information.

Table 1: Road Network Coverage

Category	Edges	EV Covered (%)	CV Covered (%)
Motorway	2226	2111 (95)	2187 (98)
Primary	22 175	14 798 (67)	19 985 (90)
Secondary	53 271	38 274 (72)	39 020 (73)
Residential	568 307	82 799 (15)	82 799 (15)

Table 1 shows the coverage of the most important road categories for Denmark. The *Edges* column shows the total number of edges in each category as defined in the road network [14]. The *EV Covered* and *CV Covered* columns show the number of edges that the EV and CV data sets cover, respectively. Table 1 shows that the data sets cover most of the important road-network infrastructure in Denmark. That is, the EV and CV data sets cover 95% and 98% of the motorways, respectively, and 67% and 90% of the primary roads, respectively.

3. METHOD

The road network is modeled as a directed graph **G = (V, E)**, where **V** is a set of vertices and **E** is a set of directed edges **E** ⊆ **V** x **V**. The road network is from the OpenStreetMap project [7] and consists of 1.5 million directed edges.

The location updates are map-matched to the road network (using the algorithm from [8]), converted into a network-constrained representation, and logically divided into *trajectories*.

A trajectory, *t*, is a sequence of network constrained location updates $t = [m_1, m_2, \ldots, m_n]$ during the course of one trip. Each m_i is a tuple $(e_{id}, time_{enter}, time_{leave}, SoC)$, where e_{id} is the id of the network edge, $time_{enter}$ and $time_{leave}$ are the times at which the moving object entered and left edge e_{id}, respectively. Both $time_{enter}$ and $time_{leave}$ are linearly interpolated between two location updates. $time_{enter}$ is linearly interpolated between the location update prior to entering e_{id} and the first location update on e_{id}. $time_{leave}$ is interpolated between the last location update on e_{id} and the immediately following location update. Finally, *SoC* shows the current state of charge of the battery in percent.

To study energy consumption, we convert the change in SoC into the corresponding energy consumption. According to the company CLEVER[1] that collected the EV data, a change in SoC of 1 percentage point (the smallest observable in the EV data set), corresponds to an energy consumption of 154 Wh.

4. RESULTS

We first study and compare overall statistics of the trajectories for both EV and CV data. We then compare the average speed of both EVs and CVs on different road categories throughout the year. Finally, we analyze the energy consumption with respect to season for EVs.

4.1 Trajectory Comparisons

A distinctive challenge for wider adoption of EVs is the limited range compared to CVs. For instance, the vehicles in the EV data set have a specified maximum range of 160 km [3]. CVs typically have a range of 500-600 km [2]. Additionally, an EV may require more than one hour to be recharged fully [4] whereas CVs can be refueled within a few minutes. To see whether the lower range of EVs affects the individual trajectory, we compare the relative frequency of trajectories of a certain length.

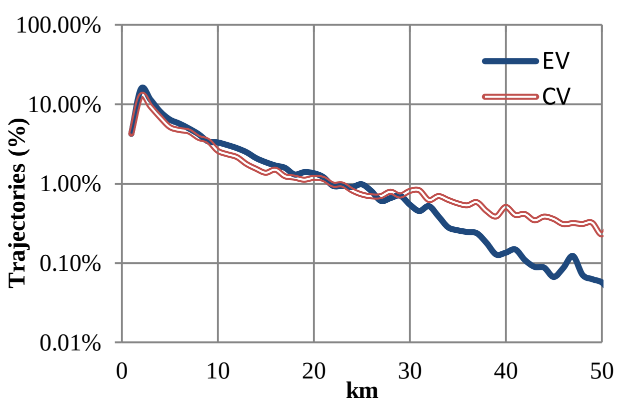

Figure 1: Length of Trajectories

[1] Private email communication with the data provider.

Figure 1 shows the relative frequency of trajectories of a specific length. From this figure it can be observed that most trajectories from both the EV and CV data sets are short. In fact, 99% and 90% of trajectories are shorter than 50 km for EVs and CVs, respectively. CVs have relatively fewer trajectories shorter than 20 km, and relatively more trajectories longer than 30 km. Overall however, the two data sets appear to have comparable trajectory lengths, which suggests that the limited range of these EVs only to a limited extend affects the individual trajectory.

