Speed and Energy Consumption for Electrical Vehicles

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ABSTRACT

Reducing emissions of greenhouse gases has become a major challenge for the next decades. The transportation sector is responsible for about a quarter of all the CO_2 in most developed countries. This study uses a large set of trajectory data (272.289 trajectories, built from 75.178.775 GPS points) to analyze and quantify, on a road segment level, the impacts of driving at a steady speed on the energy consumption of electrical vehicles. The results show that drivers should strive to maintain a steady speed for as much as possible as it can reduce the consumption by up to 42% while increasing the travel time by just 10%.

CCS CONCEPTS

• **Information systems** → **Geographic information systems**.

KEYWORDS

Eco-driving, Energy Consumption, Electrical Vehicles, EVs, GPS, OBD, Trajectories, Steady Speed

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1 INTRODUCTION

The transportation sector is responsible for 23-26% of all the emissions of greenhouse gases (GHG) across developed countries, with passenger vehicles accounting for as much as 45% of that [18]. Better understanding how these vehicles relate to GHGs can be of paramount importance to reduce gross emissions.

Relating GHGs to internal combustion engine vehicles (ICEV) is straightforward, but doing it for purely electrical vehicles (EV) is subtle. ICEVs release GHGs to the atmosphere as they burn fuel to power their engines, but EVs use electricity to do so, and while the vehicles do not emit any GHGs themselves, the generation of the electricity they use do. For example, in 2019, for each kWh of electricity produced in the United States, 393 grams of CO_2 were released to the atmosphere, for EU-28, 306 grams, and for China, 560 grams [15].

Eco-driving [4] is a collection of simple advice aimed at changing driving behaviour in order to reduce both energy consumption and GHGs emission. While there has been a great amount of interest on eco-driving over the last decade, the vast majority of the research about it was conducted for ICEVs only, leaving EVs underrepresented in the literature [16]. With the electrification of vehicles gaining momentum around the world, quantified information about the operation of EVs becomes more relevant.

In this study, we use trajectories built from high-frequency GPS and OBD data to analyze and quantify the impacts of driving at a steady speed on the energy consumption of EVs. Figure 1 shows a trajectory and the heat map of the energy consumption as the vehicle travels from origin (O) to destination (D). Each scale represents two consecutive GPS points and the energy consumption (Wh/hm) during the one-second interval between them. Note how high consumption happens during acceleration, low consumption happens during braking, and medium consumption happens during cruising.

Figure 1: Heat map of the energy consumption of a vehicle during a trajectory.

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We use a large dataset - 272.289 trajectories, built from 75.178.775 GPS points - of high-frequency data - 1 Hz - collected over a period of 29 months, from January 2012 to May 2014. This allows us to go beyond the trajectory level to the subtrajectory one. This means that instead of limiting the analysis to trajectories as a whole, from origin to destination, we do it at a road segment level. As the OBD data gives us information about the vehicle, such as how much power it is consuming at an instant, we can analyze and quantify how the energy consumption changes on every road segment the vehicle travels by.

To the best of our knowledge, this is the first study to use this combination of data features. Previous studies either used a lower number of trajectories (7.989 trajectories in [19]), or low-frequency data (0,1 Hz in [6]), or data collected over a shorter period (3 months in [3]), or under controlled conditions (fixed route in [5]).

The remainder of the paper is organized as follows. Section 2 discusses the related work. Section 3 describes the data foundation of this paper. Section 4 presents the definition for steady speed. Section 5 discusses the data analysis. Finally, Section 6 concludes the paper.

2 RELATED WORK

The authors of [9] used GPS and OBD data to evaluate five different eco-driving advice. Results indicated a connection between low fuel consumption and steady speed. Trajectories with more proportional time driven at a steady speed often showed a lower fuel consumption when compared to trajectories with less time.

GPS and OBD is also used in [6] to develop an eco-driving system that provides instant feedback and real-time warnings regarding fuel consumption for public buses. The system was tested for 90 days and, when compared to the same period of the previous year, it improved the average fuel consumption by 2.6% to 4.5%.

A compilation of eco-driving research findings can be found in [1] and [8]. The former reported benefits ranging from 5% to 30%, with trial reports being typically placed at the lower end of the scale, at 4.8% to 6.8%. The study also pointed to an overlooked benefit of eco-driving: several studies have claimed that eco-driving can reduce the accident rate by 40%, improving traffic safety. The latter compared the results from different eco-driving training programs. Aggregated maximum reduction in fuel consumption ranged from 10% to 40%.

In [3], the authors created an eco-driving technique that manages speed and acceleration to reduce fuel consumption. The goal of their technique is to smooth traffic flow to avoid sudden acceleration and deceleration, which results in high fuel consumption. Experimental runs showed that a reduction of 24% in maximum speed reduced fuel consumption by 13% while increasing travel time by only 6%.

The authors of [5] proposed an online implementation to minimize the energy consumption of EVs by finding the optimal speed to travel through a road segment. The speed is calculated and fed to the driver at the beginning of each segment. Under the same conditions, results showed that an average reduction of only 2.5% in average speed reduced the average consumption by 14.1%.

A real-time speed advice is also proposed in [20]. The authors studied different speed profiles to better approach a signalized intersection in order to reduce the energy consumption for EVs. Results showed that the eco-driving model provided reduced consumption by up to 8%.

3 DATA FOUNDATION

In this section, we go over the different data sources we use in this study. We discuss GPS and OBD data, the road network, trajectory data, and how we compute the energy consumption. At the end of the section, we present the data statistics.

3.1 GPS and OBD Data

GPS data [7] describes a vehicle's location in time in terms of latitude, longitude, and timestamp with high accuracy. GPS data represents a rich yet cheap source of spatiotemporal data and it has been used in a wide variety of mobility applications, from humans and animals to hurricanes and vehicles [11].

The On-Board Diagnostics (OBD) [10] is a standard of protocols for vehicular diagnostics. The system aggregates information from multiple sensors in the vehicle, such as the instantaneous speed and the amount of power the engine is consuming.

By synchronizing the GPS and OBD data, we have what we call *GPS+* points. Each *GPS+* point g is a tuple $\langle gid, lat, lon, ts, spe, pow \rangle$, in which gid is the unique identifier of the data point, lat and lon, the latitude and longitude coordinates, ts, the timestamp, spe, the instantaneous speed of the vehicle, and pow, the instantaneous power of the engine. The value of gid is created during the experiment setup, lat, lon, and ts, comes from the GPS data, and spe and pow, from the OBD data.

