Defining the Accuracy of Real-World Range Estimations of an Electric Vehicle

Stewart A. Birrell, Andrew McGordon, and Paul A. Jennings

***Abstract*—Range anxiety is a major barrier for the mass adoption of electric vehicles (EVs), a contributing factor to this is the variability of the predicted range remaining presented to the driver in the vehicle. This study aims to better understand the causes of potential inaccuracies and how ITS can help resolve these issues. Eleven participants completed 141 logged journeys, with results showing that range (as predicted by the EV and presented to the driver) was overestimated by approximately 50% in comparison to journey distance. Driving style had the most significant impact on range prediction accuracy, where a more aggressive driving style led to greater inaccuracies. However, journey distance and type of road driven, which can be calculated from Satnav systems, were factors which were correlated with having a significant effect on range accuracy. Therefore incorporating these into future range prediction algorithms has the potential to increase the accuracy of information and subsequently increase driver trust.**

***Index Terms*—Electric vehicle; Driver behaviour; Driver information systems; Intelligent transportation systems; Range anxiety; Range accuracy; Real-World driving**

I. Introduction

Electric Vehicles (EVs) have long been proposed as a viable method to accelerate the reduction in carbon emissions of road transport. Carbon emissions in the EU (i.e. EU-28) have been reducing overall steadily since 1990 and by 1.3% between 2011 and 2012, with a strong decline in road transport emissions of 5% in 2012 alone [1]. However, this reduction may be slightly exaggerated by the global economic downturn which resulted in a reduction in both passenger and freight transportation by up to 20% in some EU countries [1]. Despite this, road transportation in general has a key role in delivering CO_2 reductions in line with the International Energy Agency's (IEA) "2DS" (2°C Scenario), where the sector's potential share of overall CO_2 reductions world-wide is predicted to be 21% by 2050. In order to meet this share, three-quarters of all vehicle sales by 2050 would need to be plug-in electric of some type [2].

Research supported by the Technology Strategy Board through the WMG centre High Value Manufacturing Catapult

S. A. Birrell is with WMG, University of Warwick, Coventry, CV4 7AL, UK (+44 24 7657 3752; S.Birrell@warwick.ac.uk).

A. McGordon is with WMG, University of Warwick, Coventry, CV4 7AL, UK (A.McGordon@warwick.ac.uk).

P. A. Jennings is with WMG, University of Warwick, Coventry, CV4 7AL, UK (Paul.Jennings@warwick.ac.uk).

Research and innovation into electrically and alternatively powered vehicles is continuing at pace, specifically surrounding battery technology and light-weighting. Despite these efforts there still remain many barriers to adoption for electric vehicles, which have thus far limited EV sales primarily to early adopters of innovative technologies and company fleets looking to reduce carbon emissions. A report for the European Council suggested that the main barriers for adoption were: high purchase price; range anxiety; uncertainties associated with battery life; and other factors relating to new and unfamiliar technology [3]. Range anxiety is a common term given when drivers experience anxiety about their car's ability to cover the distance required before needing to be recharged. It occurs almost exclusively in EV drivers because of limited charging infrastructure [4]. More complex than the phenomenon of range anxiety is how to combat it in users in order to remove one of the barriers to mass uptake of EVs. Long term goals would be to increase electric range to over 300 miles (similar to that of a traditional internal combustion engine (ICE) vehicle), and / or to make plug-in charging facilities as commonplace as fuel stations are today. Both of these are vastly expensive options in terms of research and infrastructure costs, and are unlikely to be achieved in the next 10 years. Intelligent Transportation Systems (ITS) can offer solutions to these problems in the shorter term by developing integrated charging management and services (such as pre-booking and payment of charging points), improved traffic management and delivering eco-driving advice [5]. In addition by improving route guidance to minimise energy consumption of EVs, by taking into account congestion levels and topography [5, 6]. However accurate range prediction, which is subsequently presented to the diver in the vehicle, underpins these solutions.

