Investigating the effects of topography and traffic conditions on the driving efficiency of Electric Vehicles to better inform smart navigation

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Abstract
This paper investigates the effects of topography and traffic conditions on the energy consumption of electric vehicles using real-world data from the Switch EV trial. This data was used in conjunction with road network data to show how the routing choice and thus energy consumption could change under certain topographical and speed conditions. The results from this paper could be used to better inform the decisions of the smart navigation and eco-driving assist systems in electric vehicles.

1 Introduction
The North East of England is one of the pioneers in the wide-scale demonstration of electric vehicles in the United Kingdom. The Switch-EV trial is one of only 8 projects across the UK to have won funding through the TSB's (Technology Strategy Board), Ultra Low Carbon Vehicle (ULCV) Demonstrator Programme. As part of the three year trial, 44 all-electric vehicles have been equipped with data loggers to provide an insight into how early adopters are driving and charging their vehicles. The data collected from the loggers are correlated with attitudinal data from questionnaires and focus groups to understand the behaviour and attitude of the participants to driving range, charging of the electric vehicles and Intelligent Transport Systems (ITS). The trial has shown that the perceived driving range of an electric vehicle (EV) is one of the main barriers to the widespread uptake of electro-mobility [1]. Intelligent Transport Systems (ITS) embedding Information and Communication Technologies (ICT) that would provide the driver journey information such as topography, traffic and charging points' location and availability have the potential to make the range estimation provided to the individual more accurate. This would enable the user to have more confidence in their journey and could alleviate the range barrier through smart navigation and eco-driving assist.

The aim of this paper is to investigate the effects of topography and congestion on the driving range by analysing real time data collected from the vehicles. The objective is then to determine the driving efficiency of the vehicle in various topographical conditions and traffic levels which would then be translated into the effect on the driving range illustrated with spatial analysis. As a result, the information from this work could be used to support and inform the decisions of the smart navigation and eco-driving assist systems.

2 Methodology
The analysis and calculations are based on driving data from electric vehicles for a period of over a year, monitored using on board vehicle data loggers throughout the North East of England as part of the Switch EV trial. In addition, the analysis is based on the Integrated Transport Network layer from Ordnance survey, the topography of the area using a Digital Terrain Model from Ordnance Survey and capacity of the roads based on the COBA manual to infer traffic information for all the roads of the study region.

2.1 Vehicle data
The loggers enable the collection of real-time second by second driving data by connecting to the CAN bus through the vehicles OBD (on-board diagnostics port). In addition to the CAN bus the loggers can also record external analogue and digital inputs. These inputs include the GPS and time-stamp as well as a number of analogue inputs from current-clamps which are attached to various electrical systems of the vehicle to measure current flow and battery drain (and regeneration) [2]. The raw data collected (Figure 1) monitors all aspects of vehicle usage and it is used in this work to calculate the performance of the vehicles under different topographical and traffic levels. The performance is expressed in terms of energy consumption (kWh) per kilometre driven.

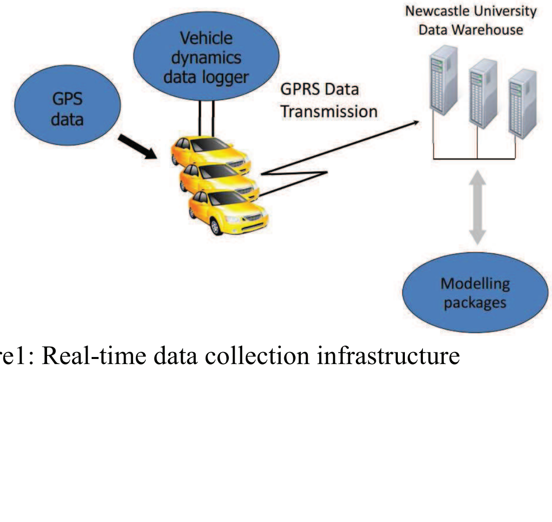

Figure1: Real-time data collection infrastructure

To determine the effect of topography on the performance of the EV, the slope of the roads travelled using the altitude data logged every second of the journey and the related energy consumption from the raw battery information was calculated. The raw data from the vehicles was aggregated into 100 meter 'blocks'. By aggregating the data in this way, it thought that a good balance is struck between capturing altitudinal changes in the vehicle's position whilst reducing the noise inherent in the higher resolution recording. By dividing the driving data into blocks in this way it is possible to keep the altitude change between the start and end point of that driving event linear. Figure 2 illustrates an example where an individual data block exhibits non-linear altitude change between the start and end point over the 100 meters. The car is going up and down in this individual 100 meter journey instead of going either only up or only down and this will make the calculated slope unrepresentative of the actual path.

