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Routing systems to extend the driving range of electric vehicles

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Abstract: This study develops a more accurate range prediction for electric vehicles (EVs) resulting in a routing system that could extend the driving range of EVs through calculating the minimum energy route to a destination, based on topography and traffic conditions of the road network. Energy expenditure of EVs under different conditions is derived using high-resolution real-world data from the SwitchEV trial. The SwitchEV trial has recorded the second-by-second driving events of 44 all-electric vehicles covering a distance of over 400 000 miles across the North East of England, between March 2010 and May 2013. Linear models are used to determine the energy expenditure equations and Dijkstra's graph search algorithm is used to find the route minimising energy consumption. The results from this study are being used to better inform the decisions of the smart navigation and eco-driving assist systems in EVs, thus improving the intelligent transport systems provisions for EV drivers. The outputs of the research are twofold: providing more accurate estimations of available range and supporting drivers' optimisation of energy consumption and as a result extending their driving range. Both outputs could help mitigate range anxiety and make EVs a more attractive proposition to potential customers.

1 Introduction

The North East of England is one of the pioneers of wide-scale demonstration projects of electric vehicles (EVs) in the United Kingdom (UK). The SwitchEV trial is one of only eight projects across the UK to have won funding through the Technology Strategy Board's (TSB's), ultra-low carbon vehicle demonstrator programme. As part of the 3-year trial, 44 all-electric production vehicles have been equipped with data loggers. The data collected from the loggers and charging network are correlated with attitudinal data from questionnaires and focus groups to understand the behaviour and attitudes of the participants on driving range and to understand what new intelligent transport systems (ITS) and services are required to support the roll-out of EVs and their associated charging infrastructure. With more than 90 000 recorded journeys and over 400 000 miles driven (as well as over 20 000 re-charging events recorded), the SwitchEV project has created a unique dataset on the driving behaviour of EV users. The real-life driving behaviour of the users, their energy use and re-charging behaviour has been charted and analysed to identify barriers to the introduction of EVs and to inform future policies on electric transport. Utilising the data from tens of thousands of recorded driving events, an understanding of the real battery performance and real range of EVs has been developed. Using this as a 'ground truth', a series of equations have been derived to calculate the range available to an EV based upon the traffic conditions and topology of the road. This enables, for the first time, the ability to predict more accurately the available range of the vehicle and in addition to provide advice on selecting the most efficient route for an EV for a particular journey.

2 Range of EVs

2.1 Background

The Stern review [1] highlighted the potential future economic costs because of climate change. It recommended cutting greenhouse gas emissions by 60–80% by 2050, relative to 1990 levels. As a response to the Stern Report, the UK government passed the Climate Change Act [2] that set the legally binding target of cutting 2050 greenhouse gas emissions by 80%. In 2011, the UK Government published the Carbon Plan [3], which sets out how the UK will achieve decarbonisation targets across all sectors. It anticipated that the average carbon emissions of new cars will fall by one third because of new legislation on European Union (EU) vehicle emissions standards. However, to meet long-term climate change targets, the private vehicle fleet will have to ultimately be converted into ultra-low emission vehicles such as full electric cars and plug-in hybrids recharged using renewable energy sources, as well as hydrogen fuelled cars [4, 5]. Yet, the real uptake of EVs is falling short of Government and industry expectations despite Government efforts to promote the uptake of EVs [4, 6, 7]. According to the Society of Motor Manufacturers and Traders (SMMT), new full-electric car registrations were 1262 units in 2012 and a total of 2237 plug-in-car grants of up to £5000 each were awarded [8]. The main reason is that the public still see a large number of barriers to the uptake of EVs such as limited range, insufficient availability of public charging infrastructure and the high purchasing cost of EVs [9–13]. Franke and Krems [14] argue that drivers are only comfortable utilising between 75 and 80% of the available range of electric cars. The authors discuss that driving an electric car on a daily basis has a positive effect on the driver's comfortable (the preferred range safety margin that an EV driver likes to have at the end of a journey) and competent range (the maximum range utilised by an EV driver throughout the trials) and that feedback should be given to drivers in order to help them expand their range. ITS could therefore provide the driver with optimised route choice to minimise energy expenditure and more accurate range predictions based on their journey information, topography, traffic conditions, temperature as well as the location and availability of charging points along their chosen route. All of which will provide the driver with more confidence in their available range.