Range prediction in EVs is not a simple procedure with algorithms needed which take into account aspects such as Peukert's coefficient, temperature and depth of discharge [7]. The driver also has significant influence on range predictions with the use of heating, ventilation and air conditioning (HVAC) and auxiliary use, or driving style. Road parameters also have an important impact on energy usage for a journey (and hence range prediction) these include topography, number of stop/starts and sharp turns, traffic congestion and speed limit. Many of the parameters mentioned above are not unique to EV range prediction but common to ICE distance to empty calculations too. However this coupled with the reduced absolute range (300-500 miles for an ICE compared to approximately 100 with an EV) and lack of convenient refuelling leads to range anxiety on behalf of EV drivers. For these reasons research has shown that EV users deploy ‘safety buffers’ for ensuring that they do not run out of range, these buffers have been shown to be as much as 25% of vehicle range capacity [8, 9].

One of the key factors for increasing anxiety is a lack of trust in the range prediction presented via the in-vehicle display and the subsequent use of high safety buffers. The accuracy of range prediction has also been identified as one of the top five priorities for research and development into ITS to support electromobility [5]. In order to facilitate improvements in range predictions first we need to understand where the inaccuracies are present and what impact the have on EV range. This paper evaluates range predictions over 140 journeys taken by 11 drivers on familiar commuting routes during real-world driving.

II. Methodology

A. Data Collection

A 2011, right-hand drive, Nissan Leaf full battery EV was used for the data collection. According to the owner’s manual [10] this specific EV has a fully charged range of ‘approximately 100 miles’, adding ‘the majority of drivers will experience vehicle ranges between 62 - 138 miles based on the many factors that affect vehicle range’. No modifications were made to the vehicle; however a GPS data logger was installed for all trials.

Eleven participants took part in the trials; with journeys taken predominately over familiar routes (i.e. commute to and from work). Each driver typically completed six journeys in a one week period, with a minimum of four journeys being considered the threshold for inclusion in the analysis. The mean age of the participants was 38 years (Standard Deviation = 9.3 years), all were employees of WMG at the University of Warwick, with positions from technicians, engineers and researchers. Given the nature of the trials those who volunteered were intrinsically interested and curious regarding EVs and new technology; however were novice EV drivers.

Two phases of data collection were adopted with four of the 11 participants completing trials in both phases 1 and 2. The two phases were adopted for two reasons, firstly to evaluate any possible effects of range prediction over a greater array of environmental temperature (phase 1 was UK summer, phase 2 autumn), and secondly to allow more data to be collected (table 1).

TABLE I
PERTINENT INFORMATION RELATING TO THE PHASES OF DATA COLLECTION

	Phase 1	Phase 2
Dates	23/05/13 – 25/07/13	16/09/13 – 27/10/13
Mean Temperature	16.2 deg C	13.1 deg C
No of Participants	9	6
No of Trials	85	56

B. Procedure

All participants were emailed an information sheet containing details of the study, they were also given some basic information about the EV (i.e. charging, conditions of use etc.). Also to avoid participants being placed in difficult situations regarding the distance of journeys they wish to take, they were informed of the range prediction accuracy with wording similar to that contained in the owner’s manual. Inclusion criteria for the study were simply that they were registered to drive a University owned vehicle on the University’s insurance policy.

On the participants first day of the trials they were given an introduction to the driving controls and in-vehicle systems of the EV, they were also shown how to plug in and charge the vehicle. The principal form of data collection for the study (see below) was data captured from the in-vehicle systems relating to range and energy use. This data were collected via a log sheet, which the participants were also instructed how to complete. After a brief practice drive participants were left to their own devices with the EV to experience use in real-world driving scenarios.

C. Variables Collected

As indicated above data were collected via a datasheet based on what they could read on the in-vehicle information system (IVIS; figure 1), or what they could select as driving related options. Route characteristics were also recorded. Below is listed the data that were collected, and options given to the participants to select from:

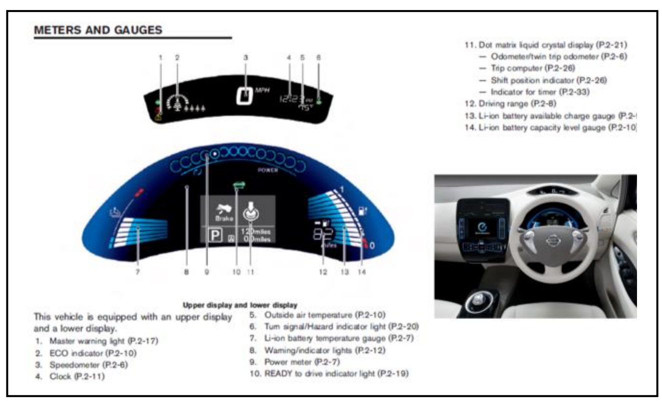

Figure 1. Nissan Leaf in-vehicle driver interface (taken from Nissan Leaf 2011 Owner’s Manual [10]).

Time and Date of journey taken

Temperature of the external environment according to IVIS (figure 1, number 5)

Driving Mode: The EV has two selectable driving modes, either 'D' or 'Eco'. D, or Drive mode, is intended for all normal driving and delivers all of the available power when accelerating, with regenerative braking delivering similar deceleration when removing the foot from the throttle as a typical ICE vehicle. Eco mode is intended to help extend the driving range by limiting power when accelerating, more aggressive regenerative braking and reduced HVAC capability. Depending on external conditions and previous driving behaviour, when fully charged the Eco mode predicts that between 10 and 20 more miles could be completed on a single charge

Start and End of journey predicted range remaining according the IVIS (figure 1, number 12)

HVAC: Heating and air conditioning use draws a significant amount of power from the battery and hence reduces range, therefore recording accurately its use is essential. Options given for the driver to record were: AC; Heater; Fan; Occasional (indicating cyclic or intermittent use HVAC); Demist; or None. More than one option could be recorded

AUX: Again use of the auxiliary power systems will draw power from the battery, options available were: Radio; CD; MP3; Satnav; 12v Charger; Lights; Wipers; or None (Status screen). For analysis this was simplified to: Infotainment; Navigation; Safety; or None. More than one option could be recorded

Driving Style: In an attempt to establish driver behaviour a self-rating of driving style was also recorded, options included: Eco; Conservative; Normal; Progressive; Aggressive; or Mixed. For the analysis this was simplified to: Eco; Normal; or Progressive

Traffic flow was also estimated by the driver, options available were: High; Med; Low; Mixed Density; or Free flow (i.e. busy but moving freely)

Route: The percentage of driving time (not distance) on each type of road category was estimated by participants. A percentage of driving time was recorded for: Urban (town or city); Rural (or countryside); Inter-Urban (major A-roads linking conurbations); Motorway (aka freeway, highway etc.)

Distance of the journey was also recorded.

Comments: In the final sections participants were encouraged to make free-form comments on: Range Estimations; IVIS; Driveability; and Charging

Statistical data analysis was conducted in SPSS 21 and significance was accepted at $p<0.05$. The nominal data (Driving Mode, HVAC, Aux, Driving Style and Traffic Density) were analysed using a One-Way ANOVA, and the numerical data (Temperature, Start and End range, Route and Distance) analysed using regression analysis.

D. *Normalisation*

A normalisation process was needed in order to evaluate the accuracy of the EVs ability to predict range used for a specific journey. Simply using distance minus range used would not accurately reflect the prediction accuracy for long or short journeys; therefore the following equation was used:

$$\text{Normalised Range} = \frac{(\text{Journey Distance} - \text{Range Used})}{\text{Journey Distance}}$$

A normalised range value of zero would indicate that the range prediction was completely accurate (i.e. range used equals journey distance). If the equation returned a positive value then the EV was underestimating the range needed to complete the journey, a negative value was an overestimation (i.e. the range used was greater than the journey distance).

III. Results and Discussion

A. *General Findings*

Results from the study (table 2) show that the average journey distance completed by the participants in this study was 16.8 miles (SD = 13.1). The maximum journey distance was 65.4 miles, with 56.7% of journeys being longer than 10 miles. The average range used was 25.3 miles, and normalised range accuracy was -0.48. This suggests that the range predicted for an average journey was almost 50% greater than the actual journey distance. This results in a real-world theoretical maximum range for this particular EV (when fully charged) of approximately 70 miles. This is similar to results found in the literature which showed average energy consumption of 1.5% State of Charge (SoC)/mile which extrapolated to a theoretical range of 66.7 miles (for a vehicle with a 100 mile certified range) [7], or 1.9% SoC/mile with a maximum range of 53 miles (70 mile certified range) [11].