Figure 2 shows the specific energy consumption per trajectory. Note that the y-axis is logarithmic. Most trajectories (93%) use less than 4 kWh, which is less than 25% of the 16 kWh battery capacity. Thus, in most cases the battery has more than enough capacity to complete the individual trajectory.

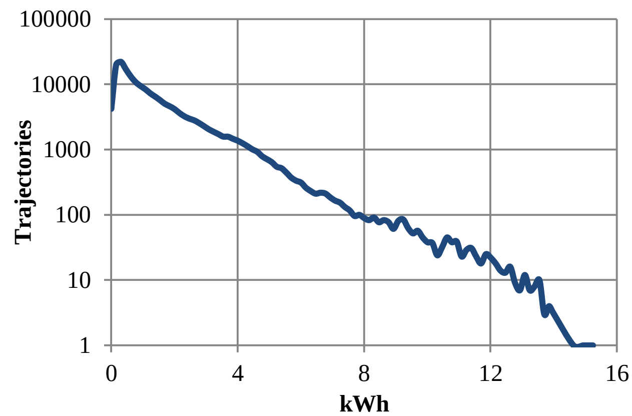

Figure 2: Energy Consumption of EV Trajectories

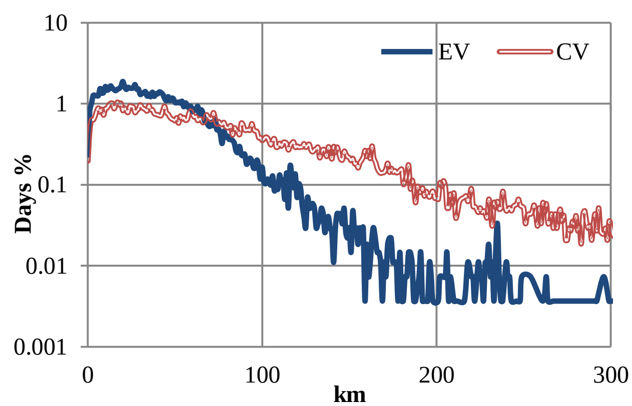

Figure 3: Kilometers per Day

Although the EV trajectories appear to be only slightly affected by the limited range, this does not mean that the EVs satisfy the full transportation requirements of the users. Indeed, one may argue that an EV only satisfies your transportation requirements, if the EV can get you *both* to and from work. To analyze this, we compare the total driven distance per day of both EVs and CVs. Figure 3 shows the relative frequency of days with a certain total travelled distance for both EVs and CVs. From Figure 3 we observe that EVs and CVs are used significantly different. More than 99% of all days for EVs have a total travel distance of less than 160 km (the specified range limit of the EV). For CVs, only 86% of all days travel less than 160 km. As such, on 14% of all days the limited range of EVs cannot satisfy the transportation needs of families without recharging during the day.

4.2 Speed Comparisons

Figure 4 shows the average speed of EVs and CVs on motorways with a 130 km/h speed limit. We observe that the EVs drive significantly slower than CVs on motorways. EVs are between 7 and 20 km/h slower than EVs. We note that the top speed of the EVs is limited to 130 km/h [9], thus the EVs should be able to maintain the average speed of CVs. We assume this difference between EVs and CVs is because the drivers of the EVs lower their speed to increase the range. The EVs continuously report the expected range to the driver based on the energy consumption of the last 25 km driven [4]. Since a high speed significantly increases the energy consumption, see Figure 9, the vehicles will therefore report a significantly lower expected range. The speed distribution diagrams in Figure 5 confirm this assumption. The speed distribution of EVs corresponds to the speed distribution of CVs reduced by 20 km/h.