3.2 Road Network

A road network can be seen as a directed graph $G(V, E)$, with V as the set of vertices and E, the set of edges, and $E \subseteq \{(x, y) | (x, y) \in V^2$ and $x \neq y\}$. In this case, a road segment is an edge of said network, while vertices are intersections. This way, a road segment is any continuous segment of road between two intersections.

We use OpenStreetMap [13], an open-source geographic database, and the Viterbi algorithm to match each *GPS+* point to a road segment [12]. After all *GPS+* points are matched to a road segment, we build the trajectories taken by the vehicles.

3.3 Trajectory Data

A trajectory is a sequence of *GPS+* points. Consider the set of trajectories $T = \{t_1, t_2, \ldots, t_m\}$. For each trajectory $t \in T$, there is a list of *GPS+* points $G = \{g_1, g_2, \ldots, g_n\}$. In this case, t is considered a trajectory as long as, for all of the n elements in G, $g_{n-1}.ts < g_n.ts$. In this study, each trajectory represents a trip between an origin O and a destination D.

A subtrajectory is a sequence of consecutive *GPS+* points contained inside a trajectory. Consider a trajectory t and its list of *GPS+* points $G = \{g_1, g_2, \ldots, g_n\}$. Any sequence t' with a list of *GPS+* points $G' = \{g_i, g_{i+1}, \ldots, g_{i+k}\}$, for $i + k \leqslant n$, is considered a subtrajectory of t as long as $G' \subseteq G$. Note that, by definition, a subtrajectory is also a trajectory.

In this study, trajectories are split into subtrajectories based on the road segments the vehicle travels through. Each subtrajectory contains only the *GPS+* points that are matched to a respective road segment. This way, each trajectory t is a list of subtrajectories $T' =$

$\{t'_1, t'_2, \ldots, t'_p\}$. Each subtrajectory t' is as a tuple $\langle stid, tid, rsid, G \rangle$, in which $stid$ is the unique identifier of the subtrajectory, tid, the unique identifier of the trajectory, $rsid$, the unique identifier of the road segment, and G, the list of *GPS+* points.

Figure 2 shows a heat map of the Copenhagen region. The figure shows the road segments with subtrajectories. The different colors show the number of subtrajectories per road segment.

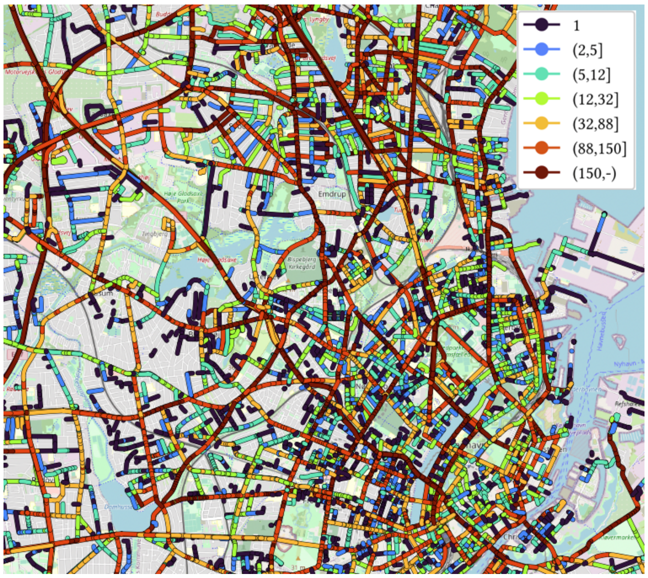

Figure 2: Heat map of the road segments in the Copenhagen region.

Figure 3 shows an example of a subtrajectory. Notice that all the *GPS+* points are within a road segment of the road network. Each blue circle represents a *GPS+* point and the table highlights the attributes of the selected point. Table 1 lists the *GPS+* points of the subtrajectory in Figure 2.

gid	*lat*	*lon*	*ts*	*spe*	*pow*
1	57.043595	9.923151	2012-07-04 15:40:22	65	9.800
2	57.043597	9.922850	2012-07-04 15:40:23	65	9.600
3	57.043598	9.922549	2012-07-04 15:40:24	66	9.800
4	57.043599	9.922251	2012-07-04 15:40:25	64	9.400
5	57.043598	9.921948	2012-07-04 15:40:26	67	9.800
6	57.043600	9.921651	2012-07-04 15:40:27	66	9.600
7	57.043601	9.921352	2012-07-04 15:40:28	64	9.000

Table 1: List of *GPS+* points of the subtrajectory in Figure 2.

In this study, the unit for the speed spe is km/h and the unit for the power pow is Watts. Also, all values of speed and power are rounded to their nearest integer.

3.4 Energy Consumption

To calculate the energy consumption between two consecutive *GPS+* points we use the latitude lat and longitude lon to calculate

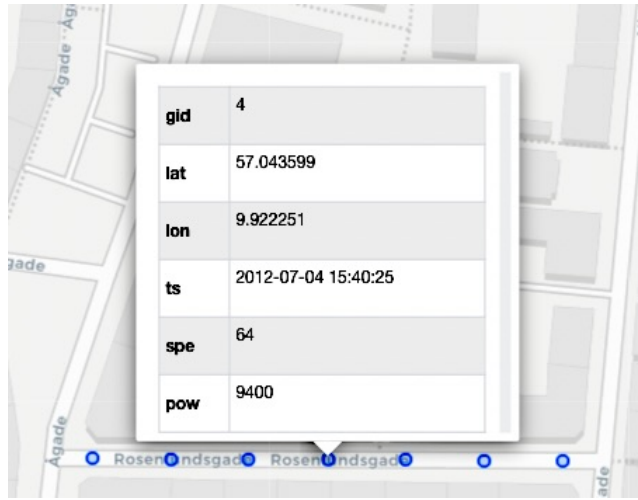

Figure 3: A subtrajectory in a road segment in Aalborg, Denmark.

the distance d and the timestamp ts to calculate the time difference t between them. Together with the power pow, we calculate the energy consumption e between two consecutive points g_j and g_k as follows:

$$e_{j,k} = \frac{\overline{pow}_{j,k} \cdot t_{j,k}}{d_{j,k}}$$

To calculate the energy consumption for any sequence of points, we calculate it between all two consecutive points and then, as the sampling rate between any two points is fixed (1 Hz), we calculate the average between them. Therefore, for any sequence of *GPS+* points G, its energy consumption E is calculated as follows:

$$E_G = \frac{1}{n} \cdot \sum_{i=2}^{n} e_{i-1,i}$$

If we consider the values from Table 1, we have the following:

Points	$\overline{pow}(W)$	t (h)	d (km)	e (Wh/km)
1,2	9.700	2,78x10^{-4}	18,21x10^{-3}	148
2,3	9.700	2,78x10^{-4}	18,21x10^{-3}	148
3,4	9.600	2,78x10^{-4}	18,03x10^{-3}	148
4,5	9.600	2,78x10^{-4}	18,33x10^{-3}	145
5,6	9.700	2,78x10^{-4}	17,97x10^{-3}	150
6,7	9.300	2,78x10^{-4}	18,09x10^{-3}	143

Table 2: Values of $\overline{pow}$, t, d, and E for each two consecutive points in Table 1.