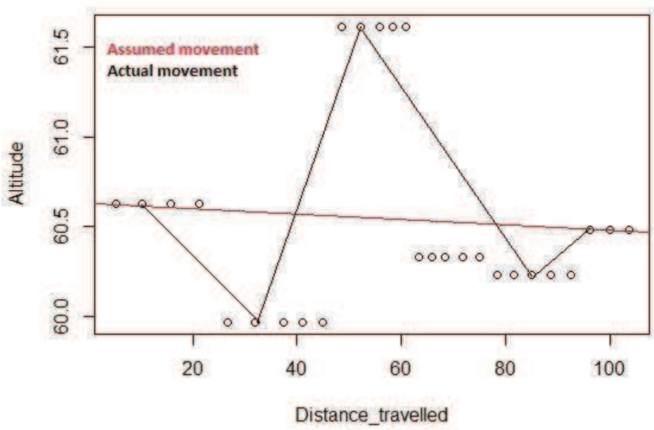

Figure 2: Non Linear Altitude Change

In order to test the linearity of the data blocks and ensure that 100 meters is a representative choice, a check of the altitude change was undertaken. First the difference between the maximum and the minimum altitude in the 100m block was calculated. Second, the absolute value of the difference between the end and start altitude was calculated. The absolute value was used because the end altitude could be lower than the start altitude and this metric was only concerned with the magnitude of the difference. If the altitude change is continuous then the two values calculated above should be equal and "Linearity_check" should equal zero.

$$linearity\ Check = (max\_alt - min\_alt) - |end\_alt - start\_alt| \quad (1)$$

Figure 3 shows that the majority of the linearity check values are equal to zero which confirms that the altitude change in the vast majority of the data blocks is continuous. Hence, the 100 meter path can be used as an accurate approximation for the overall altitude change. A linear regression was used to determine the slopes of the paths.

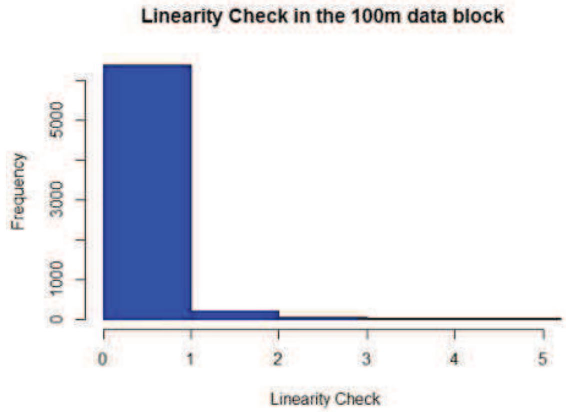

Figure 3: Distribution of the Linearity Check

At this stage of the analysis, the different slope gradients for the driving data and the related energy consumption per km for every slope was calculated (Figure 4). The data is concentrated around low slope values and it follows a linear trend. Figure 5 confirms that the majority of the slope values in the data are in the range of – 6 to plus 6 degrees. With 98% of the data lying within +/-6°there are very low occurrences for slope values outside this range. The significant reduction in data outside the +/-6° range leads to an increasing uncertainty about the efficiency in these ranges and as such it is not possible to empirically derive working efficiency values for gradients greater than +/- 6°.