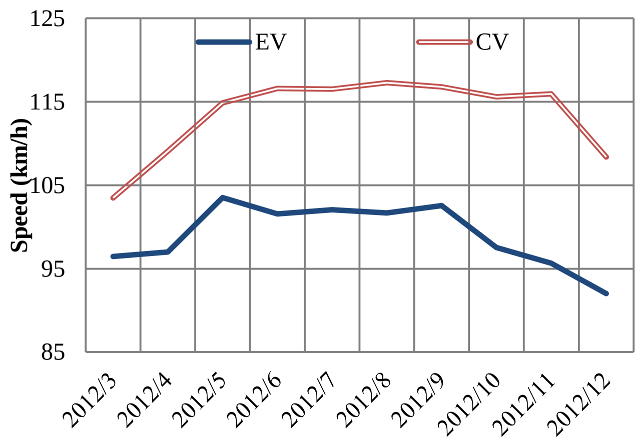

Figure 4: Average Speed on Motorways

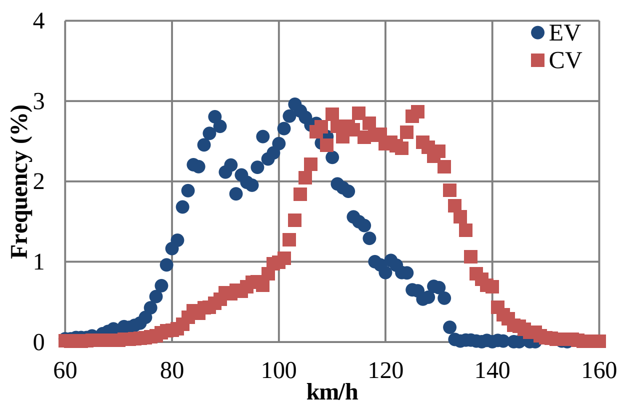

Figure 5: Speed Distribution on Motorways

Figure 6 shows the speeds of EVs and CVs on residential roads. Surprisingly, the EVs are slightly faster than the CVs. We assume this is because EVs accelerate more quickly at low speeds than CVs, partly due to differences in transmission and engine torque. Most CVs in Denmark have a manual transmission whereas the EVs have a single speed transmission [4]. Further, the speed-torque profile of electric engines is close to the ideal [1], which results in higher acceleration at low speeds.

The overall speed distribution of EVs and CVs on residential roads is shown in Figure 7. Note that the distribution for EVs and CVs are very similar. However, in contrast to Figure 5, the speed for EVs is now slightly shifted towards higher speeds than for the CVs.

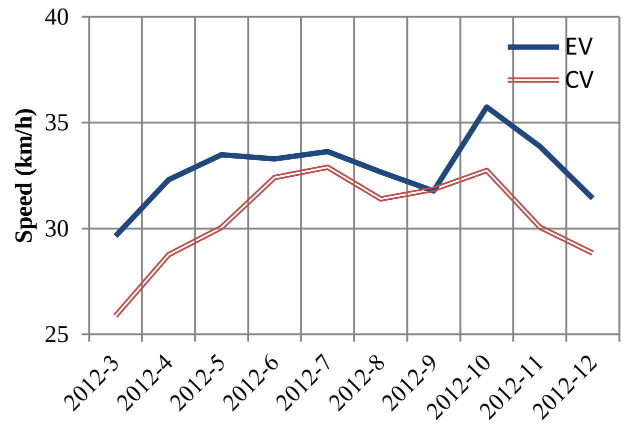

Figure 6: Average Speed on Residential Roads

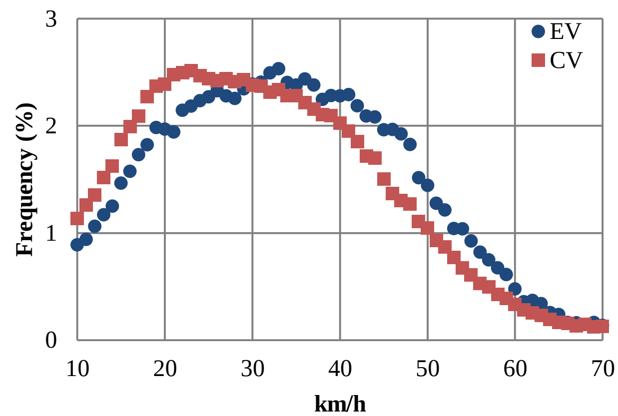

Figure 7: Speed Distribution on Residential Roads

4.3 Seasonal Variations

Denmark has significant variations in weather over the four seasons. In the winter season, it is generally necessary to heat the cabin, whereas in the summer it is necessary to cool the cabin. The EVs use the battery for both heating/cooling and driving [9]. The range of EVs is therefore affected by the outside temperature.