Results from this current study and surrounding literature suggest that inaccurate real-world range prediction is a common EV problem and not specific to any particular manufacturer. Anecdotal evidence from consumer blogs suggests that newer EV have improved range accuracy predictions and increased real-world ranges over first generation vehicles. This could be as result of more efficient management of the HVAC system[1], by presenting actual state of charge on the in-vehicle display[2], or over-the-air updates to range algorithms[3].

[1] http://insideevs.com/nissan-leaf-side-by-side-range-comparison-2012-vs-2013/

[2] http://sfbayleafs.org/commentary/2013/09/2013-vs-2011-nissan-leaf-whats-new-whats-gone-whats-changed/

[3] http://www.plugincars.com/nissan-software-update-201112-leafs-yields-promising-results-127532.html

TABLE II
MEAN RESULTS FOR EACH PARTICIPANT, INDIVIDUAL PHASES AND THE GROUP AS A WHOLE RELATING TO RANGE ACCURACY AND ESTIMATIONS. RANGES AND DISTANCES PRESENTED ARE IN MILES.

	Start Range	End Range	Journey Distance	Range Used	Normalised Accuracy
1	72.76	56.35	12.07	16.41	-0.22
2	96.35	61.71	23.24	34.65	-0.58
3	88.27	46.40	25.25	41.87	-0.73
4	84.00	72.17	7.07	11.83	-0.31
5	67.00	48.00	12.17	19.00	-0.53
6	73.33	50.00	15.17	23.33	-0.54
7	83.89	63.78	12.00	20.11	-0.82
8	77.00	47.15	18.44	29.85	-0.65
9	66.33	11.00	44.03	55.33	-0.19
10	76.38	28.50	31.88	47.88	-0.42
11	75.44	64.44	6.28	11.00	-0.78
Phase 1	75.19	51.31	15.96	23.88	-0.48
Phase 2	84.11	56.59	17.97	27.52	-0.47
Mean	78.73	53.40	16.76	25.33	-0.48
SD	25.23	26.20	13.09	20.60	0.75

Twenty-five (or 17.3%) of the 141 trips taken resulted a positive (or zero in two cases) normalised accuracy (i.e. journey distance being greater than or equal to range used; figure 2), and of these 25 just over three-quarters were less than 10 miles in length. Of the remaining 82.7% of trips which had a negative normalised accuracy approximately two-thirds of these were greater than 10 miles in length. This highlights that the longer the trip, the more problems the EV had with accurately predicting range. Given that many such journey prediction systems use history based algorithms, it could be expected that a longer journey would give the algorithms more time to adapt to driver style or traffic conditions, and hence become more accurate. This was not observed in this current study with increased distance leading to reduced accuracy.

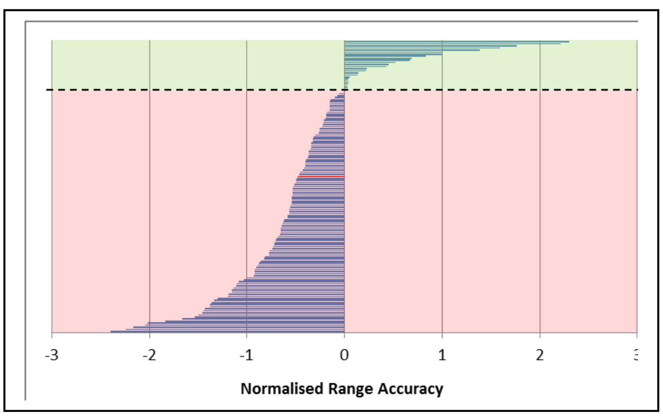

Figure 2. Normalised range accuracy for each individual trial. Dotted line indicates zero, or range used equates to journey distance.

