Enabling Long Journeys in Electric Vehicles: Design and Demonstration of an Infrastructure Location Model

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THESIS SUMMARY

This research develops a methodology and model formulation which suggests locations for rapid chargers to help assist infrastructure development and enable greater battery electric vehicle (BEV) usage. The model considers the likely travel patterns of BEVs and their subsequent charging demands across a large road network, where no prior candidate site information is required. Using a GIS-based methodology, polygons are constructed which represent the charging demand zones for particular routes across a real-world road network. The use of polygons allows the maximum number of charging combinations to be considered whilst limiting the input intensity needed for the model. Further polygons are added to represent deviation possibilities, meaning that placement of charge points away from the shortest path is possible, given a penalty function. A validation of the model is carried out by assessing the expected demand at current rapid charging locations and comparing to recorded empirical usage data. Results suggest that the developed model provides a good approximation to real world observations, and that for the provision of charging, location matters. The model is also implemented where no prior candidate site information is required. As such, locations are chosen based on the weighted overlay between several different routes where BEV journeys may be expected. In doing so many locations, or types of locations, could be compared against one another and then analysed in relation to siting practicalities, such as cost, land permission and infrastructure availability. Results show that efficient facility location, given numerous siting possibilities across a large road network can be achieved. Slight improvements to the standard greedy adding technique are made by adding combination weightings which aim to reward important long distance routes that require more than one charge to complete.

Keywords: electric vehicle, charging, infrastructure, location modelling, flow capture, GIS.

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GLOSSARY OF TERMS

BEV	Battery Electric Vehicle – vehicle run entirely from its battery
CABLED	Coventry And Birmingham Low Emissions Demonstrators – a 27 month long BEV trial carried out in the West Midlands, UK
CF	Charging Facility – recommended locations where charging provision could be placed
CO	Carbon monoxide – a toxic gas if inhaled in high concentrations
CO_2	Carbon dioxide – a predominant greenhouse gas
CZ	Charging Zone – zone which represents the potential surface where BEVs could charge to complete their route
FCEV	Fuel Cell Electric Vehicle – vehicle powered by hydrogen (stored in on-board tank), which is converted to electricity via fuel cells
FCHEV	Fuel Cell Hybrid Electric Vehicle – similar to the PHEV, except that electric power generated from on-board hydrogen tank. Also can be run from gasoline engine
GIS	Geographic Information Systems – system used to capture, store, and analyse various layers of spatial data
GPS loggers	Global Positioning System loggers – in vehicle data loggers which record geographical location (and speed) of vehicle
HC	Hydrocarbons – a collection of toxic carbon based gases
HEV	Hybrid Electric Vehicle – predominantly gasoline vehicle with a supplementary battery powered from the engine
ICEV	Internal Combustion Engine Vehicle – where gasoline is the fuel
MILP	Mixed Integer Linear Programming
NEDC	New European Driving Cycle – standardised dynamometer drive cycle test performed on all vehicles in EU to replicate 'typical' driving conditions and fuel consumption
NO_x	Nitrogen oxide – contributes towards air pollution and smog
NP-hard	Non-deterministic Polynomial time-hard – a process that increases in difficulty and computational intensity by a polynomial degree as it gets bigger
NSFC	Net Specific Fuel Consumption – equivalent to fuel economy in an ICEV
NTS	National Travel Survey – survey of ~16,000 individuals in England regarding their travel patterns over a week (results are then extrapolated across the year/population) (Department for Transport UK, 2013a)
OD location	Origin-Destination location – A distinct point representing a geographical area, denoted as a node on a network
OD network	Origin-Destination network – a network constructed from a set of OD locations connected by OD pairs
OD pair	Origin-Destination pair – a route from one OD location to another
PFlow	Potential Flow – flow designation indicating that a route needs more than one charge facility to make it feasible. Thus the placement of a single facility only has the potential to