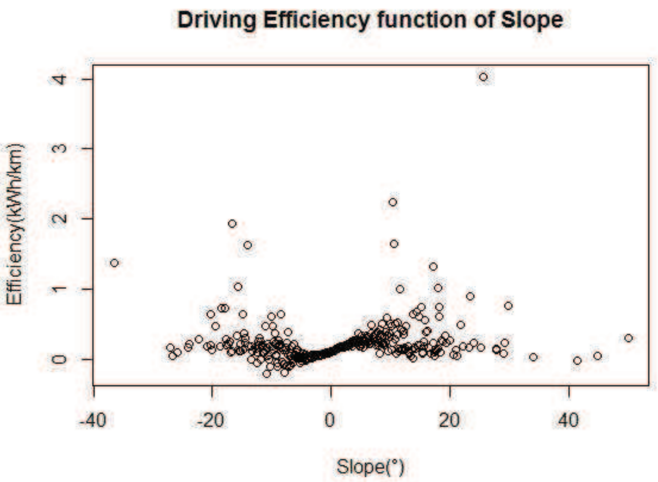

Figure 4: Overall Driving Efficiency

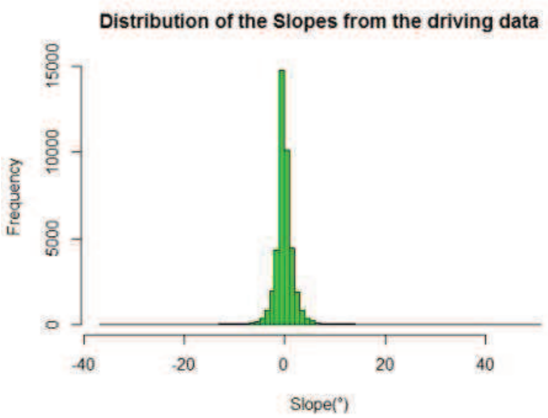

Figure 5: Distribution of slope values

To overcome the small number of data events outside the +/- 6° range that cannot be used to infer the efficiency of the vehicle, regression analysis was used to fit a linear model to the robust set of data (low slope) to determine the driving efficiency for the rest of the slopes (Figure 6).

$$y = a + bx \quad (2)$$

Where :

y: Efficiency (kWh per km)

x: Slope (Degree)

a: first coefficient from the linear regression (Intercept)

b: second coefficient from the linear regression

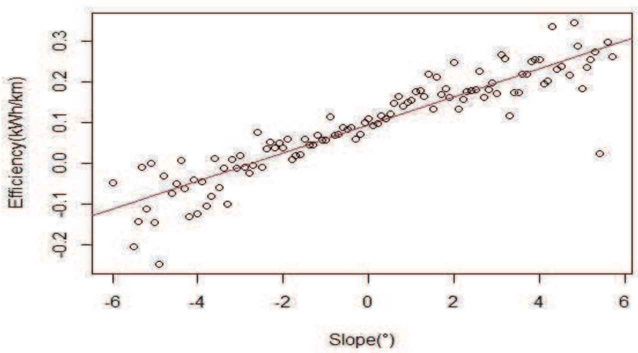

Figure 6: Fitting a Linear model example

It is believed that this approach is justified due to the basic physics behind power consumption in an electric vehicle. When moving on a gradient there will be a proportion of the vehicle's power which is used to overcome the energy required to move the car up an incline; in addition to the power needed to overcome friction and to supply any acceleration. The general formula for this is given by:

$$Power = mv(a + g(\mu + \sin(\alpha))) \quad (3)$$

Where μ is the coefficient of friction, a is the acceleration, g is the standard gravitational acceleration and α is the angle of slope. Wind resistance has not been included in this equation but it is not dependent on gradient. For small values of α:

$$\sin(\alpha) \approx \alpha \quad (4)$$

Equation (3) may be then reduced to the form:

$$Power = a + b \cdot \alpha \quad (5)$$

This is equivalent to that shown in (3). It is believed that by extending the data through the use of a physically valid equation rather than using the increasingly scarce data beyond the +/- 6° range will give a more accurate estimate for power consumption on a gradient.

Whilst power is linearly dependent on gradient it is also dependent on the speed of the vehicle, in addition the coefficient for the dependence of power on the gradient, b in equation (5), may also vary with speed. To capture this behaviour more accurately the two coefficients for the power equation were calculated for a variety of different speed regimes. Table 1 shows the results of the regression analysis and the subsequent linear models used.

