On the effects of a centralized computer routing and reservation system on the electric vehicle public charging network.

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Abstract

One solution to the limited range of battery electric vehicles is the provision of a public charging infrastructure to enable longer journeys. This paper describes a simulation model of a centralized computer routing and reservation system based on the current charging infrastructure deployed (early 2016) in Ireland using the Irish population density and a trip length distribution. Monte Carlo simulations show quantitatively the effects of EV on-board charger power rating and the advantages of a routing and reservation systems on a country wide scale in terms of the number of electric vehicles that can be supported. The effect of charge point fault rates based on the currently deployed charging infrastructure is also assessed.

1 Introduction

The advantages of electrified transportation are well known since the 1900’s. Battery powered electric passenger cars and light commercial vehicles are presently being manufactured and sold to the general public in many countries. The technology of electric vehicles (EVs) is well developed and mature. Modern battery electric vehicles can meet the needs of the majority of users most of the time. However, the small percentage of trips that exceed the available range, present a stumbling block to their widespread adoption by consumers. This ‘range anxiety’ [1][2] needs to be addressed if EV adoption rates are to increase.

One possible solution is the deployment of a charging infrastructure, available to EV users, to allow recharging of the vehicle battery at intermediate points during their trip [3]. Therefore, it is of considerable interest to evaluate the performance of such infrastructure and determine its potential in addressing long trip requirement of EV users. Prior work using stochastic models network models [4] and recently intention aware routing models [5] show improvements in journey times using prior history statistics. Deterministic central planning has been proposed previously with data presented for a grid road network.
with stations randomly deployed [6].

In this paper, the Republic of Ireland is taken as a case study, as already a comprehensive network of public charge points have been deployed [7]. A simulation model of the presently deployed charging infrastructure is developed in section 2, based on the geographical population density, a trip length probability distribution function and a routing algorithm that allows for reservation of charging points and minimization of travel time. Monte Carlo simulations are run based on a specified number of EVs with metrics calculated to show the performance of the system on a countrywide scale.

The results show the importance of the on-board charger power rating which would be intuitively expected. They also show the key importance of providing a charge point reservation systems in addition to the physical charge points. Such a reservation system together with an optimizing routing algorithm is shown to provide a significant improvement in the number of EVs that can be supported under minimum average trip speed specifications.

While average trip speed is important, the concept of 'range anxiety' is really related to the chance of being stranded, i.e. running out of battery energy and being unable to recharge. In this paper, the effect of charge point faults is also considered. This is the case of arriving at a charge point with a deeply depleted battery energy level only to find the charge point is not functional. If it is not possible to travel to another charge point, then the EV is considered stranded and the user is unable to complete their trip. The probability of this occurrence must be comparable with current levels of trip failure, such as mechanical breakdown, if extensive adoption of EVs is to occur.

In this paper, a system simulation model is described in section 2. The results of Monte Carlo simulations on this model are presented in section 3.

2 System Simulation Model

The simulation model employed assumes that a specified number $N_{EV}$, of EVs are deployed and that each one will make a trip, all starting at the same time. The start location of the trip is chosen from a geographical population density map of the country as described in section 2.1. The length of the trip is randomly chosen from a trip length probability distribution function as developed in section 2.2. The destination location is then chosen based on the population density map of locations that are the chosen trip length distance from the start location.

Using a typical EV specification detailed in section 2.3 a routing algorithm is run for each trip. If the trip length is less than the available range, then no recharging is required and the trip is assumed to be achievable with the normal vehicle speed. Otherwise, the routing algorithm chooses a route using charge points to ensure the trip can be completed. The arrival time and charging time at each charge point is calculated and a database entry made of this information. Subsequent trips being routed use this reservation database to ensure that any charge point is not allocated to more than one EV at any given time. As more trips are routed and charge points reserved, it may become necessary for EVs to wait at a charge point, thus decreasing the average trip speed for that vehicle. The routing algorithm may choose a longer distance trip through other charge points with less waiting if the overall achievable trip time is less. After processing $N_{EV}$ trips, the trip statistics are
calculated.

2.1 Population Distribution

A population distribution model for the Republic of Ireland is developed based on data from the 2011 Irish census [8]. The data is used to create a geographical map of the population density. Fig. 1 shows the population density based on 1 km by 1 km area blocks.