	enable the route
PHEV	Plug-in Hybrid Electric Vehicle – vehicle which can be run in battery only mode, or in combination with gasoline engine. Can be refueled via gasoline pump or via electric charging
PM_{10}	Particulates – air pollutants which can cause inhalation related diseases
Rapid charging	Charging facility that allows BEVs to recharge in a short time period (~30 minutes). For the purposes of this thesis, the provision of rapid charging is interchangeable with provision of methods which allow BEVs to replenish their battery en-route (which could include fast charging or battery swapping)
SFlow	Serviceable Flow – flow designation indicating that a route can be serviced by the placement of a single charging facility
W0.5max	Model output indicating a weighting of SFlow + 0.5*PFlow, and maximum deviations considered (up to 7.5km)
W0min	Model output indicating a weighting of SFlow + 0*PFlow, and minimum deviations considered (up to 2.5km)
WFlow	Weighted Flow – flow designation which describes a weighted combination of SFlow and PFlow

1   INTRODUCTION

1.1   Overview of Research

Funding for this research was made possible through concurrent work on the CABLED project – an ultra-low carbon vehicles trial in the West Midlands, UK. For these early adopters of electric vehicles, who leased the vehicle for a minimum of 12 months, several behavioural adjustments had to be made. The majority of these revolved around the dual issues of range and charging. For most, the ability to charge at home constituted a convenient advantage, but a limited range – at least compared to conventional vehicles – meant that charging had to be a more frequent practice than refuelling. With a little more planning and forethought, most adapted to this without problem, but the inability to travel beyond the vehicle's normal range was restrictive for some. Based on this problem, the research described in this thesis was developed to offer a methodology as follows:

Aim of Research: Determine a method for locating a network of rapid chargers to enable extended BEV (battery electric vehicle) journeys in order to assist research and development into encouraging uptake and usage of BEVs.

The structure of this thesis is organised into 7 chapters. In this first chapter, a background to the battery electric vehicle (BEV) is provided, and its place within the wider transport sector is discussed (with reviews of combustion engine improvement, journey substitution methods, and hydrogen vehicle technology also provided). Findings from several real-world BEV trials are then introduced with discussions following on the continuing barriers to their uptake, including a review of current and future BEV cost, a discussion on vehicle range and how this affects journeys, and an assessment of current charging and infrastructure options. As a conclusion to this chapter, the research needs and objectives are established based on described observations from the industry, and a description for the following layout of the thesis is given.

1.2   The Need to Reduce Vehicle Emissions

The beginnings of the automobile, as we know it today, can be traced back to the end of the 19th century. Although the internal combustion engine (ICE) dominates road transport today, the picture was very different back in the 1880s. In 1881, Gustave Trouvé demonstrated a three-wheeled

electric-powered automobile at the International Exhibition of Electricity in Paris (Guarnieri, 2013). Despite the invention of the ICE car a few years later, the electric vehicle actually outsold other modes of propulsion up until the early part of the 20th century thanks to their ease of use and high performance (Volti, 2006). ICE vehicles of this era, on the other hand, were not built for their performance. Carl Benz's car of 1885 had a horse power of only 0.75, a limited top speed and required a vigorous turn of a crank handle to get it started (Eckermann, 2001). And, unlike today, a dedicated refuelling infrastructure was not in place. Petrol at this time could only be purchased from chemists and transported to the car via a jerry can (Lord, 1997). Despite the difficulties however, these early forms of road transport provided a drastic improvement in personal mobility, and it was this characteristic which spearheaded the car's popularity (King, 2007). With the invention of the starter motor, an increasing availability of fuel and the introduction of the Ford Model-T in the 1910's the automobile was made available to the masses, and since then ICE car ownership has boomed (King, 2007; Volti, 2006).