By taking the average between the six values of e from Table 2, we find the energy consumption E of the subtrajectory as 147 Wh/km. Note that, in this study, we do not estimate the energy consumption. It is calculated from the ground-truth data obtained from the GPS and OBD devices. Also, the term *energy consumption* is preferred over *energy efficiency* because 1) it is more common when referring to energy or fuel consumed per distance travelled and 2) we want to avoid any confusion with efficiency of electrical motors.

Finally, EVs are capable of recovering some of their kinetic energy back when braking or going downhill due to regenerative braking [16]. The regeneration is represented by a negative power pow, which can lead to a negative energy consumption E. This study does not focus nor make any evaluation regarding regenerative braking, but it is important to keep in mind that it exists and makes braking less impactful for EVs when compared to ICEVs.

3.5 Data Statistics

We use 177 vehicles - 35 Citroën C-Zero, 63 Mitsubishi iMiev, and 79 Peugeot Ion - permanently equipped with both GPS and OBD devices to collect a total of 218.834.510 *GPS+* points, between January 2012 and May 2014. From this data, we build 275.994 trajectories, for a total of 14.473.006 subtrajectories.

As we use sensor data from both GPS and OBD devices, it is reasonable to expect failures. Therefore, we cleanse the dataset to remove the points in which there is invalid or missing data. In this case, we removed all the *GPS+* points with:

- Instantaneous power pow lesser than -16600 W
- Instantaneous power pow greater than 50000 W
- Instantaneous power pow missing
- Instantaneous speed spe missing
- Timestamp ts missing

We remove all subtrajectories that lose any *GPS+* point during cleansing. We also remove all subtrajectories that have any two consecutive points with a time difference greater than one second, which can happen when the GPS device loses coverage.

Although subtrajectories are removed in case they are affected by the data cleansing, trajectories that lose any subtrajectory are not removed. As subtrajectories are matched to a road segment, they are independent from each other on a segment level, the level of focus of this study. After cleansing and processing the data, we have:

- 75.178.775 *GPS+* points
- 272.289 trajectories
- 7.579.386 subtrajectories
- 174.182 road segments

4 STEADY SPEED

There are multiple definitions for steady speed. The authors of [17] define steady speed as "absolute incremental speed changes of less than or equal to 0.1 m/sec/sec during the 1-sec interval". The authors of [9] claim that steady speed happens when "the speed does not vary with more that $\pm 1 km/h$ from the speed at the beginning of the period (the cruise speed) for at least 20 seconds". The authors of [8] and [16] sustain that, when it comes to eco-driving speed, "it is usually recommended at or safely below the speed limit". In this study, we define steady speed as a period of time in which the speed only varies $\pm\delta$ compared to the speed of beginning of the period. The δ represents how much fluctuation in speed is allowed for the period.

In a subtrajectory built from *GPS+* points, the period is a list of points in which the speed spe of the first point g_1 is the starting speed of the period and the speed spe of all the other points g_n are equal or greater than $g_1.spe - \delta$ and equal or lesser than $g_1.spe + \delta$. Furthermore, the *GPS+* points immediately before and after the period are outside the δ allowed or at the start (or at the end) of the subtrajectory. We call such period a *steady speed period* (*SSP*).

If we consider the subtrajectory from Figure 3 and the values from Table 1, we have the following:

- for δ = 0 km/h: $SSP_0 = \{\{g_1, g_2\}\}$
- for δ = 1 km/h: $SSP_1 = \{\{g_1, g_2, g_3, g_4\}, \{g_5, g_6\}\}$
- for δ = 2 km/h: $SSP_2 = \{\{g_1, g_2, g_3, g_4, g_5, g_6, g_7\}\}$

Also, for each subtrajectory, we calculate its amount of steady speed, in time percentage. The *steady speed time* (*SST*) is calculated by dividing the sum of the time of all the *SSPs* of a subtrajectory by its total time. Again, if we consider the subtrajectory from Figure 3 and the values from Table 1, we have the following:

- for δ = 0 km/h: $SST_0 = 1s/6s = 16\%$
- for δ = 1 km/h: $SST_1 = 4s/6s = 66\%$
- for δ = 2 km/h: $SST_2 = 6s/6s = 100\%$

The total time of the *SSP* is the time difference between the last and the first points of the period. We can also calculate the total distance, which is the sum of the distance d between any two consecutive points in the period, and the average speed, which is the average between the speed spe of all the points in the period. If we consider the subtrajectory from Figure 3 and the values from Table 1, we have a total time of 6 s, a total distance of 108 m, and an average speed of 65 km/h.

5 DATA ANALYSIS

In this chapter, we analyze and quantify the impacts of driving at a steady speed on the energy consumption and the travel time of EVs.

5.1 Delta Speed

We start by quantifying the impact of different levels of fluctuation in speed, which are represented by the δ (or delta speed). Figure 4 shows the energy consumption of the steady speed periods (see Section 4) for each δ (from 0 to 4 km/h).

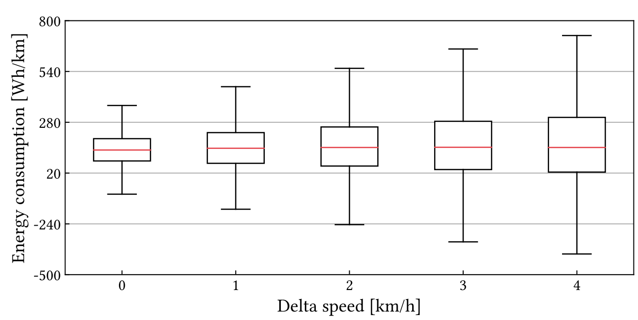

Figure 4: Energy consumption per delta speed.

There is a slight increase in the median value, from 138 to 151 Wh/km, or 9.4%, but a great increase in variance. On the consumption side, the maximum value increases from 366 to 724 Wh/km, or 98%. On the regeneration side, it goes from -88 to -394 Wh/km, or 348%. The negative consumption is due to regenerative braking (see Section 3.4).

