Transportation Research Part D 43 (2016) 207–225

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

An investigation into usage patterns of electric vehicles in Ireland

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ARTICLE INFO

Article history:
Available online 25 January 2016

Keywords:
Electric vehicle
Data analysis
User behaviour

ABSTRACT

This paper examines the charge and trip making behaviour of a fleet of electric vehicle (EV) users in Ireland. Through the analysis of real data from data loggers located within the EVs, valuable information is obtained on trip event characteristics, consumer preferences, timing and consumption patterns of charge events. The findings from this trial can be used to inform infrastructure providers in other small and medium size cities and in suburban or rural settings. An understanding of the likely usage patterns of EV users is critical for the rollout of charging infrastructure. Vehicles were separated into private use and business use vehicles, and the timings of EV usage events were divided into weekday and weekend events. Along with a descriptive analysis of the results, interquartile range (IQR) and analysis of variance (ANOVA) analyses were employed to quantify and characterise EV user behaviour. An early morning peak in charging behaviour was identified, and state of charge (SOC), charge consumption, and time and distance since last charge analyses indicate EV users charge more frequently than required. Trip event patterns identify the fact that EVs are generally available to be charged overnight, reducing demand on the electrical grid during peak hours. Trip distance analyses show that EVs are typically driven short distances, confirming their suitability to urban driving environments. The results can not only account for the effects of EV integration into the Irish vehicle fleet, but it can also provide information on the likely impacts of mass integration into European energy systems.

Introduction

The electrification of transportation is desired by many European countries due to concerns over the growth of the transportation sector and its associated greenhouse gas emissions, fossil fuel depletion, and urban air pollution. In 2011, the transportation sector in the European Union consumed 364.1 million tons of oil equivalent (Mtoe), accounting for 33% of the total energy consumption, the highest of any sector (European Commission, 2013). Globally, fuel consumption in the transportation sector is dominated by fossil fuels, with just 3% of road transportation being generated from renewable sources in 2011 (REN21, 2013).

Various European countries have set targets in terms of greenhouse gas (GHG) reductions and electric vehicle (EV) penetration levels in order to combat issues of climate change and oil dependence. The European Union has committed to reducing its GHG emissions by 20% by 2020 when compared to 1990 levels (European Environment Agency, 2013). Furthermore, Ireland has announced plans to have 10% of the Irish car fleet powered by electricity by 2020 (Dempsey, 2008).

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http://dx.doi.org/10.1016/j.trd.2015.12.013
1361-9209/

Studies have shown the potential EVs exhibit to improve emission levels and assist in achieving long-term climate goals when coupled with low carbon-generated electricity. In an Irish context, Brady and O'Mahony (2011) found net reductions in carbon dioxide (CO_2) and other tailpipe emissions under various EV penetration scenarios. Davis and Figliozzi (2013) arrived at similar conclusions, estimating reductions in all harmful air pollutants, resulting in improved public health, especially in urban environments. Faria et al. (2012) and Thiel et al. (2010) conducted well-to-wheel (WtW) analyses concluding that EVs are clearly and robustly preferred in terms of CO_2 emissions.

The benefits of EV adoption are met with numerous barriers with respect to their seamless integration into the existing transportation network. Integrating large numbers of electric vehicles into a country's transportation network can incur a large capital investment and difficulties arise in determining where to site such facilities (Schroeder and Traber, 2012). In addition to the difficulties that arise in the costs of the provision of capital infrastructure, the potential for local imbalances in the electrical grid due to the addition of charging facilities may require mediation measures such as grid reinforcements which can be complex in nature (Bayram et al., 2013). Huang et al. (2013) reported however, that if properly managed and controlled, an increased number of electric vehicles can have very positive impacts on electrical grid systems particularly in areas such as stabilising intermittent renewable energy sources (such as wind energy) and providing power supply through vehicle batteries during peak grid loading. Rezaee et al. (2013) noted that the loads arising from electric vehicles is difficult to predict and therefore their potential impacts cannot be well defined. In that regard, it has been noted that not enough research has thus far been conducted on the likely behaviours of EV users and their associated impacts on society (National Research Council, 2013). In order to better understand these effects that EVs will incur, various projects have been developed to analyse the behavioural and mobility patterns of EV users. An early example of one such trial was the MINI-E field study which was carried out in the USA, the UK and Germany starting in 2009 (Cocron et al., 2011) the results of which indicated a positive attitude to pure EVs amongst users where range was limited. There have been a number of other examples of EV trials including: the SwitchEV trial (Robinson et al., 2013), the EV Project trials (Smart et al., 2013), the CABLED trial (Bruce et al., 2012) and the ECOtality trials (Saxton, 2012). It must be noted that the majority of these trials have been concentrated in large population cities in a more urban environment or amongst urban city commuter belts (Franke et al., 2014a). Other trials are also ongoing in the wider area of electric transportation and are not just focused on passenger car units. The FREVUE trial (FREVUE, 2015) focuses on freight electric vehicles in urban Europe and the ZeEUS trial (ZeEUS, 2015) is investigating zero emission urban bus systems. The city of Malaga has embarked on a project entitled ZeM2All (ZeM2All, 2015) which seeks to find an integrated solution for future city transport involving electric vehicles together with other sustainable transport systems. Many of the early EV trial projects had, as one of their primary aims, the promotion of EV acceptance by allowing users to experience 'driving electric' and reporting back on their experiences and this has exposed generally positive attitudes amongst EV trial users (Bühler et al., 2014). It has been reported from many of these studies that one common issue that arises amongst EV trial users is the issue of range limitation (Franke et al., 2012, 2014a,b). In response to these increasingly common range anxiety concerns, various studies have taken place and are ongoing which seek to investigate how the effects of these concerns can be quantified and alleviated without major advances in EV range (Rauh et al., 2015).

Given the existence of the trials mentioned above, there still exists limited availability of real EV data and primarily data which is applicable to small population cities and suburban/rural settings such as is predominantly the case in Ireland, for example. This limited availability of data relating to EV usage has contributed to assumptions being made during modelling for research and infrastructure planning purposes. Wi et al. (2013) and Molina et al. (2012) assume arrival and departure times of EVs and the battery states of charge (SOC) before and after charge events. Lojowska et al. (2012) and Tamor et al. (2013) use national travel surveys to derive EV data from internal combustion engine vehicle (ICEV) data for trip making behaviour. The usage and analysis of real EV data may assist in strengthening research conclusions and reduce the negative effects of assumptions.

As such, the primary aim of this paper is to conduct in-depth analyses of the charge and trip events recorded by a fleet of EVs in Ireland as part of the Green eMotion project (Green eMotion, 2015), a pan-European project developing the European framework for an interoperable electromobility system. An understanding of the likely usage patterns of EV users is critical to the rollout of charging infrastructure and the management and distribution of this charging infrastructure is imperative to the success of EV integration. The timings and consumption patterns of charge events can provide an opportunity to determine the effects of EV integration on the electrical grid. Trip usage characteristics, such as the daily distance travelled per EV and number of trips undertaken per vehicle per day, can further develop an understanding of the usage patterns and probable timings of energy demands. Direct evidence is provided for the assessment of consumer preferences in a wide range of areas. This analysis can not only account for the effects of EV integration into the Irish vehicle fleet, but it can also provide information on the likely impacts of mass integration into European energy systems.

Data collection and infrastructure

Ireland as an EV study area

Ireland is uniquely placed to become a model for EV integration. The size and location of the country combine to provide almost ideal circumstances for the nationwide use of a clean, efficient transport network powered by renewable sources. As an island state with closely spaced urban centres the country is ideal geographically for the widespread use of electric transport. Ireland also has tremendous potential to generate large amounts of electricity from renewable sources, particularly wind power. The Irish government has published the National Renewable Energy Action Plan, which commits to producing 10% of all road transport energy from renewable sources by 2020, equating to 482 kilotonnes of oil equivalent (ktoe) or 5606 gigawatt-hours (GW h) (DCENR, 2009). The adoption of the EV is seen as integral to this initiative.

As the state's largest energy provider, the Electricity Supply Board (ESB) have a central role to play in the electrification of Ireland's road transport fleet, primarily with their "ecars" initiative (ESB, 2014). As such, the ESB are endeavouring to develop a nationwide infrastructure capable of fully supporting the number of EVs planned for Irish roads. Almost 1000 publically accessible charge points have been installed in the country up to the end of 2013. Every town in Ireland with a population of greater than 1500 people will have a minimum of one charge point. Fast chargers will be installed across the nation's motorways to create "electric highways" between the major urban centres, and 50 of these fast chargers have already been installed.

In order to promote the adoption of EVs throughout the country, the Irish government are providing a number of financial incentives, the most significant of which is a €5000 grant towards the purchase of any vehicle with CO_2 emissions of less than 75 g per kilometre. A budget of €5 m was allocated to this fund, allowing the first 1000 EV adopters to avail of the scheme. Furthermore, EVs are exempt from Ireland's vehicle registration tax (VRT), and as Ireland's road tax is based on CO_2 emission levels, EVs fall into the lowest tax category. In addition, the first 2000 citizens to adopt an EV avail of home charge point installation free of charge. As such, the Irish government is actively seeking to achieve the goal of 10% EVs by 2020.