In the century following Ford's breakthrough, vehicle ownership increased throughout the developed world. In Britain, the expansion of the motorway network in the 1960's helped connect the country like never before, and as towns and cities expanded, so too did peoples' reliance on the car to get around (Charlesworth, 1984). As a result, road traffic across the country increased significantly – nearly 8 fold from 1950 – 1990 (Department for Transport UK, 2013b). Since then, the rate of increase has slowed, but in developing countries car numbers are expected to rise rapidly, leading to an increase in congestion, noise and air pollution around the world. In the year 2000 for instance, there were only 7 cars per 1,000 people in China. By 2011 this figure had grown to 54 (The World Bank, 2014a) and by 2050 Farmer et al. (2010) predicts it to have grown to 363. Such inflation in car usage will increase emissions and lead to rising atmospheric pollution. A consequence of heavy car use is the release of CO_2 into the atmosphere, which is directly correlated to fuel consumption and is a major contributor to greenhouse gas levels (An and Sauer, 2004; Great Britain. HM Government, 2011a). In 2010, transport accounted for 12% of the world's CO_2 emissions, nearly 6 billion tonnes (The World Bank, 2014b). In the UK, where vehicle ownership is high, 20% (or 122 million tonnes) of CO_2 released into the atmosphere comes from transport – of which passenger vehicles contribute more than half (68 million tonnes) (Department of Energy & Climate Change UK, 2014).

Globally, the human-induced release of CO_2 and other greenhouse gases into the atmosphere has been strongly linked to a rise in global average temperatures, according to the Intergovernmental Panel on Climate Change (Barker et al., 2007). From this they conclude that 'warming over the last

three decades has likely had a discernible influence at the global scale on observed changes in many physical and biological systems' (Barker et al., 2007, p. 72). CO_2 however, is not the only damaging gas released by ICE vehicles. CO, HC, NO_x and PM_{10} are all potentially harmful to either the atmosphere or human inhalation. Between 1997 and 2005, Gehring et al. (2010) ran a study in the Netherlands to measure the effect of traffic related pollution on the development of asthma in children. They asked nearly 4,000 parents whether asthma-related symptoms had developed in each of their child's first 8 years, correlated the results with estimations of pollution levels around each address (Brauer et al., 2003), and reported the link to be statistically significant. Since then, improvements in vehicle technology and tightened regulation have helped reduce, but not eliminate, these emissions (André and Rapone, 2009) which suggests that ICEVs will continue to contribute to asthma and inhalation related incidences, especially if emissions reductions are offset by increases in traffic levels (as suggested above). Furthermore, ICEVs rely on oil and petroleum, and the future availability, cost, and reliability of these resources could become more problematic in years to come (Kemp et al., 2010; Rozenberg et al., 2010; Turton and Barreto, 2006; Vivoda, 2009).

Given the need to reduce air pollution and cut CO_2 emissions, a mandate of 34% reduction in CO_2 emissions by 2020, and 80% by 2050, from 1990 levels was set by the UK government in 2008 (Great Britain. Climate Change Act, 2008). Further, this target fits within EU legislation and is part of a global effort to reduce emissions in the transportation sector. Figure 1-1 shows CO_2 emission targets for road vehicles in several major world economies. Historical trends show that emissions have been falling steadily since 2000, but for long term goals to be achieved, the decarbonisation of the transport sector, enabled by a transition towards lower emissions vehicles, is seen as key by King (2007), Hansen et al. (2008), Great Britain. HM Government (2011b), and the Committee on Climate Change (2013).