![Figure 1: Population density map based on 2011 census data from [8]](image)

The 2011 Irish census further reports "1.36 million households having at least one car". This number is taken as the potential maximum adoption of electric vehicle ownership for the purpose of the developed model. Hence a 20% electric vehicle adoption rate is interpreted as \( N_{EV} = 272000 \) electric vehicles. The users of these vehicles are assumed, for the purpose of the model, to be distributed in the same manner as population density.

2.2 Journey Distribution

The distribution of journey distances is a key factor in the analysis of electric vehicle usage models. The Irish central statistics office report that "On average, each private car travelled 16,736 kilometers in 2013" [9], but the distribution of journey distances is not available. However, an extensive survey by the US Federal Highway Administration is available based on the 2009 National Household Travel Survey (NHTS). Data extracted from this survey [10], provides the distribution shown in Fig. 2. This data shows an average journey length of 8.9 miles (14.2 km) per trip with less than 1% of trips being over 100 miles (161 km). The empirical probability density function in the journey length \((y)\) in km is developed based on this data and yields an average journey length of 16.7 km with 1% of trips over 161 km. The annual travel distance of 16736 km indicates an average of 2.74 trips per day.

\[
p(y) = 1.2059ye^{-2.7733y^{0.33}}
\]  \hspace{1cm} (1)

2.3 Electric Vehicle Characteristic

While there are a number of electric vehicles available with different characteristics, the parameters in table 1 are taken as representative of
a typical family sized electric car at the present time. As a baseline scenario, it will be assumed that the user has the ability to charge at their home and their work location to 100% at the 6.6kW rate using level 2 charging.

![Image: US journey distance distribution from [10].](image)

Table 1: Typical electric vehicle parameters.

| Parameter                  | Value    |
|----------------------------|----------|
| Battery Capacity           | 24 kWhr  |
| Average Speed              | 90 kph   |
| Max Range                  | 110 km   |
| DC charge rate (to 80%)    | 45 kW    |
| AC charge rate (to 100%)   | 6.6 kW   |

With these characteristics, starting from a 100% charge then travelling until 20% of the battery energy remains, a journey distance of $110km \times 0.8 = 88km$ would be viable without charging. Based on the distribution in Eqn. 1, only about 2% of journeys would require charging, en route.

For short trips, where no charging is required, an average speed of 90 kph, is assumed. With a maximum charging rate of 45 kW, a 20% to 80% recharge time of 19.2 minutes is required and a distance of 66 km can be travelled between recharges. At 90 kph, the time travelling between charges is 44 minutes. This results in a lower effective speed of 62.7 kph if no waiting at charging facilities is assumed and the maximum charge power that the vehicle can take is available. With 22 kW charging availability, the lower effective speed is 47.6 kph.

The effective speeds represent the limitation imposed by the charging requirement. Speeds below these values represent limitations imposed by the finite charging infrastructure, a useful metric in assessing the quality of deployed infrastructure.

2.4 Charge Point Allocation Algorithm

The charge point allocation algorithm uses a database of available charge points consisting of their physical location, maximum power capability and their reservation schedule. A request for a journey route is handled upon the arrival time of a reservation request.

The allocation algorithm processes each reservation request by performing a breadth first search of all reachable charge points. The departure time from the charge point (including travel, charging and waiting times) is used as as a metric. To avoid infinite loops, any charge point considered is removed from the subsequent available list of charge point locations for that journey. Any consideration of a charge point that is within range of the final destination results in a
viable route for the trip. The search paths are extended until all viable routes are found. The best route in terms of the earliest arrival time is chosen. Note that once any viable route is found, an overall arrival time is known. Paths with a departure time later than the best time so far can be pruned with no loss of optimality. This achieves improved computational times by avoiding extension of paths that can never be the optimum.

If a successful route is achieved, then the charge points on that route are reserved for the relevant times, otherwise a failure to route is declared.