Monitored vehicles

As part of the Green eMotion pan-European project, fifteen EVs were deployed and monitored in the Irish demonstration region of the project during the trial period. All vehicles are of the same make and model, the Mitsubishi i-MiEV, which is a four-seater battery electric-vehicle (BEV), drawing all of its propulsive power directly from the on-board battery rather than using plug-in hybrid electric vehicle (PHEV) technology, combining the battery with an internal combustion engine (ICE). All of the monitored vehicles are owned by the ESB, a private company, and are leased or "loaned" at the ESB's discretion.

Each of the vehicles are fitted with a lithium-ion battery pack with a storage capacity of 16 kW h, and the electric motors within each vehicle have a nominal power consumption value of 47 kW. The electric motor provides 180 N m of torque, enabling the vehicles to be capable of reaching a top speed of 130 km/h. The regenerative braking system within the vehicles allows for the transfer of kinetic energy from momentum back into the battery, which causes deceleration whenever the driver takes their foot off the accelerator. The battery can be charged from empty in approximately 8 h, and the maximum achievable range under ideal driving conditions is 130 km. The range limit is based on the best available information along with data returned from the vehicles. The vehicles were manufactured in 2010, and as such it is worth noting that battery technology has improved since then to achieve longer ranges and higher top speeds.

In order to investigate whether there are differences between the behaviours of various categories of EV users, the vehicles were separated into two use cases: business use and private use. Seven of the vehicles are business use vehicles, meaning that the vehicles are used for business purposes independently of the owner. The remaining eight vehicles are private use vehicles, used for private purposes independently of the owner. These vehicles are leased to the successful applicants of the ESB e-Car ambassador programme, which aims to promote electric vehicle ownership in Ireland. The vehicles are essentially "loaned" to the selected candidates for no charge, with a lease agreement in place for legal purposes only. The different use cases enable the analysis of the differing schedules of use and the different behavioural characteristics of the user types to be conducted.

Data collection

The monitored vehicles were deployed in March 2011, and data was collected up until February 2014, encompassing three years of data collection. In order to maximise and diversify the dataset, the private use vehicles were leased and trialled for periods of four months meaning that, in general, every private use EV user in the trial could be considered an early stage EV user. As such, in total there were 72 unique users of the private use vehicles during the analysis period. The business use vehicles were used as pool vehicles by employees of the ESB, allowing the employees to use the vehicles whenever desired. The usage rate of each of the business use vehicles remained high throughout the analysis period.

Data was collected from the EVs via data logging equipment installed within the vehicle infrastructure. These data loggers were configured to read information from each vehicle's control area network (CAN) bus and to store these data in internal memory. In addition, the location and time information of each vehicle were monitored using a global positioning system (GPS) device and this information was also stored in internal memory. GPS data and CAN bus messages were logged every five seconds and every one second, respectively. Various parameters of data were recorded, allowing for a review of the actual behavioural and usage patterns of the EVs during the trial period.

Data was then automatically uploaded via general packet radio service (GPRS) with a file transfer protocol (FTP) each night. In order to distinguish each EV, hence facilitating the analysis of the different use cases, a unique ID was assigned to each EV. Trip and charge events were recorded, defined by the initial and final time of each event. The data were then collected by the Irish fleet management company Transpoco (Transpoco, 2014), allowing the data to be readily downloaded and analysed. While Dublin is considered the primary location for data collection of the business use vehicles, the private use vehicles were distributed throughout the country.

Vehicle deployment

Throughout the three year period of data collection, the business use vehicles were available as required by employees at the ESB. For the first four month trial period for the private use vehicles, the trial participants were selected from a pool of ESB employees who had expressed prior interest in engaging in the trial. Following this initial period, an application process was opened to the public through various forms of advertising whereby EV enthusiasts would declare their interest in leasing a vehicle (at no charge) for a four month period with the intention that the EV would replace the primary household vehicle. The trial attracted over 20,000 applicants, and the vehicles were rotated to selected users for four month cycles.

As well as fulfilling the necessary financial and legal requirements, the selection process was structured to achieve a number of criteria:

- A mixture of male and female EV users.
- A mixture of age cohorts.
- Distribution of the vehicles nationwide.
- Varying travel-to-work distances.
- A variety of businesses and places of work.

Detailed information was not available on each specific user, however given that the selection process was tailored to ensure an adequate demographic mix the dataset can be considered as representative as possible, within the constraints of confidentiality and data protection promised to the trial participants. As part of the trial process, the selected candidates had a charging facility installed at their home. These were standard external single phase 16 A (3.7 kW) wall box units. In addition, the entire public charging network was available for the candidates' use. The public infrastructure includes standard charging units located in various locations such as street parking, train and bus stations, fuel stations and shopping centres. These charging units can supply power at either 16 A (3.7 kW) or 32 A (22 kW) depending on the car that connects to charge; for this study the Mitsubishi i-MiEV would be limited to 3.7 kW from these chargers. In addition there is a connected network of fast (DC) chargers around the country located adjacent to major highways; these units are rated at either 63 A (44 kW) or 120 A (50 kW). The Mitsubishi i-MiEV can connect to these fast chargers using the on-board socket connection. The trial therefore represented the same charging opportunities that would be available to all other EV users in the country who were not partaking in the trial and therefore the conclusions from this study can be considered representative of actual EV user behaviour and are therefore relevant to other countries when planning for EVs.

Methods

Aims and objectives

Using a selection of the parameters of data returned by the EVs, the aim of the analysis was to profile the behaviours of EV users in terms of their charge and trip making patterns. Due to data confidentiality issues, user specific information was not available to accompany the data results such as their age, location or sex, however the selection process was structured to ensure that an adequate mix of demographics was included. In that regard the results can therefore be considered representative of typical EV users for countries similar to Ireland across a range of potential owners. The data was disaggregated into private and business use cases which is described in more detail in section 'Aggregation and disaggregation'. It is useful to determine how EVs are being utilised through time with respect to the implications these behaviours may have on the electrical grid and on whether the vehicles are being driven in a manner similar to ICEV driving. Through investigating the charging events recorded by data loggers, the timings of the charges and their consumptions can be analysed, along with how the vehicles are being used between charges and the likely state of charge remaining in vehicle batteries before and after charges.

With regard to trip events, the timings of trips can show when the vehicles are not in use and may therefore be available to be charged. The usage characteristics of EVs, such as the distances travelled and the energy discharged during typical trip events, can assist in determining the likely consumer preferences for the EVs. Therefore, possible market penetration outcomes may be predicted through the analysis of these usage patterns. The evaluation of real-world data from the usage of EVs may also provide information on the theoretical assumptions thus far used in EV analyses and modelling.

Categories of data

Of the various categories of data returned, a selection of thirteen parameters was chosen for analysis, with six parameters encompassing charging events and the remaining seven parameters involving trip events. The parameters were chosen due to their ability to best characterise EV user behaviours, both in terms of the investigation of differences between vehicle use

Table 1
Categories of data chosen for analysis.

Category of data	Description
Charge start time	The charge start time records the instance of power flow from the electricity supply to the EV, rather than the plug-in time (hh:mm:ss)
Charge consumption	The charge consumption is the total amount of energy consumed by an EV during a charge event (kW h)
Distance since last charge	This records the distance travelled by an EV in between two consecutive charging events (km)
Time since last charge	This records the time that has elapsed in between two consecutive charging events (min)
Initial state of charge	This is the percentage of battery capacity remaining in an EV's battery prior to a charge event (%)
Final state of charge	This is the percentage of battery capacity within an EV's battery after a charge event (%)
Journey start time	The journey start time records the start time of every individual trip made by an EV (hh:mm:ss)
First journey start time	The first journey start time only takes into account the start time of the first trip of the day made per EV (hh:mm:ss)
Final journey finish time	The final journey finish time only takes into account the end time of the final trip of the day made per EV (hh:mm:ss)
Number of trips per day	This records the distribution of the number of trips a given EV makes during a given day
Daily distance travelled	This records the distribution of the total distance travelled by a given EV during a given day (km)
Energy discharged during trips	This records the total amount of energy consumed during each individual trip event made by an EV (kW h)
Trip distance	This records the distribution of the distance of each individual trip made during the analysis period (km)

cases and to analyse associated effects on the electrical grid. Table 1 displays the variables of interest chosen for further analysis.

The dataset was treated prior to the analysis in order to identify and remove any erroneous data entries that could potentially distort the analyses. A number of technical bounds were decided upon wherein values violating these bounds were removed from consideration. The bounds were based on the technical feasibility limits for the vehicle technology in use as well as values that could misrepresent the typified behaviours of EV users. Technical filters were created in order to remove these errors, and were applied to the aggregated dataset using a series of Macros developed in Microsoft Visual Basic for Microsoft Excel 2007. Following the filtration process, further data quality checks were performed to ensure the dataset was ready to be used for the resultant analyses. Primarily due to some limitations of the data loggers within the vehicles in processing and storing data on a second-by-second basis, errors were returned in the dataset. The errors were identified and eliminated in advance of data analysis. Values outside the feasible technical bounds of the battery technology, such as distances or consumption values in excess of the capacity limits of the battery, were removed. Additionally, incorrect entries such as negative charge consumptions or duplicate entries were removed. As such, an extensive data filtering process was administered on the dataset. Following the filtration process, 9.4% of the data were deemed to be unusable and were discarded, and further data quality checks were subsequently performed on the datasets. It must be noted that due to the filtration process, different categories of data are based on varying numbers of events.