2.2 ITS for EVs

The importance of accurate range prediction has been highlighted by the ITS industry. In 2012, European Road Transport Telematics Implementation Co-ordination Organisation (ERTICO) published a roadmap on ITS for ElectroMobility [15], which highlighted the limited range as one of the key challenges to be addressed through ITS services. The roadmap covered the development of ITS services and applications that were relevant for the mass deployment of EVs. The roadmap had been developed by the ERTICO Task Force 'ITS for ElectroMobility', which included representatives of the automotive industry, ITS sector, research sector and service provision sector. Table 1 shows the priorities for ITS developments for EVs. It can be seen that three of the top five priorities refer to accurate range and optimised driving and route planning to maximise the range of the electric cars.

Most electric cars have a range estimator on board. However, these calculate the range of the vehicle based on the driving style of the previous trips and do not take into account a number of factors affecting the vehicle's energy consumption and remaining range. These factors include traffic conditions, road types and topography, weight and weather conditions. A lot of work has been done to develop eco-driving algorithms for ICE vehicles [16–18]. For example, previous work has shown how energy management systems and route-based control systems can overcome some of the negative impacts of road gradients on fuel consumption of heavy duty vehicles [19] and hybrid electric cars [20]. However, little work has been done to estimate energy expenditure and driving range specifically for EVs. Moreover, satellite navigation systems specifically designed for EVs would be more relevant if, instead of optimising distance or travel times, the routing was based on optimising energy expenditure for a given journey. This would then optimise a key factor for EVs suitability, the driving range.

Table 1 Priorities for the development of ITS services for electric vehicles [15]

Priority	Service
1	electric vehicle charging management and services
2	new traffic management tools for large-scale introduction of EVs into the road network
3	accurate range prediction
4	EV route guidance and EV navigation
5	EV eco-driving

3 Methodology

3.1 Electric vehicles

This study only analysed the range of full EVs and does not refer to conventional engine cars. The vehicles used in the SwitchEV trial were Nissan LEAF, Peugeot iOn, Avid Cue-V, Liberty electric cars eRange, and the Smith Electric Vehicle Edison Minibus. For the purpose of the research reported in this paper, only data from the Leaf and iOn vehicles performance were used. Table 2 summarises the key vehicle specifications.

3.2 Driver recruitment

A 86% of vehicles were leased by organisations and 14% by private individuals. Of the vehicles leased to organisations, 51% were used by single users and 49% were designated pool vehicles. In order to understand the behaviour of the SwitchEV triallists and whether there are some specific traits and choices associated with age, gender or demographics, a pre-trial questionnaire included questions to profile the participants. From this, it was summarised that the majority of trial candidates were men with 72% of drivers being male and 28% being female. Only 5% of drivers were 17–25 years old, 16% of drivers were 26–35 years old, 31% of drivers were 36–45 years old. The largest groups with 38% were 46–55 years old and a further 10% were 56–65 years old. 90% of respondents were in full-time employment, 6% in part-time employment, 3% self-employed and 1% full-time students. This bias towards older male drivers is due to two characteristics of the trial; the first being that many of the vehicles were leased to triallists to use at work (either being an organisation single-user vehicle, or an organisation pool vehicle shared by a number of workplace colleagues), and the age profile (particularly of the single users) was quite high – this is largely correlated with the actual costs of leasing the EVs. Further research showed that the profile of the SwitchEV drivers fits well into the general EV purchasing behaviour.

Table 2 Vehicle characteristics [21]

	Peugeot iOn	Nissan LEAF
driving range	93 miles (150 km)	109 miles (175 km)
max speed	81 mph	90 mph (over 145 km/h)
battery type	lithium manganese oxide	laminated lithium-ion battery
battery capacity	16 kWh	24 kWh
battery layout	under seats and floor	under seat and floor
length	3474 mm	4445 mm
width	1792 mm	1770 mm
height	1608 mm	1550 mm
seating capacity	4 adults	5 adults
max engine power	47 kW	80 kW
max engine torque	180 Nm	280 Nm
number of vehicles on trial	20	15

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According to the DfT, 87% of recipients of the Plugged in car grant were males, working full time (in senior roles or self-employed) or retired and aged 40 years and above [22].

3.3 Soft data collection

Attitudinal data were collected through online pre- and post-driving questionnaires and focus groups. The analysis is based on three six-month trial periods between March 2011 and October 2012. Over the course of the SwitchEV project, 192 participants provided answers to the pre-trial questionnaire, 101 answers to the post-trial questionnaire and 30 answers to fast charger questionnaire. A 60 participants attended 12 focus groups, with 12 individual exit interviews and 10 pre-trial interviews conducted in order to understand drivers' attitudes towards EVs and their charging infrastructure. The number of drivers exceeds the number of vehicles because some of the vehicles are used as pool and fleet vehicles and multiple drivers have access to those vehicles.