We now analyze how increasing the δ impacts the number of *SSPs* and the average time and distance driven at a steady speed. Table 3 shows the total number of periods, the average time, and the average distance per delta speed (see Section 4).

δ	No. of Periods	Time (s)	Distance (m)
0	11.753.325	2,38	39,63
1	14.486.179	2,83	45,40
2	14.732.898	3,25	50,84
3	14.955.716	3,52	53,94
4	14.719.591	3,79	57,34

Table 3: Number of periods, average time, and average distance per delta speed of the *SSPs*.

Increasing the δ increases the number of periods and make them last longer, but there are diminishing returns in doing so. Going from δ = 0 to 1 km/h increases the number of periods by 19%, the time by 19%, and the distance by 15%. Going from δ = 1 to 2 km/h increases the number of periods by 17%, the time by 15%, and the distance by 12%. Going from δ = 2 to 3 km/h increases the number of periods by 15%, the time by 8%, and the distance by 6%. Finally, going from δ = 3 to 4 decreases the number of periods by 2% and increases the time by 8%, and the distance by 6%. This shows that allowing more fluctuations in speed indeed increases the length of the periods, but there is a trade-off, as it also increases the energy consumption.

The low number of periods for δ = 0 indicates that driving with no fluctuations in speed is too strict. The diminishing returns from δ > 1 indicates that allowing more fluctuations in speed increases the time and distance of the steady speed period, but at the cost of a higher energy consumption. Therefore, δ = 1 gives the best trade-off between number of periods, time, distance, and energy consumption. Regardless, the δ is an important aspect of the *SSPs* and we continue to use it throughout the study as a variable of interest.

5.2 Steady Speed Time

As the energy consumption increases going from a lower δ to a higher one, we expect that the subtrajectories that amount more steady speed time (see Section 4) consume less energy compared to the ones with less time. Figure 5 shows the energy consumption of the subtrajectories based on their *SST* for each δ. For this plot, we use increments of 10%, except for the first one, which represents the trips with no *SST* at all. The outlier behaviour of the ranges (0,10] for delta speeds 3 and 4 is likely due to the little amount of data in said ranges.

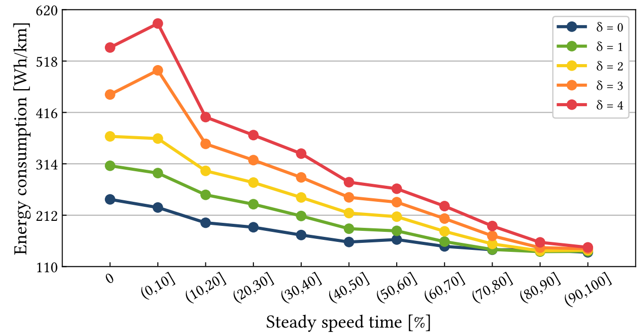

Figure 5: Energy consumption per steady speed time per delta speed.

Again, the average energy consumption increases going from a lower δ to a higher one. Most importantly, the average consumption decreases with the increase of the *SST*. For δ = 1 km/h, the subtrajectories with zero *SST* have an average consumption of 310 Wh/km. By increasing the *SST* to (10,20]%, the average consumption goes down to 252 Wh/km, a reduction of 19%. By increasing the *SST* to (40,50]%, the average consumption goes down to 185 Wh/km, a reduction of 40%. For δ = 3 km/h, the subtrajectories with zero *SST* have an average consumption of 451 Wh/km. By increasing the *SST* to (10,20]%, the average consumption goes down to 353 Wh/km, a reduction of 22%. By increasing the *SST* to (40,50]%, the average consumption goes down to 247 Wh/km, a reduction of 45%.

We also analyze if maintaining a steady speed over multiple *SSPs* makes any difference on the energy consumption. We compare subtrajectories with the same *SST*, but having a different number of periods. Figure 6 shows the energy consumption of the subtrajectories based on their *SST* for a different number of periods (from 1 to 5). As the δ is not a variable of interest for this plot, use fix δ = 1 based on the findings of Section 5.1. The ranges of (0,10], (10,20], and (90,100] are removed as the vast majority of the subtrajectories with those percentages have only one period. The outlier behaviour of the range (50,60] for 1 period is likely due to the little amount of data in said range.

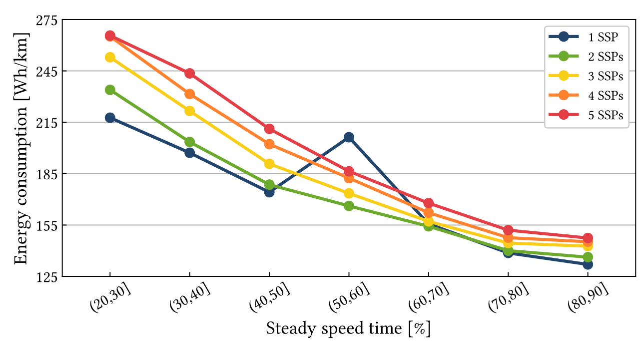

Figure 6: Energy consumption per steady speed time per number of steady speed periods.

For low *SST*, 20 to 50%, the number of periods have a higher impact on the energy consumption, with a constant difference of around 8-10 Wh/km between each curve. For medium to high *SST*, 50 to 90%, the gap is much smaller, around 4-5 Wh/km between each curve. This shows that there is a cost associated to breaking the *SSP*, specially at low amounts of *SST*. This, in combination with the results from Figure 5, shows that drivers should strive to maintain a steady speed for as much and as long as possible.

Just like the δ, the *SST* is an important aspect of steady speed and we continue to use it throughout the study as a variable of interest.

5.3 Average Speed

We now analyze how steady speed performs over different average speeds (see Section 4). Figure 7 shows the energy consumption per average speed for all delta speeds. For this plot, we use the average speed of the *SSTs* in increments of 10 km/h. The ranges of (0,10] and (10,20] are removed due to the little amount of data in said ranges.

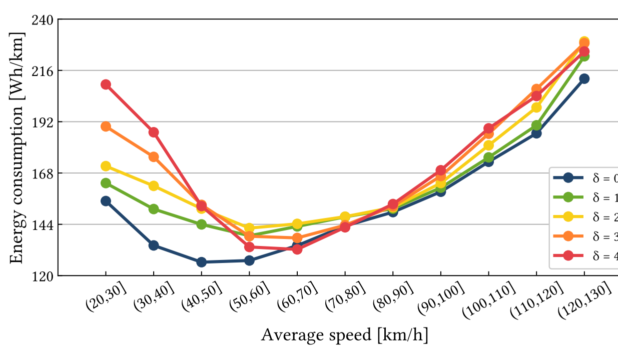

Figure 7: Energy consumption per average speed per delta speed.