Aggregation and disaggregation

In order to formulate a better understanding of the differing behaviours of variant EV user types and between varying times of the week, the dataset was disaggregated in two ways – the different use cases for the vehicles were separated, and charge and trip registers were considered during weekdays and weekends. Initially, an aggregate analysis of all returned dynamic events was conducted without dividing the data into neither use cases nor days of the week. This was administered both to determine the effects and behaviours of all monitored vehicles as a unit, and also to provide a means of comparison on which to base the results of the disaggregated analyses.

Disaggregating the dataset into business use and private use vehicles allows for comparisons to be made regarding the probable timings of various events and their associated magnitudes. In terms of the analysis of weekday and weekend events, it is expected that differences will be evident in the behaviours of EV users during these time periods due to the variation in vehicle usage patterns between commuting and recreational activities. This also allows for further analyses to be conducted comparing the different use cases across the different time periods, such as determining whether there are behavioural differences in business use vehicles during weekdays and weekends.

Statistical analyses

Along with the descriptive analysis of the resultant behavioural trends returned in the dataset, a series of statistical analyses are conducted in order to quantify the results. An interquartile range (IQR) analysis was conducted on various analyses, where applicable. This is administered by dividing the range between the maximum and minimum returned values of an analysis into quartiles. The median, a measure of central tendency that corresponds to the 50th percentile, is found, and the IQR is the range between the 25th and 75th percentiles, used as a measure of the spread of the data. The IQR can be investigated to focus on common behaviour and ignore atypical behaviour by concentrating on the most frequently returned results and ignoring the extremes of the range.

In order to examine the potential differences in user behaviour between vehicle use cases and between days of the week, analysis of variance (ANOVA) was used. The ANOVA tests had an alpha significance level of 0.05 and were carried out with the data segregated into six different categories; aggregated private and business use cases were analysed with all use cases further segregated into both weekday and weekend time periods. The output from the ANOVA analysis was then used to construct 95% confidence intervals for each of the group means which were then compared using post hoc tests which followed the Hochberg GT2 methodology. This method allowed observed differences between group means to be categorised as being statistically significant or not.

Results

EV user charging behaviour

During the study period there were 5838 charge events recorded. As a means of understanding and characterising the more common behaviours of EV users, thereby reducing the inherent variation in the returned parameters, the interquartile ranges (IQR) of various categories of data were investigated, along with the maximum and minimum returned values in the dataset. As such, Table 2 displays the IQR analysis for the aggregate EV user charging behaviour results, while Tables 3 and 4 display the IQR analysis of EV user charging behaviour for the private and business use vehicles, respectively. The analysis was applicable to three of the variables of interest, shown in the first column of each table. For the aggregate results and for the vehicle use cases, parameters were found for the total returned registers, along with entries falling on weekdays and weekends in order to inspect whether there are notable differences in user behaviours during these different timeframes and between these vehicle use cases. With regard to the aggregated charge consumption for users, it can be seen that the IQR tends to consist of a range of approximately 5 kW h, thereby accounting for an appreciable amount of variation. From the aggregate results, it can be seen that vehicles tended to consume more energy during weekends. Upon further investigation, it was found this increase in charge consumption could primarily be attributed to business use vehicles, with private use vehicles exhibiting a smaller increase in charge consumption during weekends. The maximum and minimum values are constant across all analyses due to the method of calculation. The analysis for the distance travelled between consecutive charging events revealed a central tendency to travel approximately 25–30 km between charging events.

Considerable variation was evident when analysing the time elapsed between consecutive charging events. The median value reveals a tendency to charge within approximately 18 h of the previous charging event, but a wide range is covered by the IQR. From the aggregate analysis a trend was found for longer times between charge events to occur at weekends, comparable with the distance since last charge analysis, where greater distances were travelled between charge events at weekends – it was discovered that this could be assigned to the business use vehicles.

A plot showing the charge start time distribution is given in Fig. 1. A peak in charge start times can be seen between 07:30 and 09:00 with a steady number of charge events then beginning throughout the day until values begin to reduce between 00:00 and 07:00. The peak in AM charge starts is likely due to EVs being plugged in following early morning trips; however

Table 2
IQR analysis of EV user charging behaviour for aggregate vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Charge consumption (kW h)	Total	0.63	2.39	4.54	7.56	11.97
	Weekday	0.63	2.39	4.54	7.56	11.97
	Weekend	0.63	3.02	5.29	8.13	11.97
Distance SLC (km)	Total	0.52	13.63	27.07	43.66	129.08
	Weekday	0.52	13.24	26.28	42.70	129.08
	Weekend	0.65	16.49	31.17	49.25	126.80
Time SLC (min)	Total	6.00	268.00	1094.00	1710.50	10062.00
	Weekday	6.00	245.00	1073.00	1614.00	10062.00
	Weekend	6.00	408.00	1196.00	2137.00	9932.00

Table 3
IQR analysis of EV user charging for private use vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Charge Consumption (kW h)	Total	0.63	2.39	4.54	7.56	11.97
	Weekday	0.63	2.39	4.54	7.43	11.97
	Weekend	0.63	2.77	4.54	7.75	11.97
Distance SLC (km)	Total	0.61	12.78	25.41	43.65	129.08
	Weekday	0.61	12.57	24.98	43.07	129.08
	Weekend	1.19	14.76	26.49	47.30	126.80
Time SLC (min)	Total	6.00	213.00	1023.00	1879.00	10062.00
	Weekday	6.00	200.50	1029.00	1996.50	10062.00
	Weekend	6.00	311.25	986.50	1619.00	9932.00

Table 4
IQR analysis of EV user charging for business use vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Charge consumption (kW h)	Total	0.63	2.39	4.54	7.56	11.97
	Weekday	0.63	2.39	4.54	7.56	11.97
	Weekend	0.63	3.15	5.29	8.13	11.97
Distance SLC (km)	Total	0.52	14.38	27.98	43.66	128.39
	Weekday	0.52	13.61	27.03	42.32	128.39
	Weekend	0.65	18.32	33.31	50.97	126.54
Time SLC (min)	Total	6.00	324.00	1136.00	1662.00	9987.00
	Weekday	6.00	283.25	1100.50	1513.75	9987.00
	Weekend	7.00	637.00	1271.00	2338.50	8606.00

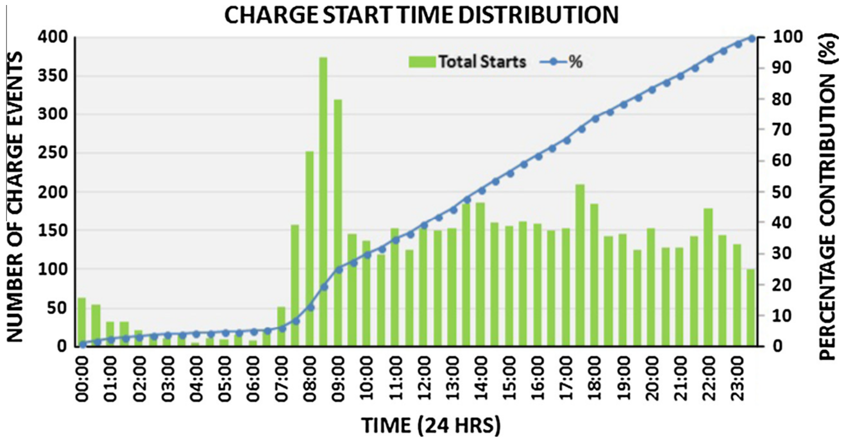

Fig. 1. Charge start time distribution for aggregated dataset.

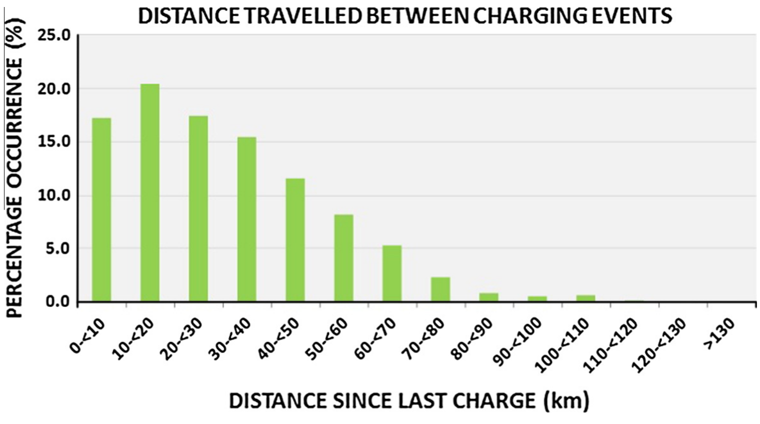

Fig. 2. Distance since last charge event distribution for aggregated dataset.

the AM peak was not expected and is not mirrored with a PM peak following the evening peak traffic period, with just a slight increase in the number of events evident.