Some direct quotes from individual SwitchEV drivers that have been provided in the results section were reproduced from their questionnaire responses or captured from oral records of the focus groups. All quotes are unedited and are presented in quotes: '…'.

3.4 Data logging

The research presented in this paper is based on driving data from EVs over 18 months, monitored using on board vehicle data loggers throughout the North East of England as part of the SwitchEV trial. The driving performance and remaining range of the EV are analysed based upon a number of dynamic parameters rather than just the state of charge of the EV battery. The raw data collected monitors all aspects of vehicle usage. The loggers enable the collection of real-time second by second driving data by connecting to the controller area network (CAN) bus through the vehicles on-board diagnostics port (OBD). In addition, the loggers record GPS and time-stamp as well as analogue inputs from current-clamps attached to various electrical systems of the vehicle [23].

3.5 EV-specific models

Linear models derived from real-life driving data are used to determine the energy expenditure of EVs for different topography and driving speed. The driving speed is used as a proxy for the road network capacity or traffic conditions. The driving data include the altitude, speed and corresponding energy consumption or regeneration derived from the raw battery data. Energy regeneration occurs due to breaking and deceleration of the vehicle. The data collected from the vehicles was aggregated into 100 m 'blocks'. Afterwards, a linear model was used to determine the slopes from the altitude data for every 100 m block. Furthermore, additional linear models were used to determine the corresponding energy use of the vehicle per km, for the different slopes and different average driving speeds. A multiple regression model was constructed to justify this work. It was demonstrated that the accuracy of range prediction is greatly improved by incorporating variables such as topography and average speeds in addition to historical data about driving conditions. Finally, based on the energy expenditure equations, a case study in the later parts of this paper has illustrated optimum routes for an EV journey.

4 Results

4.1 Attitudinal evidence from SwitchEV trials

Overall, 80% of drivers of the SwitchEV trial thought that the experience of driving an EV was either the same or better than driving an internal combustion engine (ICE) car. However, 20% of drivers thought that driving an EV was still worse than driving an ICE car. One driver explained in the focus group: 'I would say that the range must be probably the biggest barrier. If it's your only mode of transport then it probably is a problem, but not if it's for use as a second vehicle.'

Most drivers reported that they did not change their driving behaviour for most of their journeys. Many drivers reported however that they changed their driving style or their chosen routes if they wanted to go on longer journeys: 'If I was on the rare occasion going on a long journey then definitely I made the most of the regenerative braking and tried to keep the battery life but apart from that I think I probably drove a little bit faster than I would in a normal car just to try and push it and just to see what it could do really and because I did not have to worry about range then that was something that I could do was just see what it actually performed like but if it was a long journey then I would definitely change my driving style just because I was aware of the battery life.' Another driver explained their observations when asked about the key barriers to the uptake of EVs: 'the range and the battery drain. The drain is related to the topography of the roads round here and potentially how you drive it, but the range is limited and its drain is the topography. However, you do maybe change your route to take that into account. For example, to [a location] which is 30 miles I went up [one road] and deliberately chose to not come back that way because of the hills, and instead came back via the rural road where it is quite comfortable going along at 40 mph.' Other drivers also reported that they changed the routes they took when driving an EV: 'I find I did not change my driving style; but I did change my routes. When I came down a [dual-carriageway A road] and the range went down very quickly whereas when I went down the [single carriage way A road] which is exactly the same route, I ended up at the same place and I found the range did not go down that far because we were in traffic stop starting all the way through so I would use that route. I lost about five minutes but gained all the regenerative braking.' A 32% of drivers reported that they reduced the number of trips on the motorways. This anecdotal evidence shows how important it is to give EV drivers relevant information affecting the range.

4.2 EV-specific driving efficiency models

The driving events were separated into 100 m data 'blocks' then the slope, average speed and corresponding energy expenditure were calculated for each data block. By aggregating the driving data collected from the vehicles into 100 m blocks, it is thought that a balance is struck between capturing altitudinal changes in the vehicle's position while reducing the noise inherent in the higher resolution recording. By dividing the driving data into blocks in this way, it is possible to model the altitude change between the start and end point of that driving event as linear or