Output Speed (kmph)	**Y (kWh/km)**	**R^2**
<30	**Y**=0.159 + 0.028 x	0.62
[30,40[	**Y**=0.102 + 0.031 x	0.77
[40,50[	**Y**=0.107 + 0.043 x	0.85
[50,60[	**Y**=0.098 + 0.036 x	0.87
[60,70[	**Y**=0.110 + 0.032 x	0.71
[70,80[	**Y**=0.114 + 0.027 x	0.78
[80,90[	**Y**=0.121 + 0.028 x	0.80
[90,100[	**Y**=0.139 + 0.026 x	0.90
>100	**Y**=0.163 +0.026 x	0.81

Table 1: Linear models used for efficiency calculation

The linear models show that for a road with no inclination (x=0), driving between 50-60 kmph is the most efficient. In addition driving between 30 and 100 kmph looks to be more efficient than driving in congestion or driving with very high average speed (>100 kmph). Similarly, the linear models show that driving above 100 kmph is more energy demanding than being stuck in traffic with average speed lower than 30 kmph.

2.2 Base road network and assigning elevation/slope information to the road segments

The base road network in the study was created through manipulation of the Ordnance Survey Integrated Transport

Network (ITN) GIS dataset. The ITN dataset is a digitisation of the UK road network and holds within it information about the Road Class (A Road etc.) and Road Type (Single Carriageway etc.). The dataset needs to be manipulated within a GIS package to create bi-directional links. Originally, the network dataset only exhibits link geometry in the direction they were initially digitised and this is, for all intents and purposes, random.

Using the Unique Identifier within the dataset for each original feature, the original digitised geometry direction is termed direction 'A'. A carbon copy of the dataset is then created and the geometry reversed creating direction 'B'. This task is essential so that the bidirectional links can display different impedance values during the network analyst and routing algorithms. (i.e. different slope depending on the direction of the travel on that road). In order to determine the slope of a road segment, the ITN bidirectional road network was split into start and end points for each road segment.

These points were then assigned altitude information from the Ordnance Survey Land-Form PANORAMA dataset. The Open Source dataset provides, if downloaded as a Digital Terrain Model (DTM), a continuous raster surface of heights across the UK. Alternatively the data can be downloaded as 'Spot Heights' with a 10m contour interval and the interpolation method left to the user. The DTM altitude information assigned to the start and end points of the road segment and the length between the points are used to determine the slope of the road segment using Pythagoras' Theorem. Since the distance between the start and end points, otherwise known as the segment length, is measured on a flat 2d plane Arc Tangent is needed to find the slope. Given that the height is recorded only at the start and end points of a road network segment, there is an inherent assumption that the road segment connecting these two points is of a constant gradient over its measured length.

2.3 Assigning average speed at Predefined COBA capacities

In order to simulate varying levels of congestion, average speeds for different road types at different levels of capacity are determined from the COBA manual. The speed of the roads that make up the ITN network are variable in terms of speed limits, but also in terms of how the speeds of these roads vary when reacting to different levels of network capacity . The capacity conditions range from 15% capacity (essentially free flow speed) to 145% capacity (severe congestion). Each road segment in the ITN dataset was assigned to a COBA link type classification creating a lookup between road type descriptions.

3 Results

The linear models derived from real-life driving data are used to determine the driving efficiency of EV's in terms of how they react at certain speeds and under certain topographical conditions. These efficiency values will then be used in conjunction with the road network conditions (topography and average speed) to determine the energy consumption of driving on the roads within the network. In this work, the Network Analyst extension in ArcGis is used to determine the least energy demanding route between an origin and destination and to determine the area of the network that an electric vehicle with a certain level of charge could cover. These routing solvers are based on Dijkstra's algorithm. Figure 7 is an example of finding the route between an origin and destination that minimises energy consumption. It shows several routing decisions that vary depending on the road network conditions linking the two points.