The mean distance driven between charging events was 30.57 km with a median value of 27.66 km. The maximum distance driven between charge events was 129.08 km. An analysis of the recorded charge event data for all vehicles (i.e. both private and business use cases) during the full duration of the study showed that for 90.2% of cases the distance driven since the vehicle was last charged was less than 60 km. A plot showing the distribution of distance driven in between consecutive charge events is given in Fig. 2. 97.8% of charge events were undertaken when the distance since the last charge event was less than 80 km. Given that all of the vehicles included in this study have a reported range of 130 km (Mitsubishi i-MiEV), it would appear that the drivers are not willing to drive their EV beyond a considerable 'buffer' range before charging.

Table 5
Post hoc test groupings for distance since last charge event (km).

Factor	N	Subset for alpha = 0.05		
		1	2	3
Private weekday	2461	29.10		
Private aggregate	2836	29.47	29.47	
Business weekday	2693	30.41	30.41	
Business aggregate	3213	31.24	31.24	
Private weekend	375		31.90	
Business weekend	520			35.57

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 976.976.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

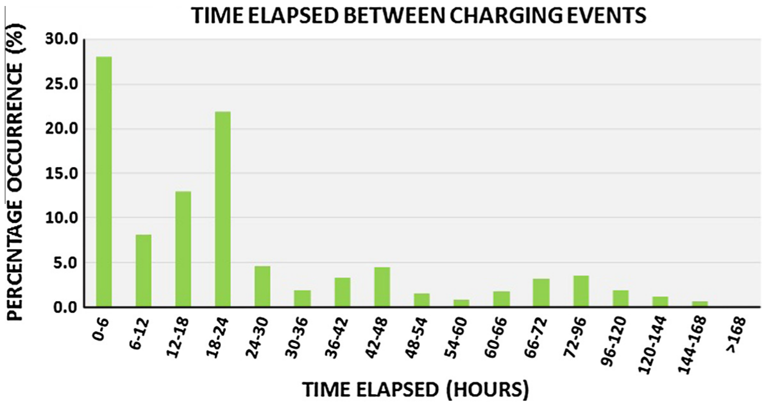

Fig. 3. Time since last charge event distribution for aggregated dataset.

The ANOVA test for the distance since last charge variable resulted in a p-value of less than 0.05; this was based on 5 degrees of freedom (df) with an associated F-value of 9.94 and an effect size of 0.43%. The resulting post hoc test groupings are presented in Table 5; groupings that do not share a subset group number are statistically significantly different from each other.

The comparison of the six group means for the distance since last charge category shows that both weekend use cases are statistically different from the remaining groups. The private weekend use case vehicles have a lower mean distance between charging events whilst this mean distance is higher for business weekend use case vehicles. The mean distance since last charge event for the six groups lies between 29.11 km and 35.58 km and this is significantly below the range of the vehicle at 100% SOC, confirming that regular charging is occurring regardless of the available range. This compares favourably with the IQR analysis which indicated that the largest proportion of charge events took place when less than 50 km had been driven since a prior charging event. Given that the means for all groups are considerably below the range of the vehicles, it is clear that the distance since last charge is low regardless of the time period or use case.

Fig. 3 gives the distribution of the elapsed time since EVs were last charged over the duration of the study. With respect to the x-axis, the bands of time are separated by six hours up until 3 days, after which each band of time represents 24 h. This was done in order to distinguish between the more common shorter charging times. The mean duration between charging events was 1524 min (25.4 h) with a median value of 1094 min (18.2 h). 71.09% of charge events took place within 24 h of the previous charge, with the greatest proportion occurring within 6 h of the last charge (28.08%). EV users are therefore charging their vehicles in regular patterns and this may explain the apparent lack of use of the available range of the vehicles.

A comparison between the means of the aggregated data and the individual use cases showed that business use vehicle charge events took place after a shorter duration following the previous charge event when compared to the private use case, and this will be investigated further in the IQR analysis. This is likely due to the higher availability of charge facilities for business use vehicles. It is clear that EVs are being used for shorter trips and then being charged regardless of the remaining available range. An examination of the initial state of charge (SOC) data, analysing the percentage of battery capacity remaining in a battery prior to a charging event, also identifies this trend in charge patterns. As shown in Fig. 4, 58.7% of charge events took place when the SOC of the EV battery before the charge event was above 50%. Only 6.29% of charge events took place when the SOC of the vehicle's battery before the charge event was 20% or less. Given the previous trends with respect to distance travelled between charging events, it is interesting to note that 25.5% of charge events took place when the state of charge of the EV battery before the charge was greater than 80%. As would be expected, the SOC after charge events was 100% in almost all cases.

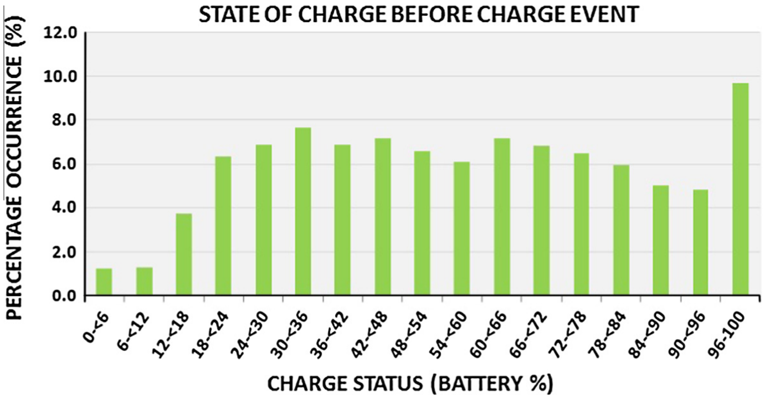

Fig. 4. State of charge before charge event for aggregated dataset.

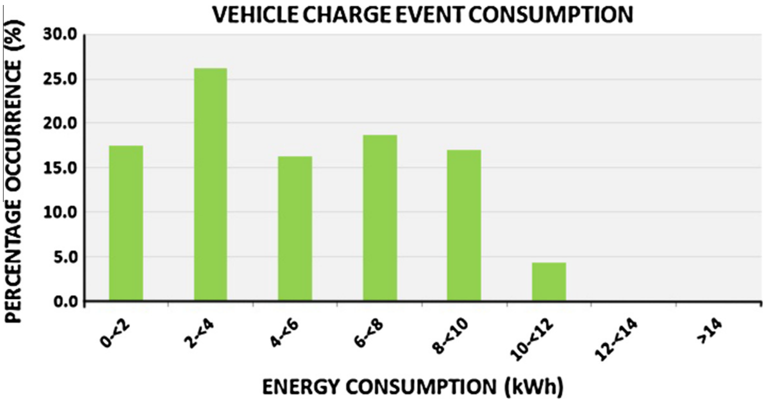

Fig. 5. Vehicle charge event energy consumption for aggregated dataset.

Table 6
ANOVA post hoc test results for charge event energy consumption (kW h).

Factor	*N*	Subset for alpha = 0.05	
		1	2
Private weekday	1709	4.87	
Private aggregate	2077	4.95	
Business weekday	2555	5.06	
Business aggregate	3071	5.15	
Private weekend	368	5.25	5.25
Business weekend	516		5.58

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 925.618.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

The plot of the distribution of charge event energy consumption data is given in Fig. 5. The highest proportion (26.2%) of charge events consumed between 2 and 4 kW h of energy. The highest amount of energy consumed during a single charge event was 11.97 kW h, due to the battery capacity reserve limits, and the mean energy consumption for all charge events was 4.46 kW h with a median value of 3.78 kW h.

The ANOVA test for the charge event energy consumption variable resulted in a *p*-value of less than 0.05 (df = 5; $F = 6.09$; Effect size = 0.29%). The post hoc test results are shown in Table 6. The test was unable to separate the group means with only the weekend business group statistically significantly different from the other group means at the 0.05 significance level. It follows that this group would have a higher charge consumption value given that the mean distance since last charge for this group was higher and therefore more charging would be required when a charge event did take place. The mean charge event energy consumption values for the six groups lie between 4.87 kW h and 5.60 kW h.

Table 7
IQR analysis of EV driver behaviour for aggregate vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Energy discharged – trip events (kW h)	Total	0.59	0.65	1.28	1.94	11.60
	Weekday	0.59	0.65	1.29	2.00	11.60
	Weekend	0.61	0.64	1.27	1.91	9.67
Distance travelled per vehicle per day (km)	Total	0.51	13.00	26.40	43.57	426.47
	Weekday	0.51	13.86	27.72	44.57	426.47
	Weekend	0.64	10.24	21.78	39.31	169.24
Number of trips per vehicle per day	Total	1	3	5	7	27
	Weekday	1	3	5	7	27
	Weekend	1	3	5	7	21
Trip distance (km)	Total	0.50	1.94	4.11	8.88	101.92
	Weekday	0.50	1.97	4.18	9.23	101.92
	Weekend	0.50	1.84	3.77	7.91	75.67

Table 8
IQR analysis of EV driver behaviour for private use vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Energy discharged – trip events (kW h)	Total	0.59	0.65	1.28	1.94	11.60
	Weekday	0.59	0.65	1.29	2.00	11.60
	Weekend	0.61	0.64	1.27	1.91	9.67
Distance travelled per vehicle per day (km)	Total	0.51	13.00	26.40	43.57	426.47
	Weekday	0.51	13.86	27.72	44.57	426.47
	Weekend	0.64	10.24	21.78	39.31	169.24
Number of trips per vehicle per day	Total	1	3	5	7	27
	Weekday	1	3	5	7	27
	Weekend	1	3	5	7	21
Trip distance (km)	Total	0.50	1.94	4.11	8.88	101.92
	Weekday	0.50	1.97	4.18	9.23	101.92
	Weekend	0.50	1.84	3.77	7.91	75.67

Table 9
IQR analysis of EV driver behaviour for business use vehicle registers.