Figure 3 shows the majority of trips were conducted in Drive mode, with no AC, heating or auxiliary load drawing power from the vehicle. Drivers were also predominantly driving in a self-rated eco style in low traffic densities, over a mixed driving route. These findings suggest that drivers were actively trying to increase the range of the EV by adopting behaviours and driving in real-world situations which could be considered advantageous for maximising energy usage from an EV. This further highlights the importance of accurate range prediction for users, as shown in this study range prediction was about 50% out even with users being conscious of the influence of power demand on EV range. What was not amended was driving route for individual journeys, i.e. avoidances of high speed roads or taking the shortest (as opposed to quickest) routes.

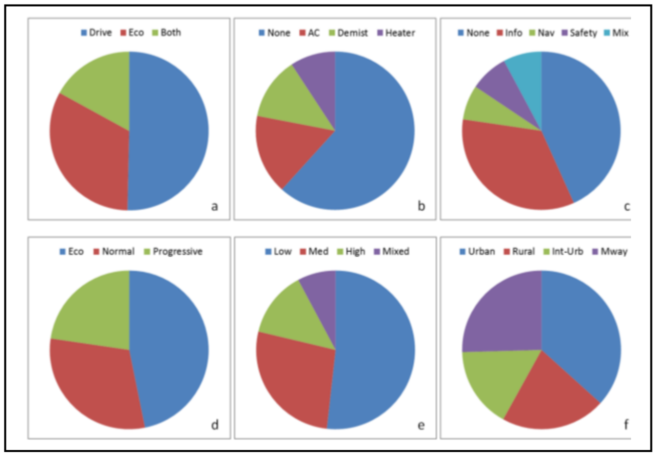

Figure 3. Results relating to a) Drive Mode; b) HVAC; c) Auxiliary usage (Info means Infotainment, i.e. radio, CD or MP3); d) Driving Style; e) Traffic Density; and f) Route.

As mentioned previously two phases of data collection were completed – separated by 3-4 months. Statistical analysis revealed that only ‘Temperature’ and ‘Start Range’ differed significantly ($p<0.05$) between the phases. Mean temperature being 16.2 compared to 13.1° C, and start range being 75.2 and 84.1 miles for phases 1 and 2 respectively.

B. *Accuracy Correlations with Dependent Variables*

When evaluating the data as a complete set of individual trials, identifying trends within the data compared to normalized range accuracy was problematic. The broad range of data from the individual trials seemed to obscure potential differences, or simply highlight that making assumptions on range prediction was very difficult. Of the variables assessed (as outlined in the methodology) only ‘Driving Style’ showed a statistically significant ($F_{(1,140)} = 3.01$, $p<0.05$) effect on normalized range accuracy. Post-hoc analysis (Bonferroni corrected) revealed that this difference was significant between Eco and Progressive driving styles (figure 4); showing that when adopting a self-rated Eco driving style normalized range accuracy improved to -0.34 from -0.75 for a progressive driving style.

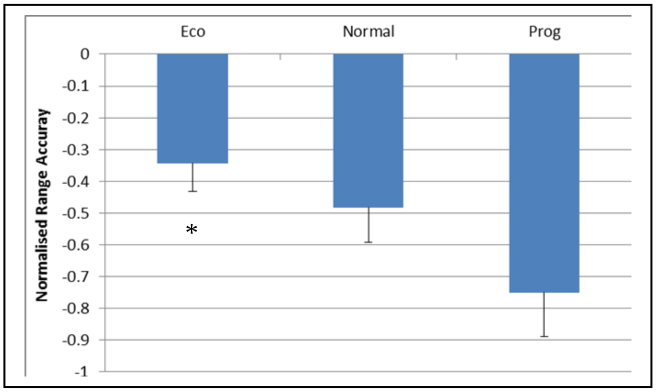

Figure 4. Driving style verses normalised range accuracy. Columns represent mean data and error bars standard error. Asterisk (*) represents significant ($p<0.05$) difference from the Progressive condition.

Auxiliary use showed a trend ($p=0.080$) for an effect on range accuracy, with post-hoc analysis suggesting the use of safety devices (e.g. lights and windscreen wipers) over no auxiliary use being responsible the decreased prediction accuracy ($p<0.05$). Whilst the lights of a vehicle may draw up to 200 W of power from the batteries, this is not a huge draw compared to the likes of the HVAC system – which can be up to 3 kW. It is the assumption of the authors that other driver behavior factors may be accountable for this difference, such as increased driving speed and reduced congestion, or reduced visibility leading to increased need for sharper braking and hence reduced opportunities for regenerative braking.