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Figure 1-1 - The downward trend in global emissions targets
Figure Source: (Miller and Façanha, 2014) compiled from (International Council on Clean Transportation, 2014)

1.3   Reducing Emissions in Road Transport

Emissions from ICE vehicles are calculated by assessing the amount of fuel that is consumed and emitted at point of use. Before market release, each vehicle model must be assessed under a standardised driving cycle. Within the EU this is achieved using the New European Driving Cycle (NEDC), which measures the vehicle's fuel economy and emissions outputs based on typical European driving patterns (European Commission, 2009). The simulated test comprises four urban cycles – characterised by moderate speeds and several stops and starts – and one extra urban cycle – which simulates highway driving with higher speeds and lower acceleration. The NEDC is carried out using a dynamometer, which allows the vehicle's engine and wheels to be operated to this strict cycle whilst in a static position (Barlow et al., 2009). For a discussion on variations between the NEDC and real-world driving see section 1.5. For gasoline vehicles, the NEDC output is usually represented with an mpg (miles per gallon) figure, allowing customers to compare fuel economy between models, and an emissions rating, which is represented by the amount of CO_2 emitted per kilometre.

The EU target for CO_2 emissions, to which the UK is bound, is set to 95gCO_2/km as a fleet average to be achieved by all new cars by 2020 (European Commission, 2014). Furthermore, although a

passenger car target has not yet been set for 2050, it is anticipated that a 95% reduction for emissions from all road transport from 1990 will be needed (Skea, 2012). This is because, even though individual vehicle emissions have been falling as demonstrated in Figure 1-1, overall emissions from road transport continued to rise until 2007 due to increasing vehicle miles (European Commission, 2014, 2012), meaning a proportionally greater reduction for individual vehicles is needed. Following the trend from Figure 1-1, average new car emissions in the UK fell to $128.3gCO_2/km$ in 2013, down from 164.9 in 2007 and 181 in 2000 - according to the Society for Motor Manufacturers and Traders (2014a), who compile data on new vehicle registrations in the UK. Despite this, only 3.3% of registrations currently meet the 2020 target of 95g/km, of which approximately half were alternatively fuelled. Thus, for the current levels to reduce further, and to achieve reductions in particulate emissions, alternatives to the current ICE are needed (Office for Low Emission Vehicles UK, 2013). Figure 1-2 (replicated from (Department for Transport UK, 2013c)) shows how new, improved technologies can reduce overall emissions. This demonstrates a lag effect of technology improvements on overall vehicle stock. Given this, the speed and uptake of new technologies could be crucial to emissions reductions.

Figure 1-2 - Average CO2 emissions of licensed cars in the UK

Figure Source: (Department for Transport UK, 2013c)

Proposals for emissions reductions in road transport can be summarised into four broad categories: improving ICEV technology and fuel efficiency, utilising electric power via an on-board battery, advancing hydrogen fuel cell technology, and encouraging substitution of car journeys with alternatives such as public transport, cycling, and walking. Publications contributing to these fields are shown in Figure 1-3. Articles which compare the technologies in reference to emissions reductions are shown in the table below.

Proposals for reducing emissions in road transport			
ICEV technology improvements	Car journey substitution	Hydrogen fuel cell technology (FCEVs)	Battery electric power (including PHEVs)
(Automotive Council UK, 2013) (Hoffmann et al., 2014) (Boretti, 2011) (Sprouse III and Depcik, 2013) (Berggren and Magnusson, 2012) (Reitz, 2013)	(Rojas-Rueda et al., 2012) (Piatkowski et al., 2015) (Redman et al., 2013) (Fishman et al., 2014) (Graham-Rowe et al., 2011) (Fujii and Taniguchi, 2005)	(Mazloomi and Gomes, 2012) (Fayaz et al., 2012) (Agarwal and Saxena, 2014) (McDowall and Eames, 2006) (Paster et al., 2011) (Eberle et al., 2012) (Yazdanie et al., 2014) (Eyre et al., 2003) (Hart et al., 2003) (Owen and Gordon, 2002)	(Kihm and Trommer, 2014) (Office for Low Emission Vehicles UK, 2013) (Helms et al., 2010) (Smith, 2010) (Boulanger et al., 2011) (Chan, 2007) (Doucette and McCulloch, 2011a) (Kammen et al., 2008)