Category of data	Register	Minimum	Q1	Median	Q3	Maximum
Energy discharged – trip events (kW h)	Total	0.59	0.65	1.28	1.94	10.39
	Weekday	0.59	0.65	1.29	2.00	10.39
	Weekend	0.61	0.64	1.27	1.91	9.67
Distance travelled per vehicle per day (km)	Total	0.51	13.38	26.71	42.52	426.47
	Weekday	0.51	14.76	28.08	43.41	426.47
	Weekend	0.76	10.18	21.72	38.33	169.24
Number of trips per vehicle per day	Total	1	3	5	7	27
	Weekday	1	3	5	7	27
	Weekend	1	3	4	7	19
Trip distance (km)	Total	0.50	1.96	4.10	8.92	93.59
	Weekday	0.50	1.97	4.13	9.23	93.59
	Weekend	0.50	1.90	3.80	8.13	75.67

EV user driving behaviour analysis

During the study 44,411 trips were undertaken, with a total distance driven of 307,469 km. The mean trip distance during the study period was 6.92 km with a median value of 4.11 km. Table 7 displays the IQR analysis for the aggregate EV driver behaviour results, while Tables 8 and 9 display the IQR analysis of EV driver behaviour for the private and business use vehicles, respectively. The analysis was applicable to four of the variables of interest, shown in the first column of each table. In a similar manner to the EV charging behaviour analysis (section 'EV user charging behaviour'), parameters were found for the total returned registers, along with entries falling on weekdays and weekends in order to inspect whether there are notable differences in user behaviours during these different timeframes and between these vehicle use cases.

When analysing the variation in the energy discharged during trip events, it could be seen that little variation was evident, as indicated by the narrow ranges of the IQRs in all cases. Across all times and all use cases, the range from the minimum to the 3rd quartile covers less than 1.5 kW h, showing a more consistent behaviour with regard to the energy discharged during trip events and with very slight differences between the analyses. The maximum values indicate that the battery capacity was almost used fully during some trips, but this is not representative of more typical EV user behaviour. The analysis for the daily distance travelled is highly comparable with the distance travelled between charging events (see section 'EV user charging behaviour'), indicating that individuals tend to charge their vehicles after they have completed their daily travels. In contrast to the distance since last charge variable, it was discovered that EV users tended to drive shorter daily distances at the weekends, and this was consistent across all use case analyses. The IQR of approximately 30 km represents moderate amounts of variation in travel behaviour.

With respect to the number of trips travelled per day, it can be seen that little variation is evident across use cases and times. In all cases, the IQR covers the range from 3 to 7 trips per day, with the majority of analyses returning a median result of 5 trips per day. The minimum number of trips undertaken in all cases is 1 trip. The analysis of individual trip distances returned registers in the lower ranges of trip distances, with the 3rd quartile values being less than 10 km in all cases. The distribution of trip distances can be compared to the energy discharged during trip events, with similar small ranges being returned. This shows that EVs are typically used for trips of shorter distances, confirming the well documented suggestions that EVs are appropriate for urban driving conditions and are well suited as a secondary vehicle in a household. It was also discovered that shorter trip distances are made during weekends when compared to weekdays for all use case analyses. This is reinforced by the fact that the maximum trip distance driven in all cases occurred on weekdays rather than weekends.

An analysis of journey start and finish times was carried out using the aggregated data with further segregation into use cases and weekday and weekend occurrences for each category of data. For the aggregated data, journey start times showed 3 clear peaks during the day; 07:00–10:00, 13:00–15:00, and 17:00–19:00. The distribution of journey start times for the aggregated dataset is shown in Fig. 6. A similar distribution for journey finish times was observed with the times shifted slightly later in the day.

The aggregated data was segregated into private and business use cases in order to identify potential differences in EV user behaviours. For both the aggregated and use case data, differences in the journey start/finish time distributions were observed when weekday and weekend data plots were compared. Plots of the journey start time distributions for the aggregated dataset segregated into weekday and weekend occurrences are given in Fig. 7. Weekend journey start times occur later and over a longer time period and the three distinct peaks observed previously do not emerge, instead taking a bell-curve shape. Fig. 8 shows the distribution of both first journey start and final journey finish times for the aggregated data.

In addition to the start and finish times of journeys, the number and distance of journeys undertaken by EV users were also recorded and analysed. The mean number of trips per vehicle per day was 5.39 with a median value of 5. The distribution of the number of trips per vehicle per day which was counted from the aggregated data is shown in Fig. 9. A wide variation in trip distribution is shown; however, the greatest proportion of recorded trips per vehicle per day occurs in the range of 2–5 trips per vehicle per day.

A p-value of less than 0.05 resulted from the ANOVA test of the number of trips per vehicle per day (df = 5, F = 6.89, Effect size = 0.18%) and the subsequent post hoc test output is given in Table 10. It can be seen that business use case vehicles undertake the highest mean number of trips during weekdays and this is statistically significantly different from all other groups. It can also be seen that both private and business use case groups for weekdays and weekends are statistically significantly different from each other.

The distribution of individual trip distances is shown in Fig. 10. The longest recorded trip was 101.92 km and again this is well below the reported range of the EVs which is 130 km. The majority of trips undertaken during the study period were less than 10 km. 97.6% of trips were below 30 km with just 0.24% of trips above 50 km in distance. Similar trip distances were

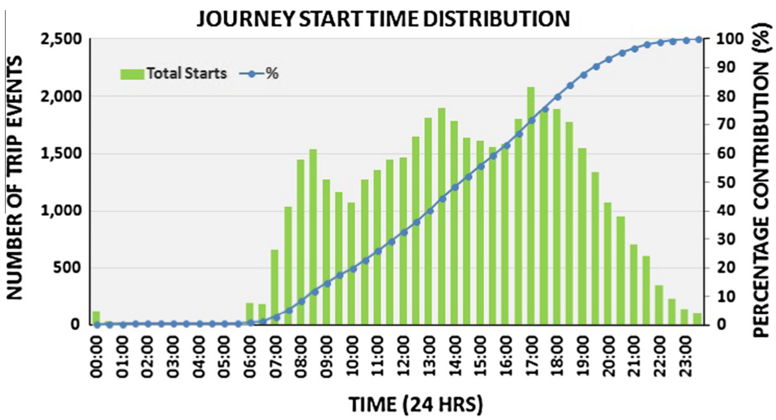

Fig. 6. Journey start time distribution for aggregated dataset.

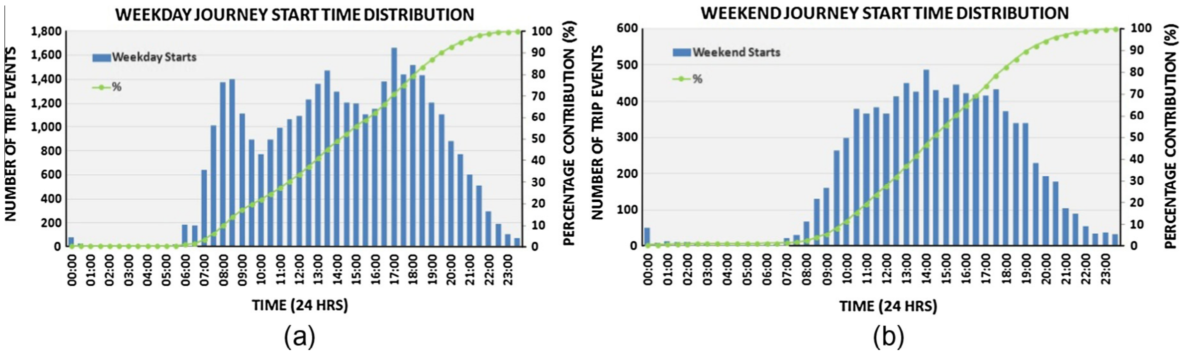

Fig. 7. (a) Weekday and (b) weekend journey start time distributions for aggregated dataset.