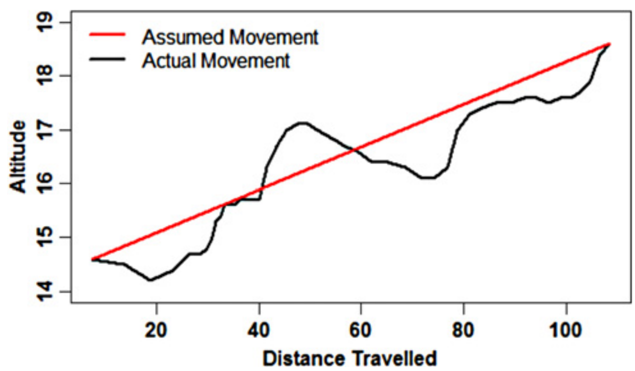

Fig. 1 *Nonlinear altitude change*

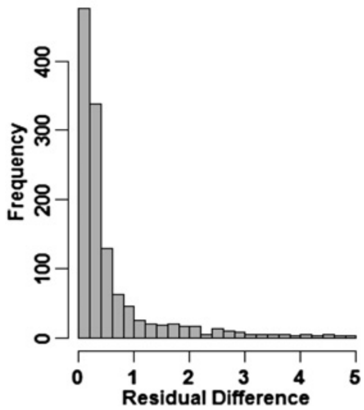

Fig. 2 *Distribution of the linearity check*

continuous (i.e. assuming the car is only moving up or down for the 100 m). However, Fig. 1 illustrates an example where an individual data block exhibits non-linear altitude change between the start and end point over the 100 m, as opposed to the assumed linear altitude change.

To validate that the altitude change would mostly be linear and cases similar to Fig. 1 are an exception, the actual altitude variation was compared to the modelled altitude change over the 100 m for the data blocks. To achieve this, the residual variation between the created linear regression model and the actual data was calculated. Then the average of the absolute values of the residuals (difference between the observed values and modelled values) was taken for every 100 m section. If the altitude change is continuous then the values calculated above should be zero.

Fig. 2 shows that the majority of the linearity check values are within 1 m of zero which confirms that the altitude change in the vast majority of the data blocks varies only slightly away from linearity. Hence, the 100 m path can be used as an accurate approximation for the overall altitude change. More details on the model were introduced in [23].

At this stage of the analysis, the different slopes for the driving data and the related energy consumption per km for every slope were calculated (Fig. 3*a*). Fig. 3*b* confirms that the majority of the slope values in the data are in the range of –6 to +6° with ~99% of the data lying within ±6°. 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 EV performance values for gradients greater than ±6° with confidence. This is reflected in the increasing variance outside the ±6° shown in the grey area in Fig. 3*a*.

To overcome the small number of data outside the ±6° range, regression analysis was used to fit a linear model to the robust set of data (corresponding to low slope) to determine the driving efficiency for the rest of the slopes. Fig. 4 illustrates fitting a linear model to low slope values and the linear model equation is represented in the following equation

$$y = a + bx \tag{1}$$

where y is efficiency (kWh per km), x is slope (deg.), a is first coefficient from the linear regression (intercept) and b is second coefficient from the linear regression.

Standardised residuals between the fitted and observed values were calculated to test if the model assumptions are correct. Fig. 5 illustrates that the model assumptions are correct where the plots of the residuals against the predictor variables are randomly scattered (Fig. 5*a*) and the residuals lie on a straight line (Fig. 5*b*).

It is believed that fitting a linear model to determine the efficiency for higher slope values is justified due to the basic physics behind power consumption in an EV [24]. When moving on a gradient, a proportion of the vehicle's power is used to move the car up an incline; in addition to the power needed to overcome friction and to supply any

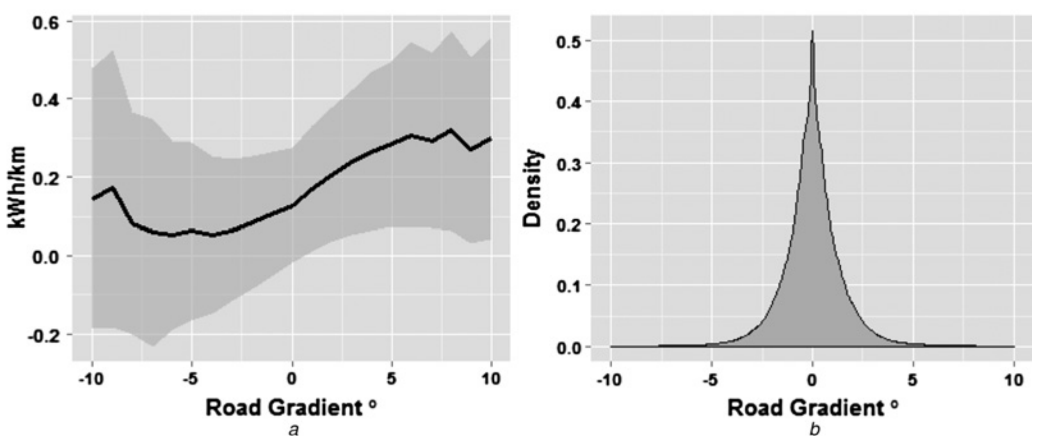

Fig. 3 *Different slopes for the driving data and the related energy consumption per km*