The analysis of the routing decisions made under different levels of capacity, and thus average traffic speed, shows that in order to minimise the expenditure of energy, the route between two points can change dramatically. For example, when using Newcastle City Centre and Edinburgh as an origin and destination, two distinctly different routes are chosen; one using predominantly the A1/A697 and the other being the A696. The reason for this is that under different capacity levels, the two A Roads of different COBA link type definition react differently in terms of their average speeds. Combining this information, along with topographical changes, the most efficient route is selected. In free flow conditions the chosen route is of a similar distance (159 and 155 km respectively) to the 90% capacity route; however there is a noticeable difference in the energy consumption figures (15.95 and 11.75 kWh) which could be related to driving at energy intensive high speeds. The shortest distance route minimises the distance and not energy consumption, hence it doesn't take into consideration the topographical and traffic conditions of the roads.

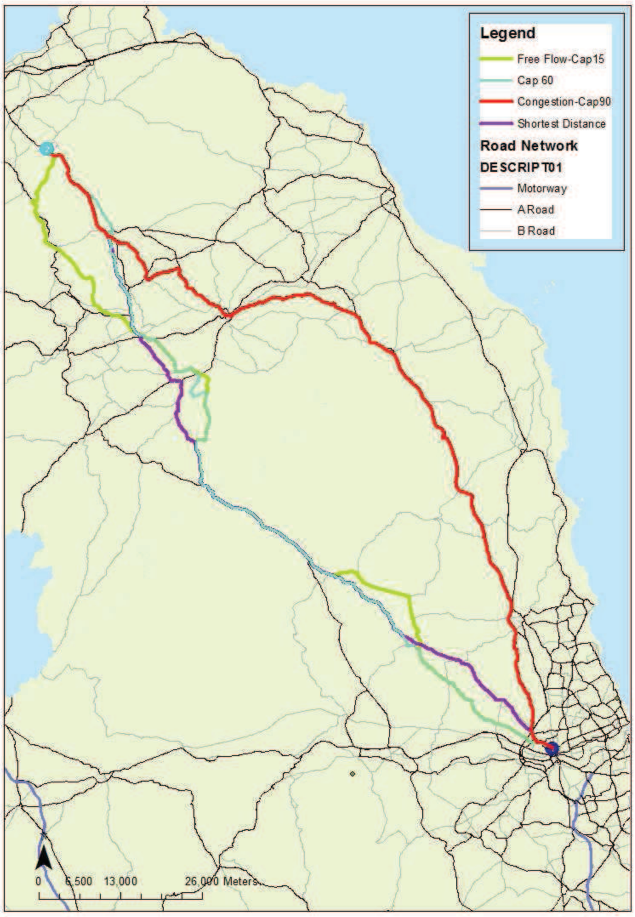

Figure 7: Routing to minimise energy consumption under different levels of network capacity.

Figure 8: Driving range of an EV for different levels of network capacity.

Figure 8 is an example of finding the area that an EV could cover when traversing the network where that area is within the specified network energy cost cut-off. In this work, the energy cost cut-off is the amount of charge on the vehicle. In other words, figure 8 shows how far the EV could go from a starting point until it runs out of charge for different levels of network capacity. Comparing the covered area of an EV between free flow conditions, congestion and cap 60, it is found that the driving range of an EV is at its minimum under flee flow conditions where average speeds are highest with related high energy consumption as showcased in Table 1. Cap 60 exhibits the largest range and this is because the average speeds for this case are optimal in terms of energy consumption. The roads are not heavily congested to have speeds dropping under the 30 kmph and they have traffic that could indirectly lead the user to drive in the optimal average speeds (30 to 70 kmph). Finally driving range on congested roads (Cap 90) shows to be better than driving at free flow speed.

4 Conclusion

The information presented in this paper shows how understanding the efficiency of EV's in terms of how they react at certain speeds and under certain topographical conditions can have a great impact on route choice and thus energy consumption. As an extension of this principle, the paper has also shown that the possible range of an EV fluctuates when these conditions change. Given that range anxiety is one of the main barriers to EV adoption, this type of information can be input into ITS applications which receive real-time and historic traffic updates to determine the best route available, minimising the energy consumed and thus extending the range. Such information can also help to reduce anxiety effects [3] by giving the driver confidence that the ITS driver aids understand the impacts of these external factors on range, allowing the driver to trust he will be able to reach a destination even on the limit of the stated range.

Acknowledgements

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