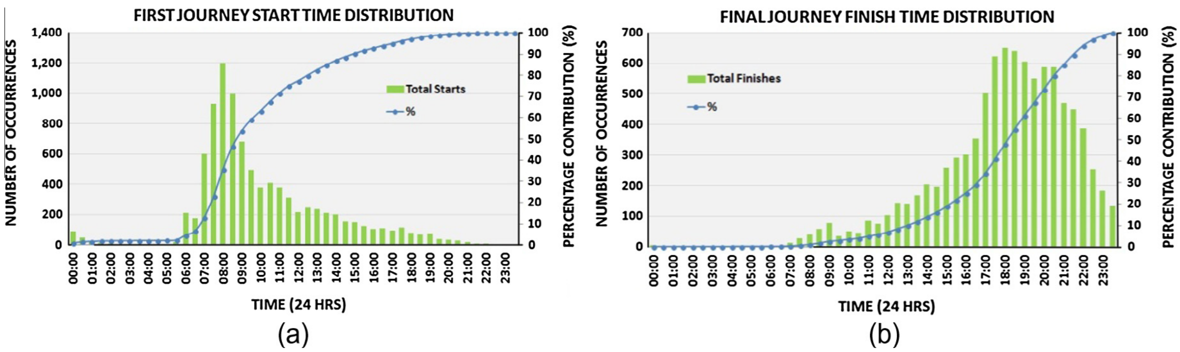

Fig. 8. (a) First journey start time distribution and (b) final journey finish time distribution for aggregated dataset.

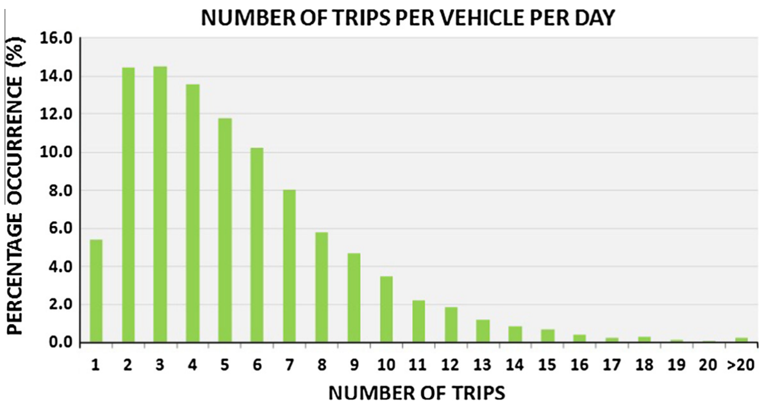

Fig. 9. Number of trips per vehicle per day for aggregated dataset.

observed for weekday and weekend travel periods. The average trip distance of 6.92 km recorded during this trial is somewhat lower than the comparable figure for internal combustion engine vehicles (ICEVs) of 10.7 km in the greater Dublin area (DTO, 2006).

In addition to individual trip distance analysis, the aggregated total daily travel distance per vehicle was also investigated. The mean daily distance travelled for all use cases was 32.17 km with a median value of 26.39 km and a highest recorded daily travel distance of 426.47 km. Given the regular charging patterns that were observed previously it is interesting to note that a number of charge events would have been required to achieve this trip, with fast chargers likely being employed to achieve this distance. This would indicate that EV users were not discouraged from making longer daily travel arrangements; however, only 2% of daily travel distances exceeded 100 km with just 19.46% exceeding 50 km. It is therefore clear that EV users did not use vehicles for high daily travel distances. Summary statistics for daily travel distances for each of the use cases are given in Table 11.

Table 10
Post hoc test groupings for the number of trips per vehicle per day.

Factor	N	Subset for alpha = 0.05		
		1	2	3
Business weekend	1085	5.03		
Private weekend	915	5.21	5.21	
Private aggregate	4395	5.32	5.32	5.32
Private weekday	3480		5.35	5.35
Business aggregate	4933		5.47	5.47
Business weekday	3848			5.6

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 2005.325.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

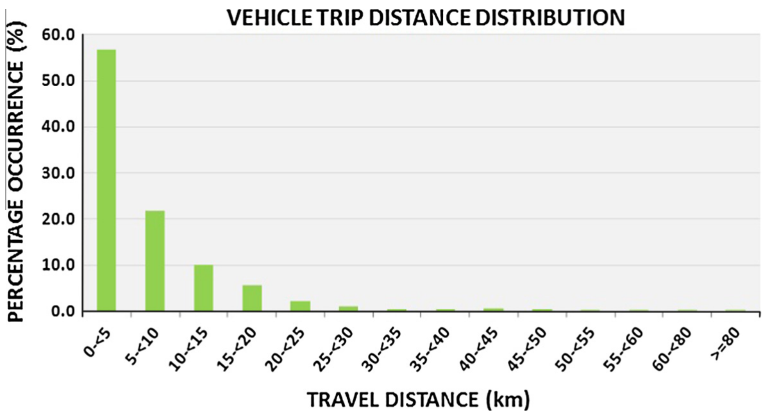

Fig. 10. Vehicle trip distance distribution for aggregated dataset.

Table 11
Summary statistics for daily distance travelled per vehicle for aggregated dataset.

Description	Private use	Business use
Mean/Median daily travel distance (km)	33.26/26.04	31.19/26.71
Highest recorded daily travel distance (km)	292.51	426.47
Proportion of daily travel distances > 100 km (%)	2.93	1.29
Proportion of daily travel distances > 50 km (%)	21.12	17.81

Table 12
Post hoc test groupings for trip distance (km).

Factor	N	Subset for alpha = 0.05				
		1	2	3	4	5
Private weekend	4649	5.92				
Business weekend	4704		6.43			
Business aggregate	22,895		6.72	6.72		
Business weekday	18,191			6.79		
Private aggregate	21,510				7.14	
Private weekday	16,861					7.48

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 9491.667.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

P-values of less than 0.05 again resulted from the ANOVA tests for both vehicle trip distance (df = 5, $F = 42.41$, Effect size = 0.24%) and daily distance travelled per vehicle (df = 5, $F = 21.34$, Effect size = 0.57%). The resulting post hoc test results are shown in Tables 12 and 13 respectively. When considering only individual trip distances for each of the six groups of data it can be seen that the two aggregated datasets for private and business use cases are statistically significantly different, and in fact each of the four disaggregated use case datasets do not share a subset grouping. Private use vehicles undertake the

Table 13
Post hoc test groupings for distance travelled per vehicle per day (km).

Factor	N	Subset for alpha = 0.05		
		1	2	3
Business weekend	1085	27.69		
Private weekend	915	27.82		
Business aggregate	4933		31.2	
Business weekday	3848		32.19	
Private aggregate	4395		33.26	33.26
Private weekday	3480			34.7

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 2005.325.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

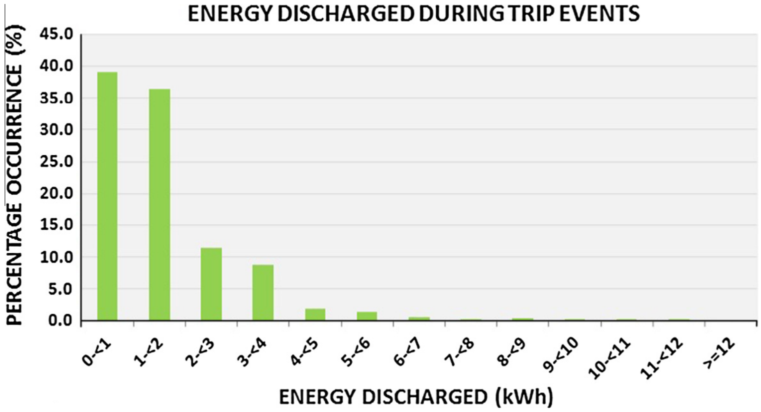

Fig. 11. Energy discharged during trip events distribution for aggregated dataset.

longest mean trip distances for weekdays (7.48 km) and this group also recorded the shortest mean trip distances at weekends (5.92 km).

Further interesting results emerge when the same data is analysed for the distance travelled per vehicle per day. The post hoc groupings (Table 13) cannot separate private and business use case data for weekends indicating that their means are statistically similar. However this is not the case for weekday daily trip distances as the use case means are statistically significantly different from each other – private use case vehicles undertake higher mean daily trip distances than business use vehicles during weekdays.

During the study period a total of 30.41 MW h of energy was consumed by the EVs during those trip events that returned a value for the amount of energy that was discharged. The majority of trip events consumed between 0 and 2 kW h with only 4.1% of trip events consuming more than 4 kW h of energy. A plot of the energy discharged during trip events is given in Fig. 11.

The p-value arising from the ANOVA analyses for the energy discharged during trip events was less than 0.05 (df = 5, F = 13.05, Effect size = 0.17%). A clear pattern emerges in the post hoc test groupings shown in Table 14 below, with weekday and weekend differences emerging. Both private use and business use weekend means cannot be separated and similarly both group weekday means cannot be separated. Therefore, on average, weekday trips will consume 1.66–1.679 kW h of energy with weekend trips consuming 1.47–1.53 kW h.

Relating the quantity of energy discharged to the associated trip distances provides useful information on the vehicles' specific energy consumption. Using this parameter of energy discharged during trip event and matching it with the corresponding trip distance, an average vehicle specific energy consumption of 0.164 kW h/km was found during the study. This can be compared to the NEDC (Dieselnet, 2013) test value of 0.135 kW h/km and is approximately 20% higher. This higher value could be due to the way in which the vehicles were driven with air conditioning, heating, lights and entertainment all potentially adding to the load on the battery. In addition, the actual consumption of the vehicle is affected by the road terrain.