External temperature has been shown in previous research to be strongly linked to battery capacity [12, 13] and hence range of an EV. However in this current real-world study figure 5 shows that ambient external temperature – recorded at the start of the journey – had no significant effect ($p>0.05$) on range accuracy. Reasons for this could be that start range was already reduced due to the temperature, hence accuracy was not actually affected. Secondly that the mean temperature changes from 13.1 – 16.2° C were not sufficient to significantly affect battery capacity, with lab tests typically utilizing a far greater range in exposed temperatures (e.g. -25 to +45° C) [12].

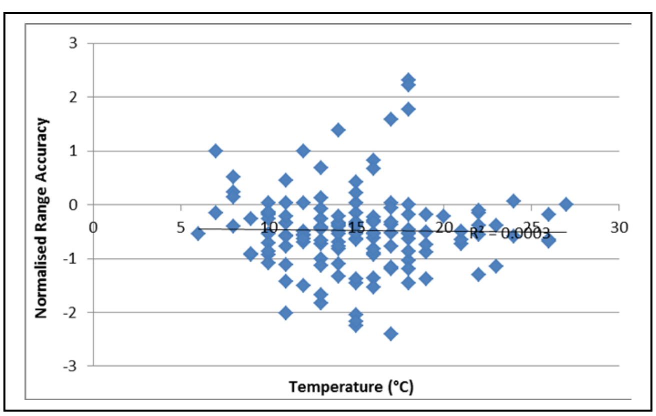

Figure 5. External temperature verses normalised range accuracy.

C. Analysis Between Similar Journeys

As highlighted thus far in the results, when considering individual trips as unique data points, identifying notable trends is very difficult (with the exception of driving style). To aid the analysis a subset of the data were considered separately for analysis. This subset included only journeys taken by an individual participant which were similar in nature, i.e. the same distance over the same route, typically a commute to and from work. As previous results showed no difference between the two phases of data collection, all data were combined. A minimum of four journeys were needed in order to be considered in the analysis. This resulted in data from seven participants, totaling 66 individual journeys being identified.

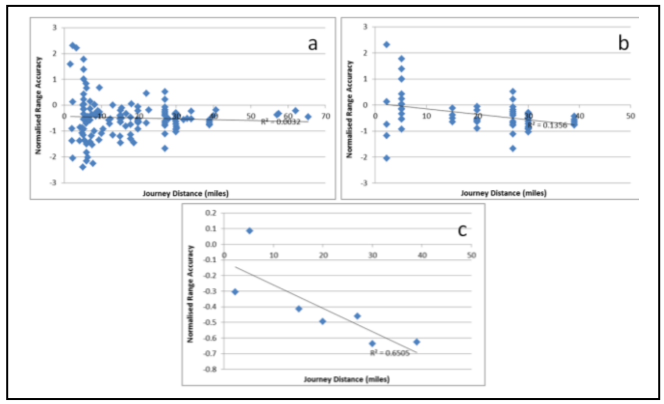

Figure 6. Normalised range accuracy against journey distance for all journeys logged in the study (a), subset of journeys identified as being similar in nature (b), and average of participants fixed journeys (c).

From this data more representative mean values for the journeys could be calculated, as all journeys taken by individual participants were consistent. An example of this is illustrated in figure 6, where graph (a) shows very little correlation when all of the data points for normalized range accuracy are plotted against journey distance ($R^2 = 0.003$). When we consider each data point for similar journeys only (graph b), a comparable pattern is observed with a slightly stronger trend for a decrease in range accuracy as journey distance increases ($R^2 = 0.136$). However when we use average range accuracy for each individual participant over their specific journey (graph c) we see a significant correlation between distance and normalized accuracy ($R^2 = 0.651$).