Comparison / review articles	ICEVs	Biofuels	BEVs / PHEVs	FCEVs	Public transport	Walking / cycling
(King, 2007)	✓	✓	✓	✓	✓	✓
(Schäfer et al., 2006)	✓			✓		
(Van Mierlo et al., 2006)			✓	✓		
(Offer et al., 2011)	✓		✓	✓		
(Torchio and Santarelli, 2010)	✓	✓	✓	✓		
(Doucette and McCulloch, 2011b)	✓		✓			
(Boureima et al., 2009)	✓	✓	✓	✓		
(Howey et al., 2011)	✓		✓	✓		
(Pasaoglu et al., 2012)	✓		✓	✓		
(Campanari et al., 2009)			✓	✓		

Figure 1-3 - Strategies from literature to reduce road transport emissions

A mix of future vehicle technologies, like those summarised in Figure 1-3 is supported by King (2007) who suggests that advancements in various transport technologies and strategies will help contribute towards staggered, yet sustained emissions reduction. As such, it is possible that certain forms of transport will become more prominent in the future, as a new technology enters the mainstream and improves upon the status quo. This idea is demonstrated figuratively by the

Automotive Council UK (2013)'s technology roadmap shown in Figure 1-4. The roadmap reflects the views and predictions of a panel of industry, government, and academic experts and was developed to help provide a unified strategy and timeline for the automotive industry to work to. As such, it provides an indicative opinion, highlighting possible pathways towards an emissions reducing future. The timescales in the roadmap are also supported by Van Mierlo et al. (2006) who suggests that battery electric and hybrid vehicles will contribute in the mid to long-term (up to 2050), with hydrogen vehicles proposed for the long-term (perhaps being established by 2050). Similarly, Offer et al. (2011) believes that battery electric and hydrogen vehicles will start to become established in the mainstream by 2030, offering superior reductions in carbon emissions and being cost competitive with ICEVs at that stage.

Figure 1-4 - Passenger car low carbon technology roadmap

Figure Source: (Automotive Council UK, 2013)

1.3.1 Improvements in ICE technology

The Automotive Council UK (2013)'s technology roadmap suggests that improvements in internal combustion engine technology will play a vital role in reducing overall transport emissions, especially while emerging technologies are still establishing. Despite the fact they have been in development for over 100 years, Reitz (2013) stresses that the scope for ICE improvement still exists, stating that only 12% of the fuel tank energy is actually used to drive the wheels. Reportedly, 62% is lost through heat and waste in the engine and exhaust, 20% is lost by running accessories and idling, and a further 6% lost in the drivetrain. He also suggests that an additional 20% of energy is required to get fuel from an oil well to a vehicle tank. Reitz (2013) compares the performance of various engine/injection types using computational fluid dynamics models – which are validated with direct engine experiments. He notes that the use of advanced engine modelling

allows exact identification of the fuel injection process, and thus identification of improvement opportunities. Using these processes he shows how advanced injection methods, such as Gasoline-Direct-Injection and Reactivity-Controlled Compression Ignition can demonstrate 20% efficiency savings compared to standard diesel engines (and 40-50% improvements over conventional gasoline engines). The use of such processes could therefore reduce overall emissions – but it is unclear to what extent they may be adopted.

Hoffman et al. (2014) also looks at the fuel injection system and argues that an increase in fuel system pressure can improve fuel economy and also reduce particulate emissions. Using a single-cylinder test engine they assess various emissions under various fuel injection pressures, and report that fuel usage decreases with higher injection pressures. These results are replicated in Figure 1-5, where NSFC is equivalent to fuel economy. They explain that an increase in injection pressure improves fuel economy regardless of the injector used (they compare 6H and 5H injectors). However, the reported savings are minimal, with reductions of ~5% achieved. As such, implementation of higher fuel injection pressure may improve fuel economy, but the savings are unlikely to be substantial without other improvements.