The *SSTs* retain the characteristic parabolic curve of EVs [2], but the plot shows a clear separation between the curves up until an average speed of 40 km/h, with a difference of 36-39% between delta speeds 0 and 4. From 40 to 90 km/h, the curves show little separation and even some overlap. And above 90 km/h, the curves separate again, but show less separation than before, with a difference of 6-10% between them.

The data indicates that the overlap between 40 and 90 km/h is due to regenerative braking. As this study is not interested in the effects of braking, we choose to not go into more details.

Now, instead of looking at just the *SSPs*, we look at the subtrajectories as a whole. For that, we use the *SST* instead of the delta speed. Figure 8 shows the energy efficiency per average speed for six different ranges of *SST*. The ranges of (0,10] and (10,20] are removed due to the little amount of data in said ranges.

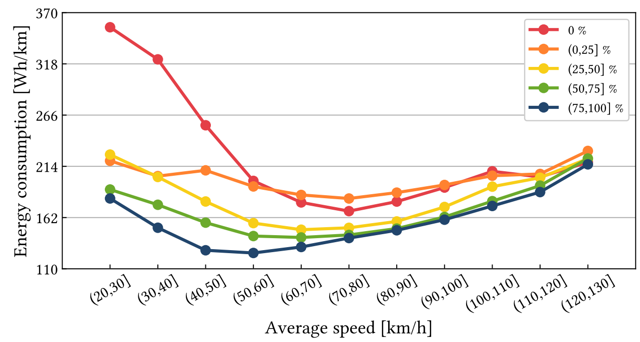

Figure 8: Energy efficiency per average speeds per steady speed time.

Again, the curves show a parabolic curve, but now they show even more separation between them. From 40 to 100 km/h, improving the *SST* from (0,25]% to (75,100]% can reduce the energy consumption by 17-50%. Also, the plot shows that from 80 km/h and above, the difference between the curves of (50,75]% and (75,100]% is around 5%. This suggests that, at high speeds, drivers do not need to maintain a steady speed all the time to get the most from it.

Overall, driving at a steady speed is beneficial across all speeds, but it is even more so at low and medium speeds, from 30 to 70 km/h. This is an interesting finding as this range is similar to the speed limit in urban areas for most countries [14].

5.4 Road Segment Type

We now analyze how different road types affect driving with a steady speed. We consider six different types available on OpenStreetMap (see Section 3.2): residential (RE), tertiary (TE), secondary (SE), primary (PR), trunk (TR), and motorway (MO). In order to assess if different road types have any impact on the steady speed, we start by looking at the average time of the *SSPs* (see Section 4) in each road type. Figure 11 shows the average *SSP* time per road type per delta speed.

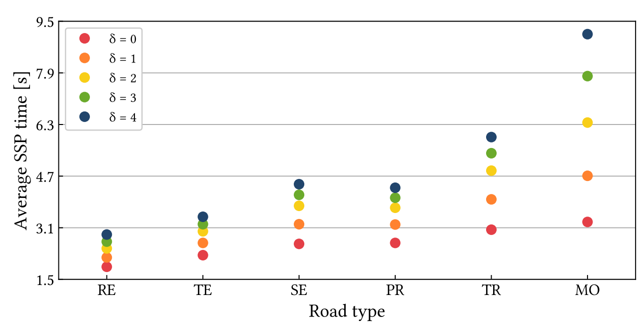

Figure 9: Average *SSP* time per road type per delta speed.

The average *SSP* time is much higher on motorways and trunks, while it is much lower on tertiary and residential roads. This is in line with their purpose. Motorways and trunks are designed to allow high-speed traffic - they have regulated traffic flow, multiple lanes, higher speed limits, few traffic calming, and few signalized intersections. Tertiary and residential roads are designed to provide access to urban areas and, in the other hand, have fewer lanes, lower speed limits, more traffic calming, and more signalized intersections. Also, the plot indicates that, regardless of the road type, maintaining a steady speed with no fluctuations in speed for a long time is difficult in any road type. This corroborates the findings from Table 3.

Another way to assess how different road types can impact the amount of steady speed is by looking at *SST*. Figure 10 shows the percentage of subtrajectories per road type per steady speed time. To simplify, we use ranges of 20% of *SST*. As the δ is not a variable of interest for this plot, use fix $\delta = 1$ based on the findings of Section 5.1.

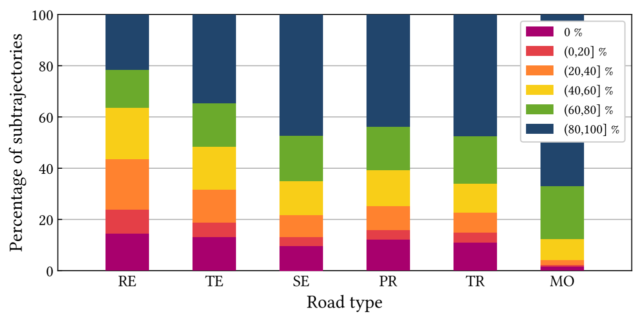

Figure 10: Percentage of subtrajectories per road type per steady speed time.

The *SST* increases as we move from residential roads to motorways. For residential roads, an average of 43% of the trajectories have up to 40% of steady speed time, while only 21% have at least 80%. For motorways, only 4% of the subtrajectories have up to 40% of steady speed time, while 67% have at least 80%. As we move from residential roads to motorways, the average length and speed limit of each road type increases. For example, for the road segments in our dataset, residential roads have an average length and speed limit of 89 m and 46 km/h, respectively. For motorways, the average length is 477 m and the average speed limit, 107 km/h. Also, moving from residential roads to motorways decreases the number of calmings, crossings, intersections, speed bumps, and traffic lights on the roads. This may indicate a strong correlation between *SST* and longer roads, higher speed limits, and less traffic elements.

Finally, we analyze the energy consumption for different road types using the delta speed as a variable of interest. Figure 11 shows the average energy consumption of the *SSPs* per road type per delta speed.