Charge and journey timing analysis

The timing of EV charge events has the potential to have a significant impact on energy demand on the national grid when the penetration of EVs into the general vehicle fleet reaches appreciable levels. The results of the aggregate analysis indicate

Table 14
ANOVA post hoc test results for energy discharged during trip events (kW h).

Factor	N	Subset for alpha = 0.05	
		1	2
Private weekend	1610	1.47	
Business weekend	2268	1.53	
Private aggregate	7297		1.62
Business aggregate	11,283		1.65
Private weekday	5687		1.66
Business weekday	9015		1.68

Means for groups in homogeneous subsets are displayed.
a. Uses harmonic mean sample size = 3810.800.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

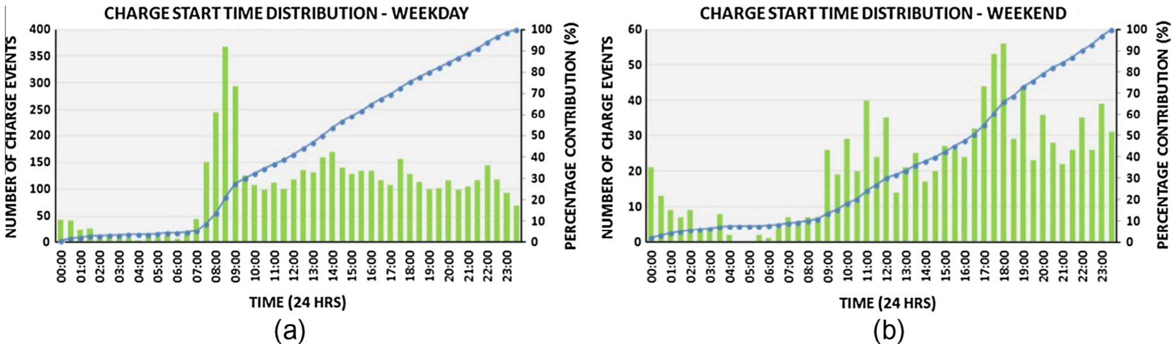

Fig. 12. (a) Weekday and (b) Weekend charge start time distributions for aggregated dataset.

a substantial peak in the morning, with almost 20% of charge events beginning between 08:00 and 10:00. While it may have been assumed that this peak could be attributable to business use vehicles, upon further analysis it was observed that the peak is present for private use vehicles also. Due to the fact that charge events were recorded by the vehicles rather than the charge points, this can primarily be ascribed to an incentive available in Ireland whereby all electricity from public charge points was free until July 2014. These behavioural patterns show the potential effectiveness of providing free electricity for charging.

As shown in Fig. 12, considerable differences in user behaviours were noted when comparing weekday and weekend charging behaviour. From the aggregate analysis on weekends, two peaks beginning at 11:00 and 17:00 were identified, representing potentially high demand on the electrical grid during on-peak times during weekends. This may be due to the aforementioned free public charge point electricity incentive, since individuals may be more likely to charge at home rather than in public locations at weekends.

When considering the influence of EVs on supply networks, it must be noted that the impact EVs will have does not solely depend on the charge-usage level of the vehicles; from a demand management perspective it is useful to know when the energy will be required from the grid. As such, the analysis of travel timing can provide information on the likely time frames for vehicle recharging. The analysis of the first journey start and final journey end time each day allows for a further analysis of vehicle availability, thus giving an indication of the likely time frames for vehicle recharging. When these analyses are considered together, the start and end times of daily travel clearly show when the vehicles will be stationary for extended periods of time. Fig. 13 shows the start and end time of daily travel for the aggregated data, with Fig. 13(a) displaying the distribution for weekday registers and Fig. 13(b) showing the distribution for weekend registers. The *y*-axis accounts for the percentage occurrence of the start and end time for each time slot.

The distribution of the first journey start times on weekends is more gradual when compared with weekdays, with daily travel tending to start slightly later in the day leading into a steadier decline, and it is more comparable with the gradual distribution of final journey finish times. The central portions of these distributions between the two relative peaks clearly show the times when it is likely the vehicles are in use and are therefore unable to be recharged. The results confirm the already well documented opportunity to charge electric vehicles during the night valley of low electricity demand, thereby enhancing the efficiency of the grid and generation plants. It must also be noted that the finish times of daily travel pose a possible risk of grid overloading due to potential consumer preferences to recharge their vehicle immediately following the last journey of the day, however this risk will be mitigated through the use of managed charging.

Fig. 14 displays the daily distance travelled vs. the number of trips made per vehicle per day for the aggregated data, exploring the range of distance travelled for each number of trips. The primary *y*-axis shows the average daily distance trav-

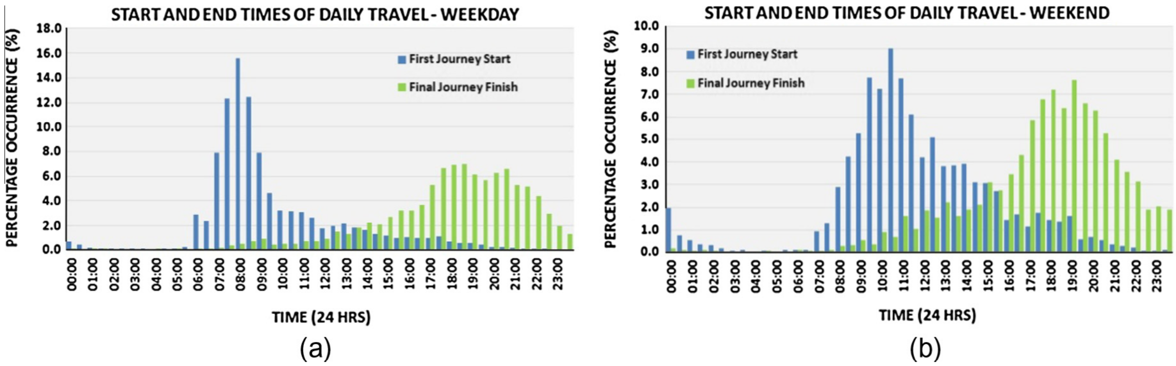

Fig. 13. Weekday start and end time of daily travel and (b) weekend start and end time of daily travel for aggregated dataset.

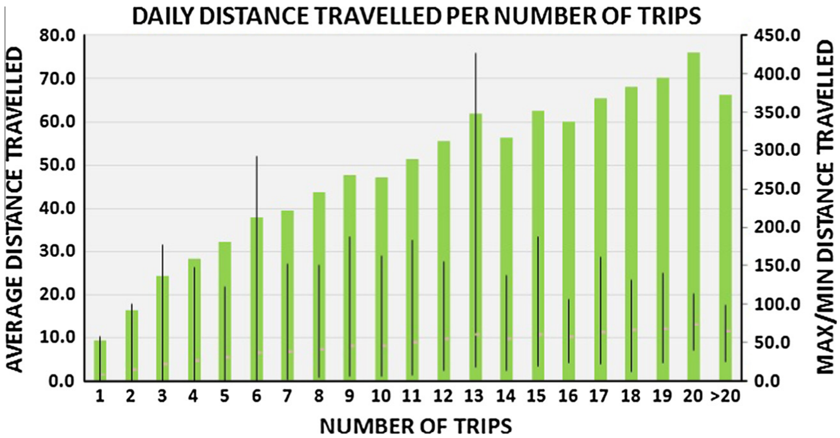

Fig. 14. Daily distance travelled vs. number of trips per day for aggregated dataset.

elled per number of trips, represented by the columns. The secondary y-axis is related to the maximum and minimum distances recorded for the corresponding daily trip count, indicated by the vertical black lines. All events were recorded in kilometres.

As would be expected, there is a notable trend for the average daily distance travelled to increase with an increase in the number of trips per day. With regard to the maximum and minimum daily distances recorded per number of daily trips, it can be seen that considerable variation exists, with the vertical lines covering a wide range of distances in most cases. As the number of trips increases, the minimum distance travelled tends to increase, but there is no dominant pattern evident with respect to the maximum distance travelled. It can be seen that the maximum distance travelled, equal to 426.47 km, was made in 13 individual trips. This case is attributable to a business use vehicle, and it is very likely the vehicle utilised fast charging infrastructure in order to be capable of completing this distance in a single day. The second largest daily distance of 292.51 km was made in 6 trips, and this is attributable to a private use vehicle.

Discussion and conclusions

Discussion

Interesting findings in relation to vehicle charging patterns emerged from the results of this study. The mean charge event energy consumption values for the six groups analysed were between 4.9 kW h and 5.6 kW h. Knowledge of this mean charge consumption range can be used with projected EV market penetration values to estimate the likely future load on the national electricity grid from charging and this can aid in determining any grid reinforcements that may be required. The availability of user data assigned to two use cases allowed a comparison to be made between the two groups and the results showed that business use vehicles tended to be used in a very different manner to private use vehicles for some charge and trip variables and very similarly for others. Given that the results of the charge event energy consumption mentioned above indicate that business and private use case EVs have similar charging demands with respect to energy, it is possible to estimate their demands as a combined load to the grid without the need for more complex analysis. In regard to vehicle charging frequency a clear difference between the two groups was observed with business use vehicles charged less frequently than private use vehicles across all analyses; it was also seen that business use vehicles also exhibited less variation in their charging demands. Private use vehicles therefore tend to be charged in a more irregular fashion based on the consumer preferences and in this regard the load profiles observed in this study can be used to inform interested EV stakeholders on normal behaviour in the absence of managed charging. This behaviour may have implications on the electrical grid as the varying charging demand of this group may not be entirely mitigated through the future incorporation of managed charging. In addition their need to charge frequently may impact on the provision of charging facilities.