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Figure 1-5 - The effect of fuel injection pressure

Figure Source: Hoffman et al. (2014)

Boretti (2011) on the other hand, proposes that efficiencies can be achieved through mechanical regenerative braking. He tests a kinetic energy recovery system on a 4l gasoline engine vehicle and reports that fuel consumption can be reduced by 25% based on the NEDC cycle (which is further described in section 1.5). However, it is unclear if this technology would be appropriate (and would

deliver similar reductions) for all ICEVs, given that the tests were carried out on a 4l engine as opposed to a vehicle with an average engine size of 1.7l (in the UK) (Department for Transport UK, 2013c). Sprouse III and Depcik (2013) review possibilities for exhaust waste heat recovery in an engine system. These methods, typically referred to as Rankine cycles, use excess engine heat to evaporate fluid and recycle energy in the engine system. Based on a review of the literature, they conclude that such systems can realistically achieve fuel economy improvements of 7-10%, and that the system cost can be paid back in 2-5 years (thanks to the fuel savings). A downside is that engine performance is slightly lessened (horse power reductions are reportedly observed between 0.2-2.5%) due to the backpressure imposed in the exhaust system.

Berggren and Magnusson (2012) investigate the effect of policy control on emissions reductions for ICEVs. They discuss how increased regulation and competition (for low-emission vehicles) from 2007 onwards helped provide the catalyst for reductions in the automotive sector (average emissions were reduced by $22gCO_2$/km from 1998-2007, yet a further 19 gCO_2/km reduction was achieved between 2007 and 2010). As a case study, they report that pre-2007, Volvo focused on spacious family cars with high performance (and resultantly high emissions). However, as the market began to change with the introduction of regulation and competition from other manufacturers, whose low-emissions vehicles were selling well, Volvo commissioned their engineers to produce an eco-car. Within 18 months they had developed a low-emissions series with CO_2 outputs of 99g/km (a 23% improvement on their best in class in 2007). As such, they argue that changes in performance measurement among manufacturers (from top-speed/size to emissions levels), instigated by tightened regulation, has led to improvements in ICEV emissions. In the long term they cite several avenues which can help the continuation of emissions reductions, including kinetic energy recovery (as described in Boretti (2011)), optimisation of the combustion system (such as those suggested by Reitz (2013) and Hoffman et al. (2014)), and waste heat recovery (like those reviewed by Sprouse III and Depcik (2013)) – but that innovation and improvement will only be achieved if continued stringent, and legally binding emissions levels are regulated.

Given the potential for efficiency savings in ICE technology, it is likely that emissions reductions will continue to be achieved in this sector. As Berggren and Magnusson (2012) suggest, it may be that tightened regulation will continue to push manufacturers towards reduction. Simultaneously, competition from other technologies – such as those discussed in later sections – may help drive innovation. However, according to Berggren and Magnusson (2012), based on the improvement percentages discussed, and the initial efficiency of gasoline combustion, it is unlikely that

emissions can be reduced in line with alternative technologies, given that hydrogen, and battery electric vehicles – discussed in sections 1.3.3 and 1.3.4 have the potential to be zero-emission.

1.3.2 Car journey substitution

As well as improving emissions from passenger cars, substitution of journeys to other forms of mobility, such as public transport, cycling, and walking, may also provide emissions reduction in the passenger transport sector. Rojas-Rueda et al. (2012) for instance, highlights the emission reducing potential of cycling and public transport if journeys by these modes replace a certain number of car trips. Their study is based on traffic conditions in the wider Barcelona region, and they hypothesise several scenarios which could help reduce emissions. Using city council data, they report that 32% of journeys in the area are by car, 2% by bike, and 66% by public transport. Their reduction scenarios involve replacing either 20 or 40% of all car journeys with a mix of bike or public transport. These assumptions lead to reductions in CO_2 emissions of ~100,000 tons (20% scenario) or ~200,000 tons (40% scenario) – figures which currently account for 0.75% or 1.25% of CO_2 emissions in the transport sector in the region of Catalonia. Reductions of this scale therefore could provide an effective means to reduce CO_2 levels (they also calculate benefits through the reduction of particulates, lower road mortality rates, and higher levels of fitness). However, no evidence is presented to support the assumed replacement rates of 20 or 40%, and it is unclear whether these could be achieved. It does though provide a benchmark for other policy workers to aim towards, and suggests emissions will be reduced if car drivers can be persuaded to use alternative modes of transport.