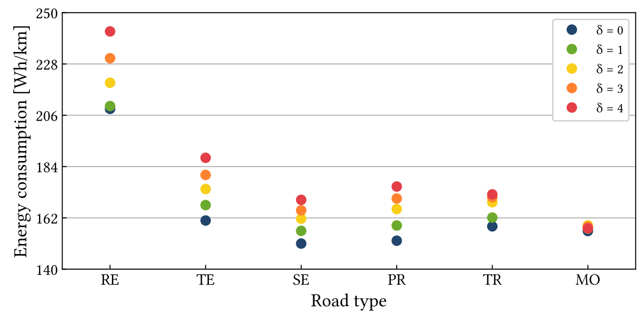

Figure 11: Energy consumption per road type per delta speed.

The plot shows two interesting findings. First, the average consumption on residential roads is much higher than the others, 30-35% across all road types. This can be due to a few reasons, like low average speeds or constant start and stop, making it harder to maintain a steady speed. Second, the average consumption on motorways is virtually the same for all delta speeds. This can be due to a higher average speed, close to the optimal speed of the vehicle, or high *SST* .

5.5 Seasonality

As previously discussed in Section 3.5, the data used in this study was collected over a period of 29 months, from January 2012 to May 2014. This allows us to explore if there is any seasonality when it comes to steady speed. We start with the day and move to the week, month, and year. Figure 12 shows the average steady speed time per hour of the day per road type. In this section, as the δ is not a variable of interest for this plot, use fix $\delta = 1$ based on the findings of Section 5.1.

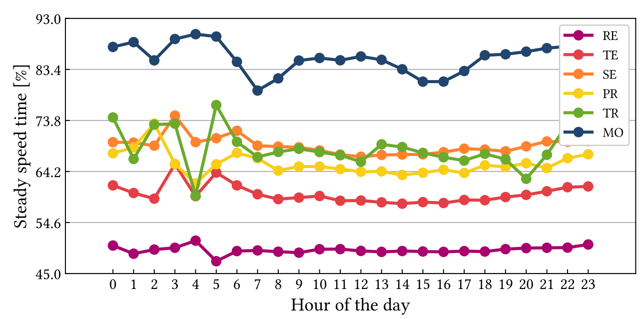

Figure 12: Steady speed time per hour of the day per road type.

There is little difference - an average of 1% - in steady speed time throughout the day for all road types, except motorways. For those roads, there is a decrease of 5% between 6:00 and 8:00 and a decrease of 4% between 15:00 and 17:00. These time frames coincide with the periods when people go to and get out of work, respectively. As this pattern does not repeat for any of the other road types, it indicates that steady speed on motorways has a higher sensibility to traffic volume. The outlier behaviour from 0:00 to 5:00 is likely due to little amount of data in said period.

We now move to the week. Figure 13 shows the average steady speed time per day of the week per road type.

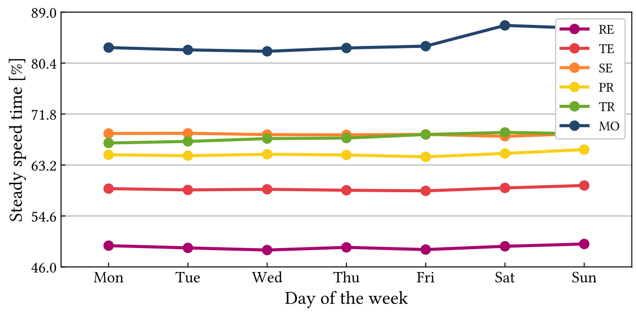

Figure 13: Steady speed time per day of the week per road type.

Once again, there is little difference in steady speed throughout the week for all road types, except motorways. For those roads, the average *SST* from Monday to Friday is 84%, but it increases to 88% on Saturdays and Sundays. As there is less traffic volume on these days, this is another indication that steady speed on motorways have a higher sensibility to traffic volume. This pattern repeats for the other road types, but the increase is of 1% at most.

We now move to the month. Figure 14 shows the average steady speed time per day of the month per road type.

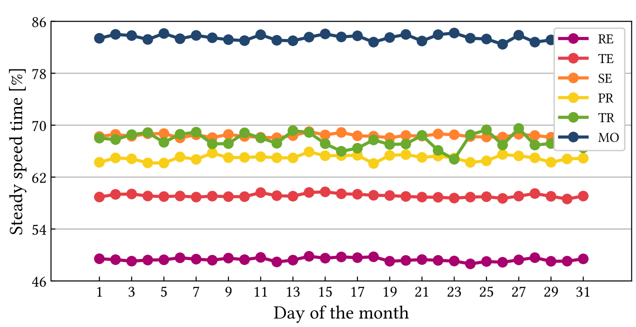

Figure 14: Steady speed time per day of the month per road type.

There is no clear pattern for any road type throughout the days of the month - changes are 0.5% at most. However, it reinforces the findings in Figure 11. Motorways are clearly the best roads for steady speed, with an average of 85% *SST*. They are followed by trunks, primary, and secondary roads, with averages between 71-73%. Then we have tertiary roads, with an average of 65%. Finally, we have residential roads with an average of 57%. This clearly shows that different road types can play a big role in facilitating steady speed.

Finally, we move to the year. Figure 15 shows the average steady speed time per month of the year per road type.

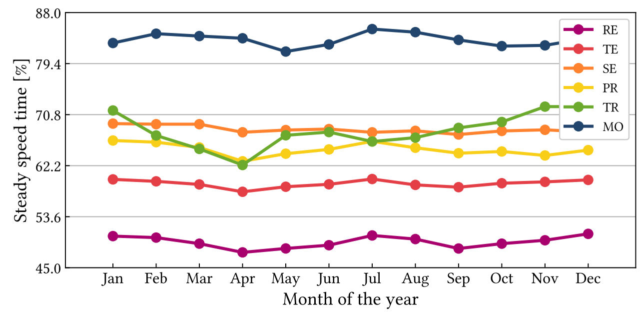

Figure 15: Steady speed time per month of the year per road type.

There is slightly more - an average of 2% - steady speed from January to March and again in July and August for all road types, except trunks. The former may be explained by the cold weather, which tends to make drivers drive more carefully and slower. The latter may be explained by the summer vacations, which reduces traffic volume. The outlier behaviour for trunks is likely due to the little amount of data for said road type.

Overall, it seems that maintaining a steady speed is mildly influenced by seasonality, except for a few circumstances and road types. On the one hand, this suggests that the drivers have even more responsibility when it comes to steady speed, with seasonal factors playing a small role in it. One the other hand, this shows when and where drivers can increase their steady speed time and save even more energy.

5.6 Travel Time

Maintaining a steady speed means accelerating less. Therefore, driving at a steady speed tends to reduce the average speed and therefore the travel time - the time to travel through a road segment. In this section, we analyze how maintaining a steady speed impacts the travel time.