Aspects of the route driven also showed interesting correlations when considering this subset of data. Figure 7 shows that both the percentage of the journey completed on either motorway or in the urban environment can have an impact on range prediction accuracy. An increase in the percentage of the journey completed on higher speed motorways had a negative effect on accuracy, whereas increased urban driving improved average range accuracy. Despite this, data shows that for only one participant where urban driving equated to 60% and motorway was 0% of the total driving time, a positive normalized range accuracy value was returned (i.e. range used was less then journey distance). Reasons for these observations may be that an increase in motorway driving may be indicative of an increase in journey distance (and vice-versa for urban driving) which as shown above resulted in a decrease in range accuracy, or that motorway driving involves constant high draw from the battery with little opportunity for regenerative braking, which again is the opposite to urban driving.

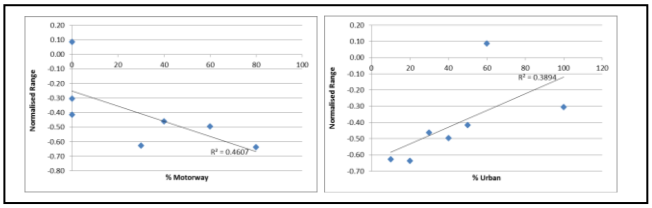

Figure 7. Normalized range accuracy verses % of journey completed on either (a) motorway or (b) urban roads.

D. *Subjective Comments on Range Accuracy*

Participant's subjective views were also collected at the end of their trials, these comments are summarized below:

Participant 1: For a few of my journeys I got to my destination with more range than I started with, other times for he some journey it would drop by 20 miles, I have no idea why as my driving was the same (I think)

Participant 2: Needs better damping; Range increase in urban and plummets on motorway; 10 miles in town - mileage estimation went from 93 to 96, battery blocks went from full to full-2, charge time went to 2 hours, what's the difference? Range estimation in D feels more accurate than E; Approx. 25 miles reduction in first 3 miles, then 10 in next 24 miles

Participant 3: Inconsistent and confusing; Would prefer a band rather than a single number; Estimated range seems to bear little relationship to driving style - only regen activity; Battery fuel gauge was far more reliable estimate

Participant 4: Fine on short distances, way out on mid-range distances that have a short section on fast roads; Being stuck in traffic seems to lower the range estimations on otherwise similar drives

Participant 6: I thought the range accuracy was quite unpredictable, steady driving would reduce range estimate quite dramatically and this can be worrying for 25+ miles journeys

Participant 7: It seems to go down rather quickly which means you feel conscious of it the whole time

Participant 9: 90→12 on vehicle was actually on 56 miles!

A common theme from the subjective comments was the unpredictable nature of the range estimations, with little understanding as to what is the actual root cause of the inaccuracies. One thing identified by the drivers, and supported by the data analysis, was that range accuracy decreased with journey distance. What is also very apparent from the comments is the type of language used, with words like 'feel conscious', 'unpredictable', 'inconsistent and confusing', 'no idea', 'dramatically' and 'plummets'. These are very emotive words and are typical of range anxiety experienced by novice users of EVs. However research has shown that whilst range anxiety (e.g. being aware of range while driving) does not reduce with EV experience, the explicit worry of range anxiety (e.g. being concerned of running out of energy while driving) does, as users increase their ability to understand changes in the EV's instrumentations [14].

E. *Limitations and Future Research*

Whilst a large pool of individual journeys were collated for this study enabling some interesting conclusions to be made, the findings only describe behaviour for one particular range estimation algorithm implemented in this specific vehicle. In addition the authors had no control over the range algorithm. Future studies will make greater use of the GPS logged data to better understand objective (rather than self-reported) driving style, but also to evaluate enhanced GPS features such as elevation and predicted verses actual road speeds. Utilising different EVs and an increased number of drivers will also increase transferability of the results.

IV. CONCLUSIONS

Results from this study have shown that during real-world EV driving trials the accuracy of the range predictions, which are presented to the driver via the IVIS, are overestimated by approximately 50% compared to actual journey distance. This resulted in a real-world theoretical maximum range for this particular EV of 70 miles. Self-reported driving style had a statistically significant impact on range accuracy, with the more aggressively driven journeys experiencing less accurate range estimations. However, external temperature was seen to have no effect on accuracy. When considering a subset of the data, which consisted of only similar journeys, the journey distance and percentage completed on motorways led to increased range prediction inaccuracies, whereas urban driving decreased these inaccuracies.