a Overall driving efficiency
b Distribution of slope values

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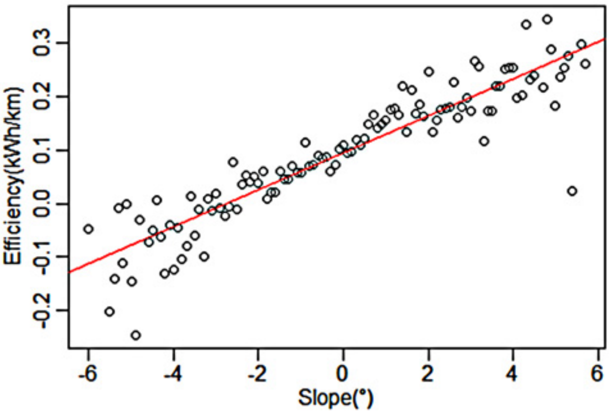

Fig. 4 *Fitting a linear model*

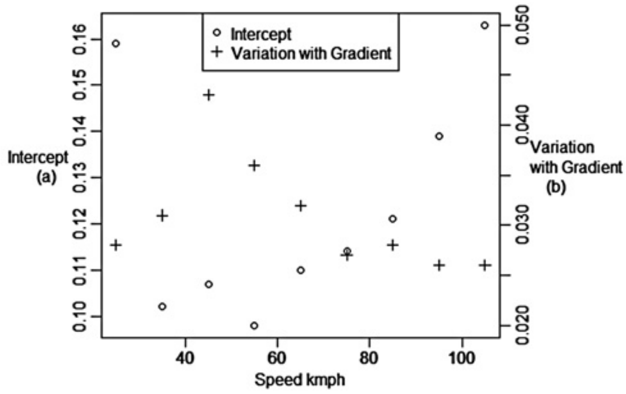

Fig. 6 *Linear models used for efficiency calculation*

acceleration. The general formula for this is given by

$$\text{Power} = mv\big(a + g\big(\mu + \sin(\alpha)\big)\big) \tag{2}$$

where m is the mass, v is the velocity, a is the acceleration, g is the standard gravitational acceleration, μ is the coefficient of friction, 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

$$\sin(\alpha) \simeq \alpha \tag{3}$$

Equation (2) may be then reduced to the form

$$\text{Power} = a + b\,\alpha \tag{4}$$

Equation (4) is then equivalent to the linear model equation shown in (1). By extending the data through the use of a physically valid (4), rather than using the increasingly scarce data beyond the $\pm 6°$ range, there will be a more accurate estimate for power consumption (and thus efficiency) on a gradient.

Although power is linearly dependent on the gradient, it is also dependent on the speed of the vehicle (mass has not been taken into consideration in this study); the coefficient for the dependence of power on the gradient, b in (4), varies with speed. The two coefficients for the power equation (a and b) were calculated for a variety of different speed regimes.

Fig. 6 shows the variation of the coefficients of the linear regression analysis used to model the effect of gradient.

The linear models show that for a road with no inclination, that is, a road where the efficiency is purely driven by the intercept (a) on Fig. 6, 50–60 kmph is the most efficient speed. The effect of gradient on the typical speed–efficiency curve can be directly observed in Fig. 7.

In Fig. 7 it can be seen that for the 50–70 kmph regime, there is greater variation in efficiency with respect to the gradient. In addition, it can be seen that at low speeds there is comparatively little variation in efficiency with respect to gradient. One implication of this is that the gradient in inner city areas, for example, is of less importance than that where greater speeds could be expected.

4.3 Justification of the work

In general, it is to be expected that the efficiency of a vehicle over a given distance will be a product of multiple different variables, with the total energy needed to complete a full journey in an EV is governed by multiple different factors such as the loading of the vehicle or the road type. Some of these variables are not predictable, or at least not easily measurable, across the whole of the journey. To successively achieve this, a multiple linear regression model was constructed using data which would either be easily available to any vehicle's on board systems (predicted speed, journey topography etc.) or could be historically derived from data already recorded by the vehicle, for