As this study focus on the road segment level, we start by looking at each road segment and how the amount of steady speed changes the average travel time. To simplify the analysis and maximize the number of road segments at the same time, we elect two variables of interest. First, we use only $\delta = 1$. As discussed in Section 5.1, this is the value that gives the best trade-off between number of periods and energy consumption. Second, we use four categories of *SST*, none (0%), low (0-33%), medium (33-66%), and high (66-100%). This combination gives us a total of 28.951 road segments that together amount 4.009.299 subtrajectories (this is 23% and 60% of all the road segments in our dataset, respectively).

We start with the difference in both travel time and energy consumption going from zero to low, medium, and high *SST*. As we are interested in how steady speed relates to travel time and as different road types have different purpose, which directly impacts the travel time, we consider the difference for each road type - residential (RE), tertiary (TE), secondary (SE), primary (PR), trunk (TR), and motorway (MO). Figures 16 and 17 the average travel time and average energy consumption, respectively, per *SST* per road type.

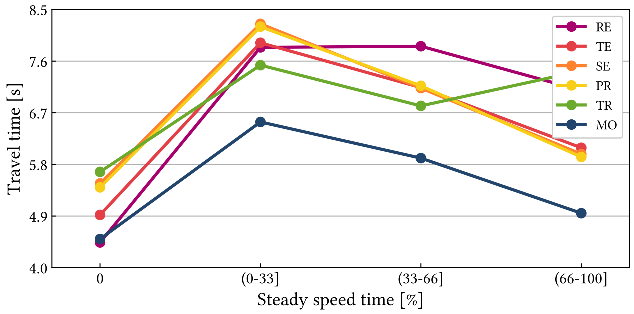

Figure 16: Travel time per steady speed time per road type.

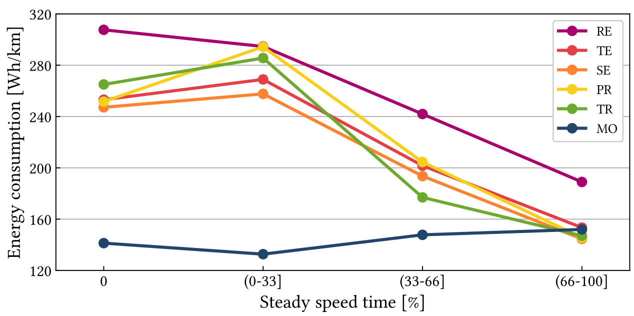

Figure 17: Energy consumption per steady speed time per road type.

The plots show that the subtrajectories with zero steady speed have, on average, the lowest travel time, but the highest energy consumption. They also show that increasing the *SST* leads to an increase in travel time and a decrease in energy consumption. Surprisingly, the increase in travel time by increasing the *SST* is not linear. It peaks at low *SST* and decreases. For example, in motorways, the average travel time for the subtrajectories with none *SST* is 4.50 seconds. For the subtrajectories with low *SST*, the average travel time is 6.54 seconds, an increase of 45%. But for the subtrajectories with medium *SST*, the average travel time is 5.91 seconds, an increase of 31%, and for the ones with high *SST*, the average travel time is 4.95 seconds, an increase of just 10%. Tertiary, cecondary, and primary roads show a similar behaviour. For tertiary roads, the percentages are 61%, 45%, and 23%. For secondary roads, they are 51%, 30%, and 9%, respectively. And for primary roads, they are 52%, 33%, and 10%, respectively.

Regarding the energy consumption, there is a slight increase moving from zero to low *SST* for trunks, primary, secondary, and tertiary roads, but there is decrease of around 25% moving from zero to medium *SST*, and a decrease of around 45% moving from zero to high *SST* for all road types, except motorways. For this type of roads, moving from zero to medium *SST* decreases the energy consumption by 6%, while moving from zero to medium and high *SST* increases the energy consumption by 4% and 8% respectively. This behaviour may be due to the fact that motorways are designed to allow for higher speeds and, as showed in Figures 7 and 8, higher speeds lead to a higher energy consumption.

The findings from both figures indicate that secondary and primary roads offer the best trade-off between travel time and energy consumption by driving at a steady speed, followed by tertiary roads. On secondary and primary roads, it is possible to reduce the energy consumption by up to 42% while increasing the travel time by just 10%. On tertiary roads, it is possible to reduce the energy consumption by up to 39%, but by increasing the travel time by 23%.

Increasing the *SST* reduces the acceleration, therefore reducing the average speed. As driving with a lower average speed increases the travel time, logically one can expect this increase to be lower on shorter segments and higher on longer ones. Now, instead of looking at the different road types, we look at the length of the road segments. Figures 18 and 19 show the average travel time and average energy consumption, respectively, per *SST* per road segment length. The range of (0,20] is removed due to the little amount of data in said range.

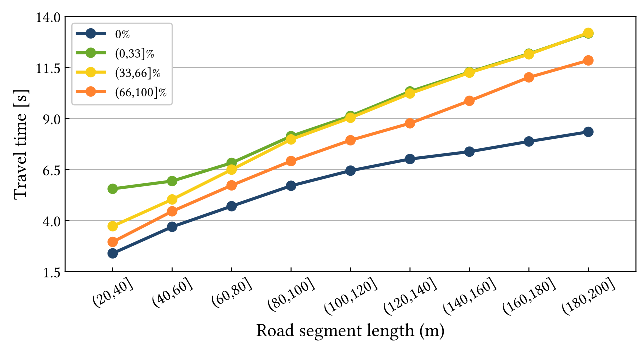

Figure 18: Travel time per steady speed time per road segment length.

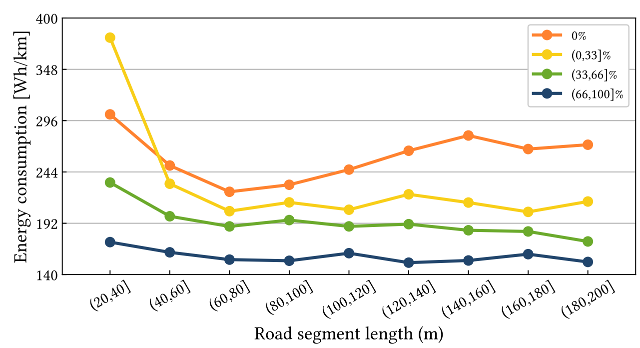

Figure 19: Energy consumption per steady speed time per road segment length.