To facilitate shifts away from car use, bike share schemes have been set up in many cities to encourage more sustainable travel. These schemes provide convenient bike rental throughout a city with people able to pick up and drop off bikes at docking stations. A series of these programs are reviewed by Fishman et al. (2014) who analyse the amount of CO_2 reduction through trips which replace car journeys. They consider 5 bike share schemes around the world in Melbourne, Brisbane, Washington DC, Minneapolis, and London. For each scheme, users were asked, for their last bike share journey, which mode of transport they would have taken had the scheme not existed. The majority mode shift was reported to be from public transport, with car substitution making up only 19%, 21%, 7%, 19%, 2% in each city respectively. Fishman et al. (2014) used this data to calculate the reduction in vehicle kilometres travelled by car, having also analysed the docking data for each journey in the scheme. For instance, in London in 2012 they estimated the bikes covered

~32 million kms. However, since only 2% of those surveyed in London said the trip was substituting a car journey, only a reduction of ~630,000 car kilometres was achieved. Added to this, Fishman et al. (2014) analyse the data from the bike scheme operators (who create journeys when redistributing bikes by truck). In London, this service generated an additional ~1.4 million vehicle kilometres – thus overriding the positive effects from the bike/car substitution journeys. In all other cases however, the ratio was approximately 2 bike/car replacement kilometres to 1 operational kilometre. This shows that emissions reduction can be achieved through such schemes – but only if a sufficient proportion of people are substituting these trips from cars. Fishman et al. (2014) conclude that this rate is linked to the proportion already driving in that city. They point out that between 70-76% of people travel to work by car in Melbourne, Brisbane, and Minneapolis. Thus, a substitution rate of 20% is more likely to be achievable. In London and Washington these figures are only 36% and 46%, meaning car substitution is less likely as many people are already using alternative transport. The substitution rates assumed by Rojas-Rueda et al. (2012) therefore, may only be likely if car usage in a city or region is already high.

To realise the benefits of modal shift, as pointed out by Rojas-Rueda et al. (2012), it is important to understand the attributes which may encourage people to switch away from their car. To this end, Redman et al. (2013) reviews this field of work to identify which attributes are key to encouraging a shift from car use to public transport. They conclude that the most effective measures are often dependent on individual circumstances, perceptions, and motivations, which they concede are difficult to influence. Piatkowski et al. (2015) agree that walking and cycling provide sustainable travel alternatives, but conclude that car journey substitution is often overestimated, and suggest that the factors involved are extremely challenging and difficult to quantify. King (2007) also supports an increase in walking and cycling, but suggests that the dramatic increase in personal mobility provided by the car means it is likely to be around for many years to come.

1.3.3 Hydrogen fuel cell technology

Hydrogen within a vehicle can be used to convert the fuel from the on-board tank into electrical energy through fuel cells (Mazloomi and Gomes, 2012) (Fayaz et al., 2012). Given this, hydrogen powered vehicles are often referred to as fuel cell electric vehicles (FCEVs) as they are powered by an electrical motor from the energy in the fuel cells (Agarwal and Saxena, 2014). As discussed in section 1.3.4, this can mean that hydrogen vehicles emit no emissions at point of use (Torchio and

Santarelli, 2010). However, similar to electric vehicles, the production of the energy can influence the overall emissions of the vehicle.