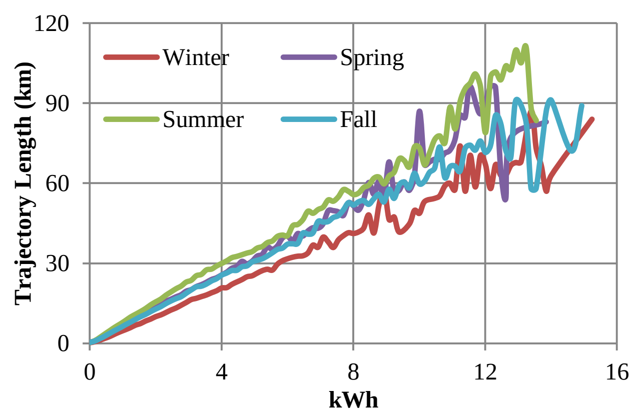

Figure 8: Seasonal Variations of Energy Consumption for EVs

Figure 8 shows the seasonal relation between the energy consumed by a trajectory and the length of the trajectory. The fluctuations above 8 kWh are due to a very limited number of trajectories that consume more than 8 kWh.

From Figure 8 we observe that the energy consumption varies significantly over the seasons. For trajectories that use less than 8 kWh, the driven distance per kWh is always lower in winter than in summer (by approx. 20%). The difference in energy consumption between summer and spring/fall is between 5% and 10%.

Figure 9 shows the average energy consumption as a function of the average speed of trajectories. Four series are shown, one for each season. Each trajectory included has a minimum length of 5 km, and the energy consumption is computed based on the difference in SoC at the start of the trajectory and at the end of the trajectory.

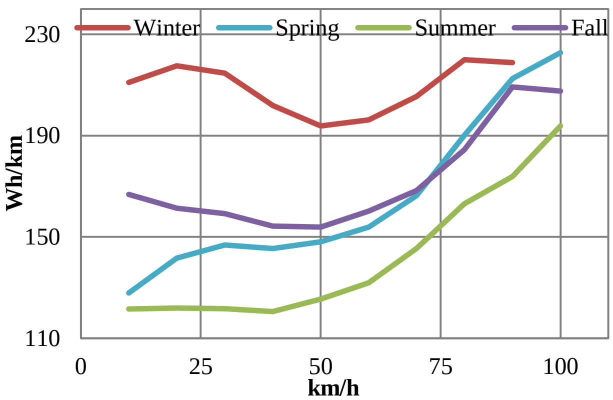

Figure 9: Energy Consumption at Specific Speeds for EVs

Figure 9 shows a significant increase in energy consumption as the average speed approaches 100 km/h. For instance, there is a 47% increase in energy consumption per km between having an average speed of 60 km/h and 100 km/h in summer. The winter series appears to decrease Wh/km until reaching average speeds of 50 km/h. We assume that this is because the heating system in these vehicles uses a significant amount of energy (up to 5 kW [9]). This suggests that the least energy consuming path varies significantly throughout the seasons, i.e., an average speed of 40 km/h is the most energy efficient in summer, whereas an average speed of 50 km/h is most efficient in winter.

5. RELATED WORK

In [10], the psychological implications of the limited range of EVs are studied. 40 EVs were used in a 6-month period, after which data were collected using questionnaires and interviews. The authors then evaluated, among other things, the fraction of battery capacity most persons are comfortable utilizing. They conclude that most drivers are comfortable using between 75% and 80% of the total battery capacity.

Routing for electric vehicles [11], and [12], has proven to be challenging because the vehicle consumption model is more complex than for CVs due to, e.g., recuperation. Many EVs generate power when going downhill, which give some edges a negative energy consumption. This makes it harder to find the energy optimal routes, because the algorithm needs to ensure that the predicted battery charge is always between 0% and 100%. Our results suggest that this line of research should account for the season and the predicted speed profile of the vehicle in order to return better results.

6. CONCLUSION

We have found that EVs when compared to CVs generally drive shorter distances, both in terms of the individual trajectory and the total travelled distance per day. We have shown that EVs are significantly slower on motorways, most likely because the drivers want to preserve energy. Surprisingly, the EVs are slightly faster than CVs in cities, which we assume is due to a close to ideal speed-torque profile [1].

We have shown that the average range of the EV is much lower than the specified range of 160 km. In summer, the average range is 118 km (25% less), and in winter the average range is 76 km (53% less). The large difference between winter and summer is likely due to heating of the cabin.

Acknowledgements

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