Figure 18 confirms that the difference in travel time as a result of increasing the *SST* increases with the increase in road segment length. On segments of up to 120 m of length, going from zero to 66-100% *SST* increases the average travel time by 22% while reducing the energy consumption by 31-43%. For road segments between 120 and 200 m of length, going from zero to 66-100% *SST* increases the average travel time by 38% while reducing the energy consumption by 42%.

The findings of this section are even more meaningful when we look at the number of roads segments per type and length. Out of all the 174.182 road segments in our dataset, 12% are secondary and 5% are primary roads. In terms of length, 62% of them have 120 m or less. If we look at the number of subtrajectories, out of all the 7.579.386 subtrajectories in our dataset, 24% of them are in secondary roads and 9% are in primary roads. In terms of length, 64% of them are in road segments with 120 m or less.

This shows that there are many roads where drivers can reduce their energy consumption by almost half if they are willing to increase their travel time by up to 10-22%.

6 CONCLUSION

This paper used a large dataset of 272.289 trajectories, 7.579.386 subtrajectories, and 75.178.755 *GPS+* points to analyze and quantify the impacts of driving with a steady speed on the energy consumption of EVs on a road segment level.

The study showed there is a strong correlation between maintaining a steady speed and low energy consumption, but most importantly, it quantified how much energy can be saved over a wide range of situations. It identified the best amount of fluctuations in speed for steady speed as δ = 1 km/h, as it gives the best balance between number of steady speed periods and energy consumption. It showed that increasing the steady speed time reduces the energy consumption in a linear fashion. In terms of average speed, it showed that steady speed is beneficial across all speeds, but mostly speeds used in urban areas. In terms or road infrastructure, it identified that trunks and motorways allow for more steady speed time. Also, it identified and quantified that it is easier to maintain a steady speed when there is less traffic volume.

Finally, it identified and quantified windows of opportunity, like on secondary and primary roads, where drivers can save energy up to 42% while increasing the travel time by just 10%. Most importantly, this study showed that it is possible for every driver to start saving on energy, and therefore on greenhouse gases, right now as driving at a steady speed does not require any new or special equipment.

Even though this paper quantified several aspects of steady speed and energy consumption, there still much to explore. For future work, we plan on dive in what and how different traffic elements - such as roundabouts, speed bumps, and traffic lights - impact the energy consumption. Also, we plan on study steady speed from the perception of the driver, mostly what it is needed for them to get better at it.

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REFERENCES

[1] Md Saniul Alam and Aonghus McNabola. 2014. A critical review and assessment of Eco-Driving policy & technology: Benefits & limitations. *Transport Policy* 35 (2014), 42–49.

[2] F Badin, F Le Berr, H Briki, JC Dabadie, M Petit, S Magand, and E Condemine. 2013. Evaluation of EVs energy consumption influencing factors, driving conditions, auxiliaries use, driver's aggressiveness. *World Electric Vehicle Journal* 6, 1 (2013), 112–123.

[3] Matthew Barth and Kanok Boriboonsomsin. 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment* 14, 6 (2009), 400–410.

[4] Jacek Caban, Jan Vrábel, Branislav Šarkan, and Piotr Ignaciuk. 2019. About eco-driving, genesis, challenges and benefits, application possibilities. *Transportation Research Procedia* 40 (2019), 1281–1288.

[5] Wissam Dib, Alexandre Chasse, Philippe Moulin, Antonio Sciarretta, and Gilles Corde. 2014. Optimal energy management for an electric vehicle in eco-driving applications. *Control Engineering Practice* 29 (2014), 299–307.

[6] Egemen Evin, Mehmet Burak Aydin, and Geylani Kardas. 2020. Design and implementation of a CANBus-based eco-driving system for public transport bus services. *IEEE Access* 8 (2020), 8114–8128.

[7] GPS.gov. 2022. GPS: The Global Positioning System. Retrieved Jun 6, 2022 from https://www.gps.gov

[8] Yuhan Huang, Elvin CY Ng, John L Zhou, Nic C Surawski, Edward FC Chan, and Guang Hong. 2018. Eco-driving technology for sustainable road transport: A review. *Renewable and Sustainable Energy Reviews* 93 (2018), 596–609.

[9] Karsten Jakobsen, Sabrine CH Mouritsen, and Kristian Torp. 2013. Evaluating eco-driving advice using GPS/CANBus data. In *Proceedings of the 21st ACM SIGSPATIAL international conference on advances in geographic information systems.* 44–53.

[10] Dan Klinedinst and Christopher King. 2016. On board diagnostics: Risks and vulnerabilities of the connected vehicle. *CERT Coordination Center, Tech. Rep* (2016).

[11] Miao Lin and Wen-Jing Hsu. 2014. Mining GPS data for mobility patterns: A survey. *Pervasive and mobile computing* 12 (2014), 1–16.

[12] Paul Newson and John Krumm. 2009. Hidden Markov map matching through noise and sparseness. In *Proceedings of the 17th ACM SIGSPATIAL international conference on advances in geographic information systems.* 336–343.

[13] openstreetmap.org. 2022. OpenStreetMap. Retrieved April 27, 2022 from https://www.openstreetmap.org/

[14] WHO | World Health Organization. 2022. Maximum speed limits. Retrieved Aug 17, 2022 from https://apps.who.int/gho/data/view.main.51421

[15] ourworldindata.org. 2022. Carbon intensity of electricity. Retrieved May 25, 2022 from https://ourworldindata.org/grapher/carbon-intensity-electricity

[16] Angela Sanguinetti, Ken Kurani, and Jamie Davies. 2017. The many reasons your mileage may vary: Toward a unifying typology of eco-driving behaviors. *Transportation Research Part D: Transport and Environment* 52 (2017), 73–84.

[17] HY Tong, WT Hung, and Chun Shun Cheung. 2000. On-road motor vehicle emissions and fuel consumption in urban driving conditions. *Journal of the Air & Waste Management Association* 50, 4 (2000), 543–554.

[18] Yee Van Fan, Simon Perry, Jiří Jaromír Klemeš, and Chew Tin Lee. 2018. A review on air emissions assessment: Transportation. *Journal of cleaner production* 194 (2018), 673–684.

[19] Weiliang Zeng, Tomio Miwa, and Takayuki Morikawa. 2015. Exploring trip fuel consumption by machine learning from GPS and CAN bus data. *Journal of the Eastern Asia Society for Transportation Studies* 11 (2015), 906–921.

[20] Rui Zhang and Enjian Yao. 2015. Eco-driving at signalised intersections for electric vehicles. *IET Intelligent Transport Systems* 9, 5 (2015), 488–497.