The routing algorithm works on the basis of taking location to location (or point to point) lengths ignoring the limitations of the road network. A scaling factor of 0.85 is applied to all the vehicle ranges to provide for some mitigation of the routing algorithm point to point assumption. For example, with a fully charged battery and allowing the battery energy to reach 20%, the typical EV range from section 2.3 would be 88 km, but this is scaled to $88 \times 0.85$ or 74.8 km as the maximum achievable point to point range before the first recharge event. With a maximum allowable discharge of 20% and recharging to 80% at each recharge event, the maximum point to point distance between charge points is $110 \times (0.8 - 0.2) \times 0.85$ or 56 km.

In a real deployment, a more realistic routing based on commercial navigation software could be employed [1], but this is beyond the scope of this study.

### 2.5 Fault Model

While the reliability of the electric grid is generally very high in Ireland, there are many reasons why public charge points may be non-operational at a particular time, ranging from telematics issues, blocked access, vandalism, etc. In the worst case, the fault may be unknown to the charging utility or may just have occurred when the EV driver arrives expecting to recharge their vehicle. Using the charge point allocation algorithm of section 2.4, the EV is always expected to have a 20% remaining capacity upon arrival at any charge point.

To evaluate the effect of charge point unavailability, simulations are run by initially assuming all charge points are operational. The charge point allocation algorithm is run with each trip needing recharging being allocated charge point which is reserved for the corresponding EV.

A simple fault model is then assumed whereby a fraction of charge points are assumed to be unavailable due to faults. In this work, each individual charge point fault is assumed to be independent. The probability of a fault is denoted $p_f$.

Any trip that includes a faulty charge point is stopped at the first faulty charge point in its trip route. The charge point allocation algorithm is run with the start location being the first faulty charge point, the destination location being the original destination for that trip and the initial battery capacity being the battery energy remaining on arrival at the first faulty charge point. All faulty charge points are marked as non-operational during the algorithm run. If it is not possible to reach any other operational charger, then the trip is considered to have failed i.e. the EV is counted as stranded.

More detailed work on failure mechanisms is needed to evaluate the independent fault assumption used here. For example, circuit breaker events may disable a bank of chargers deployed adjacent to each other. However, the independent fault assumption is used for simplic-
ity in this study.

3 Simulation Results

![Figure 3: Location of public charge points on 11 Jan 2016](image)

The baseline scenario consists of taking the current distribution of level 2 and level 3 (fast chargers) available in Ireland. It is assumed that it is possible to reserve their usage. Based on data downloaded [11] on 11 Jan 2016, there were 72 DC chargers, 1 of which was not operational. There were 636 Type 2 AC charge points of which 49 were not operational. Fig. 3 shows the location of these chargers. For simplicity, the DC chargers were assumed to be 50 KW chargers units and the Type 2 AC charge points were assumed to be 22 KW 3 phase 230V units. All the charge points are assumed operational at the start of the simulation.

3.1 Baseline Results

Two set of simulations are run. The first assumes that the charging rate at the 22 KW AC charge points is limited by the vehicle on board charger to 6.6 KW, while the second assumes that the full 22 KW is available to charge the vehicles battery. The resulting data are shown in Fig. 4. This figure shows the fraction of total trips meeting various conditions. In all cases, at least \(10^7\) sample trips were generated for each data point in the Monte Carlo simulations.

The first condition is that charging is required to complete the journey. This happens in about 2% of all the cases. Such a number would be expected based on the journey distribution as in section 2.2.

When charging is required the average speed is reduced due to the charging time as well as waiting times. The figure shows the fraction of total trips that resulted in an average speed below 60 kph, 40 kph and 10 kph. In these simulations, no trips were impossible.

From the figure, an average speed above 60 kph is not achieved in about 1 in 50 trips which are about 10% of the 1 in 50 trips that require recharging even with a very low number of vehicles. As most of the charge points are 22 KW, this result is not surprising.

Considering an average speed above 40 kph, all
trips were able to exceed this under the assumption that 22 KW on board charging was possible. This was the case for supporting more than 10000 electric vehicles. Naturally, the limitation of the 6.6 KW on board charging significantly increases fraction of trips that fail to achieve 40 kph. However, this data does show that the deployed infrastructure is extensive; potentially supporting more than 10000 electric vehicles for trips over the whole country. It also shows that employing 22 KW on board charging is a key factor in improving the achievable average speed.

Above the 20000 electric vehicles, the limitation of the infrastructure (waiting times) begins to dominate. Above 200000 electric vehicles, many are beginning to hit average speeds below 10 kph.