With respect to future ITS, in the near-term results from this study suggest that journey distance and road category could be incorporated into future enhanced route guidance systems (in addition to road topography and traffic congestion) to improve the accuracy of range prediction. In addition to this EV manufacturers should consider the grouping of repeatable and predictable journeys for data analysis, rather than analysis all individual trips, to refine range algorithms as more accurate assumptions can be made. In the longer term, further advancements could be delivered by the self-learning car, as driver behaviour measured over time can be incorporated to further increase range accuracy predictions or deliver specifically tailored eco-driving advice. However what intelligent systems will not be able to control will be the driver behind the wheel, as the human is still the biggest factor for increasing the available range of an EV.

REFERENCES

[1] European Environment Agency, "*Annual European Union greenhouse gas inventory 1990–2012 and inventory report 2014*," EEA Tech. Rep No 9/2014, Jun. 2014.

[2] International Environment Agency, *"Global EV outlook: Understanding the electric vehicle landscape until 2020,"* IEA Tech. Rep. Apr. 2013.

[3] N. Wallis, B. Lane, *"Electric vehicles: Improving consumer information to encourage adoption"*, European Council for Energy Efficient Economy, Tech. Rep. 4-514-13, 2013.

[4] T. Wellings, J. Binnersley, D. Robertson, T. Khan, *"Human machine interfaces in low carbon vehicles: Market trends and user issues"*, Low Carbon Vehicle Technology Project, Technical Report: HMI 2.0, Dec. 2010

[5] Y. Hubner, P. T. Blythe, G. A. Hill, M. Neaimeh, C. Higgins, "ITS for electric vehicle – an electromobility roadmap," *IET and ITS Conference on Road Transport Information and Control (RTIC 2012),* Sept. 2012, pp. 1-5.

[6] M. Neaimeh, G. A Hill, Y. Hubner, P. T. Blythe, "Routing systems to extend the driving range of electric vehicles, " *IET Intelligent Transport Systems*, vol. 7, pp. 327-336.

[7] S. Heath, P. Sant, B Allen, "Do you feel lucky? Why current range estimation methods are holding back EV adoption*," Hybrid and Electric Vehicles Conference 2013 (HEVC 2013)*, 2013, pp. 1-6.

[8] S. Carroll, C.Walsh, M. Burgess, M. Harris, S. Mansbridge, N. King, L. Bunce, *"The ultra-low carbon vehicle demonstrator programme – Final Report: Assessing the viability of EVs in daily life,"* Tech. Rep. Sept. 2013.

[9] T. Franke, J. F. Krems, "Interacting with limited mobility resources: Psychological range levels in electric vehicle use," *Transportation Research Part A: Policy and Practice*, vol. 48, Feb. 2013, pp. 109-122

[10] Nissan, "2011 Leaf Owner's Manual," available at http://www.nissan-techinfo.com/refgh0v/og/leaf/2011-nissan-leaf.pdf.

[11] C. Walsh, S. Carroll, A. Eastlake, P. Blythe, *"Electric vehicle driving style and duty variation performance study,"* Cenex Tech.Rep. Nov. 2010.

[12] C. Antaloae, J. Marco, F. Assadian, "A Novel Method for the Parameterization of a Li-Ion Cell Model for EV/HEV Control Applications," *IEEE Trans. Vehicular Tech*., vol. 61, Nov. 2012, pp. 3881-3892.

[13] H-S, Song, J-B. Jeong, B-H. Lee, D-H. Shin, B-H. Kim, T-H. Kim, H. Heol, "Experimental Study on the Effects of Pre-Heating a Battery in a Low-Temperature Environment," *IEEE Vehicle Power and Propulsion (VPPC) Conference*, Oct. 2012, pp. 1198-1201.

[14] M. Nilsson, "Does range anxiety exist? Experiences from the ELVIRE project," *5th International Conference on Applied Human Factors and Ergonomics (AHFE)*, Jul. 2014, pp. 1-7.