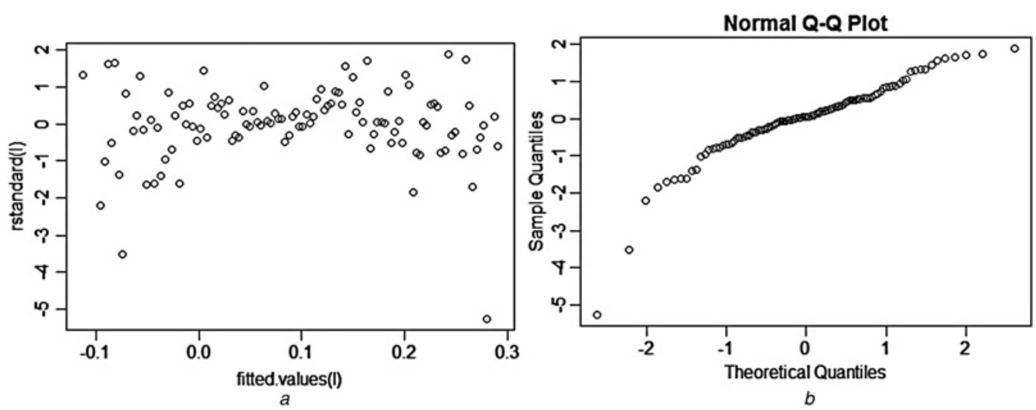

Fig. 5 *Plot of the residuals*

a Plot of the residuals against the fitted values
b *Q–Q* plot of the residuals

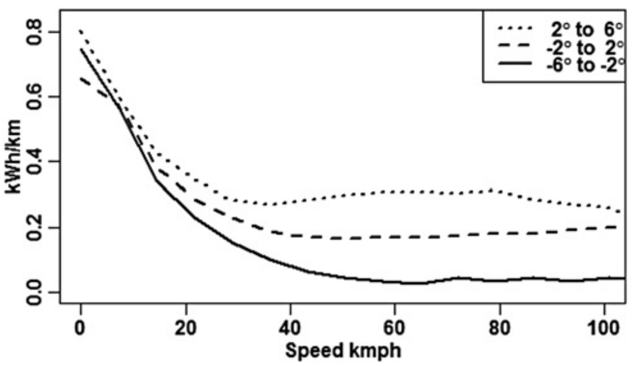

Fig. 7 *Variation in efficiency with speed as the gradient also varies is shown here*

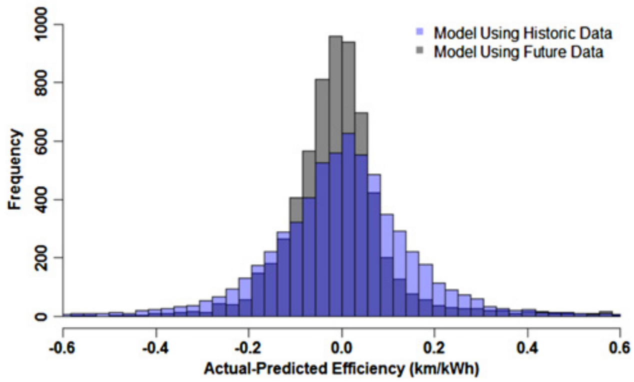

Fig. 8 *Marked improvement in predicting the efficiency of any future journey is shown here*

example, the previous efficiency recorded.

$$\mathrm{Eff}(x) = f(\text{speed, accel, gradient, previous})$$

This equation will be typically composed of multiple different interrelated variables as the effects of, for example, speed vary as the gradient varies, as demonstrated in Section 4.2. Although the specific form of this equation will be the same for each vehicle, as the vehicles rely on the same basic physical underpinnings, there will be varying coefficients because of slight differences between the vehicles.

To illustrate this, referring back to Fig. 7 it can be seen that the efficiency variation of the vehicle with respect to speed is non-linear and can be broken down into two main sections. After 35–40 kmph there is very little variation with respect to speed compared to the strong efficiency variation with speeds below 35 kmph. To improve the model (and remove multiple non-linear terms from the regression equation) it was decided to examine the two sections of data separately.

To assess the importance of each variable in predicting the efficiency, the models were systematically varied and the explanatory power of each variable derived.

Table 3 shows that the faster sections are more predictable than the slower speeds. Qualitatively this makes sense as a great deal of the energy variation at lower speeds is because of variations in hotel loads (lights, radio and air conditioning/heater etc.) rather than actual driving-related power usage. In addition, the speed forms a greater proportion of the explanatory power at lower speeds, which is expected because of the observed strong variation in speed, at lower speeds.

An example is shown in Fig. 8 where there are two distributions: one represents the difference between the actual energy efficiency of a journey and the predicted energy efficiency of that journey where the predicted energy efficiency has been calculated using historical data. The model assumes that the efficiency of a future journey will be the same as the previous journey. This is a system similar to that found in EVs today. In the second distribution, the predicted energy efficiency has been calculated using a combination of historic and available data for the future trip. At this instance, it is assumed that both the topography and the speed of the future journey will be known but it would also be possible to include traffic parameters, such as congestion, or metrological data, such as temperature.