Choosing an acceptable probability of failing to achieve 40 kph as $10^{-4}$, then the capacity of the currently deployed infrastructure would be about 36000 vehicles. This represents 2.6% of the 1.36 million households having at least one car.

While an average trip speed of 40 kph seems low, it should be recalled that this is a worst case value. For many non-professional drivers who take few long distance trips, many of which may be leisure travel, a guarantee of this as worst case speed may be acceptable and enough to alleviate the range anxiety associated with battery electric vehicles.

### 3.2 Financial Costs

The ability to support up to 36000 with the existing infrastructure (assuming 22 KW on board charging with a routing and reservations system) allows estimates of the financial cost per user to be calculated. Based on the costs reported in [7], the average installation costs of DC chargers and 22 KW AC charging posts were about 48K Euro and 12.5K Euro respectively with annual maintenance costs of 6K Euro and 350 Euro. Taking the existing infrastructure of 72 DC chargers, 636 22 KW AC charging posts and with an assumed lifespan of 20 years, then with 36000 users, the annual cost per user would be 34 Euro per annum.

If all the charge points were DC chargers, then the annual cost per user would increase to 165 Euro per annum.

While these figures exclude overheads and the cost of the proposed routing and reservations system, they are reasonable in comparison to the EV prices in the order of 30K Euro.

Presently the existing infrastructure has been subsidized on the basis of encouraging EV adoption, but ultimately, the EV users would be expected to pay. If financial charging of EV users started when an EV adoption rate of say 10% of the potential 36000 users was reached, the an-
annual cost of 340 Euro per annum would be required. This amount would likely be acceptable to most users particularly if a guaranteed quality of service was provided.

### 3.3 Effect of Reservations

The prior simulations assumed that trips were reserved in advanced. The allocated charging times accounting for waiting times, to minimize the overall journey time. However, this is not currently available. It is of interest to consider the impact of such a reservation feature on average journey speeds. Assuming 22 KW on board charging the effect of such a feature can be assessed.

Fig. 5 shows the data in the case of a reservation algorithm that minimizes waiting times against the case where each journey is planned based only on minimizing travel and charging time, i.e. without consideration of waiting times due to other users. There is a severe deterioration in the fraction of trips that fail to achieve an average speed above 40 kph. This is the case even for relatively small numbers of vehicles being electric. It occurs because many users chose the same charge point, resulting in long waiting periods. Even with only 2000 vehicles, about 1% of trips that need recharging fail to achieve the 40 kph level.

With an acceptable probability of failing to achieve 40 kph as $10^{-4}$, then the capacity of the currently deployed infrastructure with no reservation system would be about 700 vehicles. Clearly there is an important need for a reservation infrastructure to be deployed to maximize the utility of the physical charge point infrastructure.

The employment of a reservation and routing infrastructure also allows for the implementation of a demand driven financial costing model to allocate the financial cost of providing the physical electrical charging infrastructure to EV users [12]. For example, fast DC chargers can be priced at a higher rate than 22 KW AC charge points to reflect the additional costs of the DC chargers. Indeed, some EV users may be happy to pay a higher rate for peak time use of fast DC charger while others may be prepared to accept a longer trip time (e.g. using only 22 KW AC charge points) in return for lower costs.

### 3.4 Fault Simulation

In the case of charge point faults, the most serious problem is a vehicle being stranded and unable to complete its trip. The probability of a vehicle being stranded in this manner is not related to the number of electric vehicles in the system, but only the probability of a charge point
fault \( p_f \).

With the installed base of 708 charge points, if 50 were non-operational (as was the case on Jan 11, 2016), then this would suggest a charge point fault probability of \( \frac{50}{708} \) or about 7%.

Hence sequences of simulations are run for charge point fault probabilities in the range of 1% to 30% as described in section 2.5.

The primary cause of stranded vehicles is arriving at a charge point to find it non-operational and having insufficient battery energy left to travel to another charger. With the routing algorithm from section 2.4 the worst case battery level on reaching a charge point is set as 20% capacity. This corresponds to an available point to point range of about 18 km.