A clear trend that was observed across all groups was that drivers are not willing to drive their EV beyond a considerable 'buffer' range before charging. The distance since last charge parameter is the best means of accessing users' charging habits relative to their vehicles' range. EV users were found to travel only 30 km on average between charging events which when compared to the vehicles' range of 130 km, clearly indicates that individuals are unwilling to use the entire capacity of their batteries and instead opt to charge more frequently than would be required. Given that the means for all use case and aggregate groups were considerably below the range of the vehicles, it is clear that the distance since last charge is low regardless of the time period during the week or use case. The related parameter of time since last charge helps to quantify the frequency of these charging demands. It was seen that 71.09% of all charge events took place within 24 h of the previous charge, with the greatest proportion occurring within 6 h of the last charge (28.08%). EV users are therefore charging their vehicles in regular patterns and this may explain the apparent lack of use of the available range of the vehicles. If charging follows a regular pattern and daily trip distances are short, then the available range will rarely be approached. This frequent regular charging pattern will have impacts on the national electricity grid given that users appear to charge on a regular basis even when an adequate range is still available to them. It is anticipated that night charging is most suitable given the lower unit costs and spare capacity in the electricity grid. However, the peak in the time band denoting less than 6 h between consecutive charging events would indicate that users are not following this anticipated pattern as widely as would have been expected. In essence EV users were found to charge their vehicle batteries during almost any opportunity that was available to them which emphasises the need for charging facilities. An interesting trend in these results was that across both use cases there was a propensity for longer distances to be travelled between charging events during weekends indicating that the regular charging behaviour observed is more prevalent during the working week. When comparing between use cases it was seen that business use vehicles tend to travel greater distances between charging events across all time periods when compared to private use vehicles which is possibly associated with the business aspect of their travel requirements. The time and distance since last charge parameters demonstrated that charging occurs on a regular basis regardless of the charge remaining in the vehicle battery. Examining the results from the battery SOC confirmed these trends. However it is quite surprising that 25.5% of charge events took place when the state of charge of the EV battery before the charge was greater than 80%. This could possibly point to habitual charging. It has been reported that an EV battery will retain approximately 80% of its original maximum capacity after 10 years and 3000 charging cycles (LiFePO4, 2010). In addition, Winther and Holst (2015) reported negligible degradation in battery performance over time with repeated charging. A charging frequency of 1 or more charges per day exceeds this reported value of 300 charging cycles per year, however a study by Marongiu et al. (2015) on the performance of lithium-ion EV batteries indicated that whilst reduced depth-of-discharge (DOD) values for EV battery packs would increase the total number of charging events over their lifetime, the effect would be to reduce battery cycle aging. Relating charging behaviour to vehicle usage for trips is an important consideration and therefore the energy consumed during trip events is of interest. The results showed that on average weekday trips will consume 1.66–1.68 kW h of energy with weekend trips consuming 1.47–1.53 kW h. This information is useful when predicting the impacts on the electrical grid and also on the EV battery life. Given that the batteries contained with the vehicles are 16 kW h (with a usable capacity of 12.6 kW h), it can be seen that mean trip energy consumption is a small proportion of the available power and this is related to the short and frequent nature of trips undertaken. The trends suggest that the observed charging behaviour was determined by individual needs rather than being influenced by larger concerns such as demand management. As such, the results indicate the very real potential to optimise EV charging through the smart management of energy delivery such as managed charging.

When examining how the vehicles were used from a travel perspective, the results of this study again highlight interesting trends. Trips made by EV tended to be short and frequent and this is reflected in the charging patterns that were discussed previously. Average trip distances recorded during this study were found to be shorter than those recorded by comparable ICEV users. It was also discovered that shorter trip distances are made during weekends when compared to weekdays for all use case analyses. This is reinforced by the fact that the maximum trip distance driven in all cases occurred on weekdays rather than weekends. Vehicles are therefore being used for higher numbers of trips during weekdays with lower numbers of trips recorded at weekends. Business use vehicles have the highest mean number of trips during weekdays and these trips were shown to be short ($\sim$7 km), it can therefore be concluded that business use case vehicles are being used for a higher number of short trips during weekdays with private use vehicles being used for trips that are of longer distances with less trips being made. Given that range anxiety has been shown to be an issue for EV users in previous studies, it would appear that the usage patterns for business use vehicles identified in this study would be well suited to EVs as the range would not present such an issue.

The frequency of trips and the daily distance travelled in an EV is of considerable importance when planning the infrastructure to support the influx of electrified road transportation. Dependent on a user's preferred travel behaviour, long travel distances and numerous trips per day will likely require a greater network of public charging infrastructure due to the greater energy consumption during travel. Similarly, EV users who make multiple trips comprising short distances may only be able to charge their vehicles at night, thereby placing a potential additional load on the grid in the absence of managed charging. The maximum distance travelled in this study was 426.47 km which was made in 13 individual trips. This case is attributable to a business use vehicle, and it is very likely the vehicle utilised fast charging infrastructure in order to be capable of completing this distance in a single day. The second largest daily distance of 292.51 km was made in 6 trips, and this is attributable to a private use vehicle. The considerable variation in the dataset shows that different forms of charging infrastructure, such as fast charging, would be required to cater for the differences in user behaviour particularly in extending the range. However when taking into consideration the distances travelled daily by EVs in this study, the advantages of fast charging may not be desirable when weighted against the potential negative impacts on battery life. A study by Adany et al. (2013) indicated that the current passed through EV battery cells when charging and discharging has a large impact on battery performance and lifetime and therefore the high currents involved in fast charging could have negative impacts on battery life. In addition, fast charging facilities can be impractical from a cost perspective and also limit the possibility of reducing grid impacts from EV's through the absence of managed charging options. The current batteries do not like large currents as they degrade much more quickly with this procedure and it reduces energy efficiency. When comparing between weekday and weekday trips, EV users tended to drive shorter daily distances at the weekends, and this was consistent across all use case analyses. It was also noted that almost 30% of registers recorded greater than 7 trips per vehicle per day during the study. This would again indicate that public recharging infrastructure may be required to account for this variation in the number of trips particularly if overall trip distances are to be increased.

Conclusions

The findings from this study provide useful information relating to EV charging and driving behaviour to inform other small and medium size cities and regions where EV usage would predominantly take place in a suburban or rural settings. Through the analysis of the timing and consumption patterns of charge events instigated by EV users, information can be obtained regarding the likely periods of high energy demand from the grid, as well as the magnitude of this energy demand. A large early morning peak was observed for the charge start time distribution, with a somewhat constant distribution throughout the remainder of the day with moderate variation, occurring across all use cases. Significant differences were noted between weekdays and weekends. The charge consumption values show a large degree of variation in EV charging behaviour, dependent on the battery's initial state of charge. Through an analysis of the distance and time between consecutive charging events, it was also shown that EV users tend to charge their vehicles frequently, thereby placing unnecessary additional demands on the electrical grid. As the data was recorded in the absence of managed charging facilities, the potential for smart charging and load valley filling is clearly evident from the results.

Analysis of EV user trip data has shown that trips are predominantly frequent in number per day and short in distance. It is not clear whether this trend is caused by the user having anxiety about the range of their EV or whether it is based on consumer preference, as a regular charging pattern was also observed. Given that EV users tended to make short trips with predominately low daily travel distances, home charging at night would be most suitable to accommodate the required journey ranges. It would seem clear that business users undertook a higher number of short trips during weekdays when compared to private users and given the likelihood of available charging facilities at the workplace this could be a possible future target area for the promotion of EVs in order to achieve a higher penetration.

EV users tended to charge their vehicles at regular intervals without using the available range of their batteries and this was reflected both in the SOC before charge events and also the distances travelled between consecutive charge events. It would appear that EV users develop a regular charging routine similar to one that they would adopt for an electrical device such as a mobile phone or touch screen computer. This approach may be adopted by users to ensure a fully charged battery to maximise their range at all times or simply the user may be making a decision to plug in their EV at all times when not in use. Given this regular charging pattern that was observed, the power required from and the likely impacts on the national electricity grid can be easily predicted. However the battery life of the vehicle may be negatively affected from this type of use given that battery integrity is usually based on a limited number of charge cycles. With respect to the national public charging infrastructure, it would appear that based on the trends observed an extensive public slow charging network would not be required. Instead the focus of the provision of a national charging infrastructure should be to provide fast charging facilities. The provision of fast charging facilities may be more effective at shifting EV users to making longer trips and higher daily travel distances given the current behaviour of EV users.

Acknowledgements

The authors are grateful for the EU funding provided to support this work through the Green eMotion project and the substantial support of the ESB eCars project.

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