It can be seen that the predicted future efficiency, and hence the accuracy of any predicted future range for the EV is greatly improved through the use of not only historic data,

Table 4 Route planner components of the case study

Input component	Description
ordnance survey integrated transport network (ITN) GIS dataset	digitisation of the UK road network and holds within it information about the road class (a road etc.) and road type (single carriageway etc.)
ordnance survey land-form PANORAMA GIS dataset	dataset provides altitude information across the UK
department for transport COBA manual	average speeds for the road network under different levels of capacities, i.e. capacity 15 (cap 15) indicating free flow
energy cost based on Switch EV data to travel on a road in the network depending on the topography and the capacity level of that road (three capacity levels were used for this work, i.e. cap 15,60,90)	energy cost for travelling 100 m was determined for different slopes and speeds (as a proxy for the road network capacity or congestion level) using the thousands of driving data collected in the trial. These values were then used to define the energy cost of real-world driving on roads with corresponding slope and average speeds (that would match a certain road capacity level)
ArcGis network analyst extension based on Dijkstra's graph search algorithm	finds the least cost route between a chosen start and end point

Table 3 Individual and total explanatory power of each variable is shown here

		All variables, %	Variable removed			
			Speed, %	Gradient, %	Acceleration, %	Previous data, %
% of efficiency explained	<35 kmph	28.5	5.1	4.0	18.5	1.9
	>35 kmph	60.1	3.1	16.6	40.1	3.2

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but also variables which will affect the car in the future. If it were possible to predict driving patterns, including acceleration, then it would possible to improve this still further.

5 Case study: determining the minimum energy route using EV-specific energy expenditure values

EV-specific energy consumption for different topographical and traffic conditions was determined in Section 4.2. This section will visualise the route choice minimising energy consumption for a given journey on an actual road network. Two steps are needed for this visualisation. First, all the routes on a road network were assigned an EV energy cost value, depending on their topography and for various traffic levels that indicate the EV energy consumption of driving on the roads within the network. Second, Dijkstra's graph search algorithm [25] was used to find the path with the lowest cost (i.e. the path minimising energy consumption) for a given journey. Table 4 shows the input components for this case study that will be detailed in the following sections.

5.1 Modelling a road network

High accuracy road grade or topographical information is not currently widely available [19]. This paper develops a simplified road network topography and capacity level model. The base road network in this work was created

Fig. 9 *Routing to minimise energy consumption under different levels of network capacity*

through manipulation of the Ordnance Survey Integrated Transport Network (ITN) geographic information system (GIS) dataset [26] for the study area. 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.).

5.1.1 Adding topographical information to the road network: In order to determine the slope of a road segment, the ITN 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. The DTM altitude information assigned to the start and end points of the road segment, combined with the length between the points are used to determine the slope of the road segment using standard trigonometric methods. There is an inherent assumption that the road segment connecting these two points is of a constant gradient over its measured length.

5.1.2 Creating 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 copy of the dataset is then created and the geometry reversed creating