Based on the charge point location distribution, there are 3 charge points that have no neighboring charge points within this radius. Hence a fault at any of these would result in vehicles being stranded there with a probability of order \( p_f \). Otherwise, at least two non-operational charge points would need to occur as neighbors. This has probability of order \( p_f^2 \). Thus, the probability of a stranded vehicle \( p_s \) can be estimated as

\[
p_s \approx p_c p_f \frac{3}{708} + O(p_f^2) + \ldots, \tag{2}
\]

where \( p_c \) is the probability of recharging being required (\( \approx 2\% \)) and \( \ldots \) represent third and higher order terms in \( p_f \).

As an example of improving the charge point infrastructure, three additional charge points were added to the model, one each co-located at the three identified charge points with no neighbors in the 18 km radius. Simulations with these additional charge points are also run.

It is also possible to modify the routing algorithm parameters to increase robustness of the system. The original reserve level for the battery energy was chosen as 20% but increasing it to 28% would ensure that sufficient reserve energy is available to avoid being stranded in the case of a single faulty charge point.

Fig. 6 shows the result of fault simulations. The baseline case of the existing infrastructure shows a stranding probability of about \( 10^{-5} \) for a fault probability of 10%. The baseline case is close to the first term of Eqn. 2 indicating that the three charge points identified are a significant source of stranded EVs in the model.

With the addition of just three additional charge points, Fig. 6 shows almost a factor of ten improvement in the stranding probability to about \( 10^{-6} \) for a fault probability of 10%.

Choosing an acceptable probability of being stranded of \( 10^{-6} \), then the baseline case would require a fault probability of less than 1%. With the additional three charge points, the tolerable fault probability would be about 9%.

The increase in the battery reserve energy
level to 28% with the baseline infrastructure shows an even more significant improvement of the system robustness. A fault probability of more than 20% still achieves a probability of being stranded below $10^{-6}$. However, increasing the reserve level reduces the maximum allowable distance between charge points. The increase to 28% resulted in a fraction of about $1.5 \times 10^{-5}$ trips not being possible to route in the first instance. In a real deployment a location dependent reserve level could be adopted which would address this issue.

These results show that charge point fault probability and the charge point location distribution are key factors in the stranding probability of EVs for long trips using a recharge infrastructure. The robustness of the recharge infrastructure can be increased by adding redundancy at existing charge points, even if they are low power charge points just to reduce the probability of stranded vehicles. The use of a routing and reservation system can also significantly improve the system resilience to charge point faults. For example the allocation of a higher battery energy reserve when high risk charge points are being used can significantly improve the system robustness.

4 Conclusions

In this paper, a model of the complete charge point infrastructure deployed (early 2016) in Ireland is built using the Irish population density. The assumed trip length probability density function is based on a US survey (as this data was not available for the Irish case). The population density and trip length distribution are used to create a set of trips based on the number of EVs assumed present. These trips are then routed through the deployed charge points when the trip length exceeds the range of a typically EV presently available.

The results of these simulations show that with the typically EV, that the deployed charge point infrastructure is extensive and can support electrified travel across the whole country. With the majority of charge points being 22kW AC sources, the effect of the on-board charger power rating is a limiting factor in the vehicle. Manufacturers are working on this [13]. At least a 22kW power rating appears desirable.

The second key factor is the provision of a routing and reservation system, which is not presently available to EV users in Ireland. Without this, the number of EVs that the system can support is limited. As measured by average trip speed, even with the assumption of 22kW on-board charger power ratings, the present infrastructure could potentially support about 36000 EVs based on achieving an average trip speed below 40 kph with a probability of $10^{-4}$. This is under the assumption of a routing and reservation system as described in section 2.4. Without such a system, the equivalent number support is less than 1000.

The third factor that needs to be accounted for is the effect of charge point faults. The worst case scenario for the EV user is the chance of being stranded at a faulty charge point, thus being unable to complete the journey at any speed. Using a fault model that assumes faults in each charge point are independent, the system simulation can be used to assess the impact of faults rates on the fraction of EVs being stranded. The simulation results show the importance of charge point distribution with low fault rates to reduce the probability of stranding EV and the ability of an intelligent routing algorithm to improve the robustness of the system to charge point faults.
Overall, the simulation model and results in this paper show quantitatively the effects of EV on board charger power rating, the major advantage of a routing and reservation on a country wide scale, and the effect of charge point fault rates based on a currently deployed charging infrastructure.

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