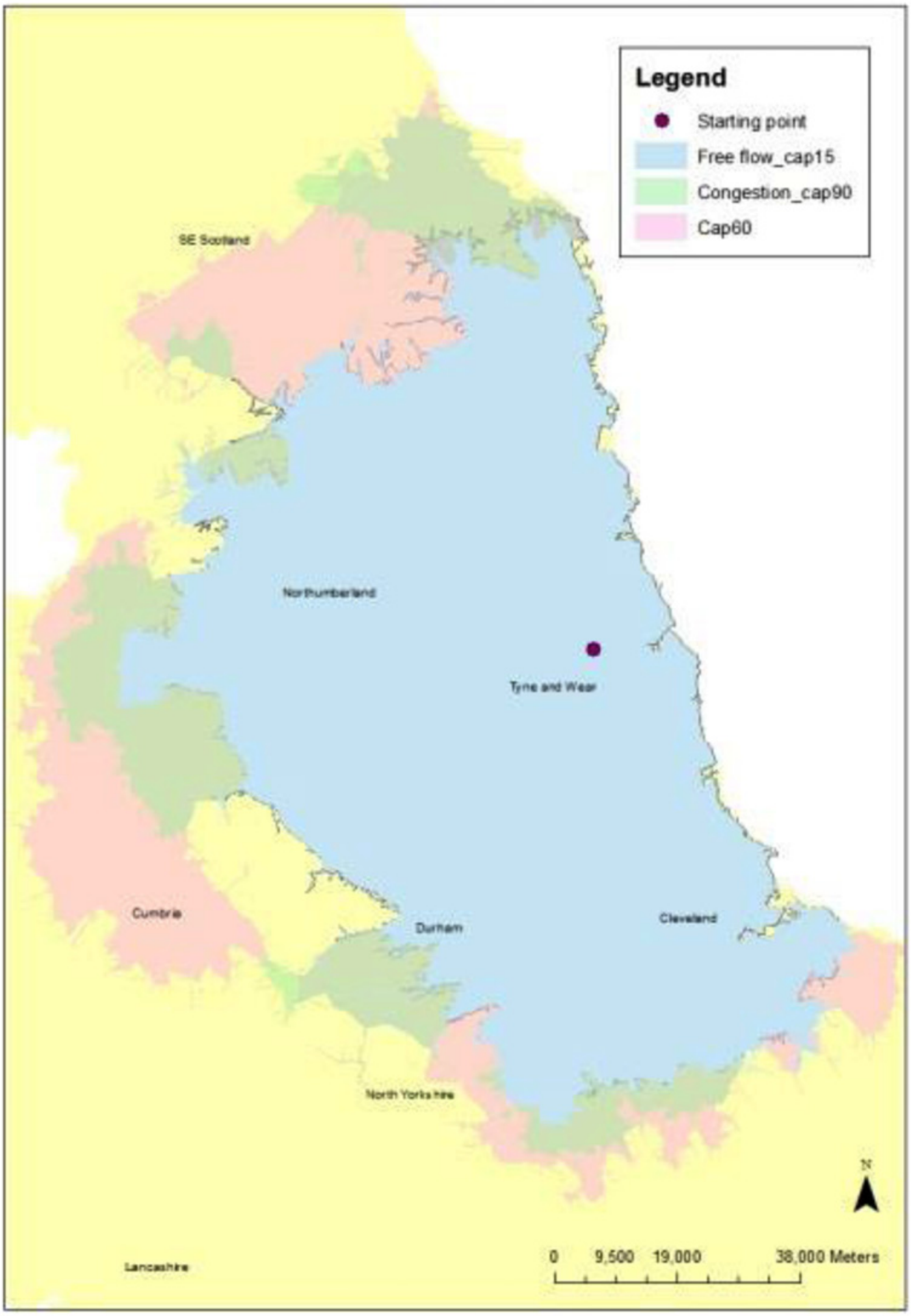

Fig. 10 *Driving range of an EV for different levels of network capacity*

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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).

5.1.3 Assigning average speed at predefined COBA capacities: In addition to determining the gradient and direction of the road network in order to visualise the EV data, it is also necessary to prepare the road networks for various levels of traffic 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. Capacities of 15, 60 and 90% (Cap15, Cap60, Cap90) are used for this work.

5.2 Route choice minimising energy consumption

The Network Analyst extension in ArcGis based on Dijkstra's graph search algorithm is used to determine the minimum energy route between an origin and destination. Network Analyst is also used to determine the area of the network that an EV with a certain level of charge could cover. Fig. 9 is an example of finding the route between an origin and destination that minimises energy consumption. It shows the route representing the shortest distance between two points and several energy minimising routing decisions.

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 minimum distance route between the 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 the A696. The reason for this is that under different capacity levels, the two A Roads react differently in terms of their average speeds. Combining this information, along with topographical changes, the most efficient route is selected. For example, 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 does not take into consideration the topographical and traffic conditions of the roads; it minimises the distance but not necessarily the energy consumption.

Fig. 10 is an example of finding the area that an EV could cover 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, Fig. 10 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 free flow conditions where average speeds are highest with related high energy consumption as showcased in Fig. 6. Cap 60 (i.e. condition in between congestion and free flow) exhibits the largest range and this is because the average speeds for this road network condition are optimal in terms of energy consumption. The roads are not so heavily congested to have speeds dropping under 35 kmph and they have traffic that could indirectly lead the user to drive in the optimal average speeds (35 to 70 kmph).

6 Conclusion

The analysis presented in this paper shows how understanding the energy consumption of EVs in terms of how they react at certain speeds and how 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 and that detailed knowledge about future journeys is necessary to accurately predict range. 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 by giving the driver confidence that the ITS driver aids understand the impacts of these external factors on range, allowing the driver to trust they will be able to reach a destination even on the limit of the stated range. Further work will be done to include other parameters not considered in this paper, such as weight (passengers and baggage) and temperature. A version of this model is going to be used for an eco-driving application that will be demonstrated across four pilot sites in Newcastle upon Tyne, Barcelona, San Sebastian/Bilbao and Reggio Emilia through the SmartCEM project [27] in the first quarter of 2014.

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