In relation to emissions, a principal issue identified by McDowall and Eames (2006), reviewing a series of published works in this area, is the generation, distribution, and storage of the hydrogen. Reported overall CO_2 emissions (known as well-to-tank/wheels) from hydrogen vehicles can vary depending on production method, transportation distance (from generation to refuelling stations), station storage techniques, and vehicle specifications according to Paster et al. (2011). This is highlighted below in Figure 1-6, which is replicated from their work. They assess various hydrogen vehicle types (which they separate based on the pressure and size of the on-board fuel tank), and calculate the well-to-tank emissions for each of these under a scenario of 15% vehicle penetration in California, USA. Their reported findings suggest these issues can have a large impact on emissions levels from hydrogen vehicles.

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Figure 1-6 - Emissions levels of hydrogen vehicles split by generation and distribution
Figure Source: (Paster et al., 2011)

Yazdanie et al. (2014) reports that emissions levels from hydrogen production can vary from 0g CO_2/km (based on on-site production using 100% renewable energy to power an electrolysis process) to ~550g CO_2/km (based on electrolysis using coal-powered electricity). They also review other methods of hydrogen production, from gasification, to reforming, and oxidation, and report variations in emission levels between these figures. The underlying power used for hydrogen production appears therefore to effect the vehicle's overall emissions, with similar findings presented by Eberle et al. (2012) and replicated in Figure 1-7. Although some of their data is from 2004 (and so could be considered outdated), they report that hydrogen vehicles using energy produced from the EU grid mix could result in higher emissions than equivalent ICEVs and BEVs. However, if 100% renewable sources of energy are used, then FCEVs are considered by Yazdanie

et al. (2014) to be very low emission vehicles, which can offer similar potential reductions in line with BEVs.

Figure 1-7 - Estimated well-to-wheels emissions by vehicle type
Figure Source: (Eberle et al., 2012) compiled from (Brinkman et al., 2012; Edwards et al., 2004)

Although hydrogen vehicles have the potential to reduce emissions, other issues have been raised about the technology by McDowall and Eames (2006), including: the absence of a sufficient refuelling infrastructure, high technology costs, and technological immaturity (no hydrogen vehicles are currently in production/on sale in the UK according to Gibbs (2014)). Given this, in line with the Automotive Council UK (2013)'s technology roadmap, Eyre et al. (2003), Hart et al. (2003), and Owen and Gordon (2002) suggest that the introduction of hydrogen vehicles may not have a positive impact on overall emissions until 2030-2050, once issues around hydrogen production and storage are addressed. Schäfer et al. (2006) also concur with this in respect to the emergence of hydrogen technology. They conclude that until the carbon releasing process of hydrogen production improves (which they don't believe will be likely until at least 2030), then the ICEV or the BEV will provide a more likely means for emissions reduction.

1.3.4 Battery technology

As discussed previously, BEVs have been around for over one hundred years and in the 19th century outsold gasoline vehicles. In the 20th century however, the technology faded away. Its initial advantages were superseded by ICE vehicles, and its limitations, namely a restrictive range, were exposed. As the road network improved, the possibility for cars to be driven further led to the

electric vehicle's demise. Since then various mini-revivals, brought about by oil shortages or environmental crises, have come and gone (Anderson and Anderson, 2009). Yet, over the last 10 years or so, improvements in battery technologies, enabling BEVs to go further and last longer, and continued environmental concerns surrounding fossil fuel consumption and availability have renewed expectations in the electric car (Kemp et al., 2010; Office for Low Emission Vehicles UK, 2013). As a result, development in the technology has increased, with most vehicle manufacturers now offering an electric or hybrid electric vehicle (Automotive Council UK, 2013; International Energy Agency, 2011), (Department for Transport UK, 2013c).

As described by Van Mierlo et al. (2006), King (2007), and Offer et al. (2011), the introduction of electric power into vehicles' powertrains provides a pathway towards emissions reduction. This is because electricity can be considerably more efficient than combustion power within a vehicle – typically less than 40% of the energy combusted in a gasoline vehicle is used to drive the wheels, whereas electric motors can have efficiencies of 80-90% (Office for Low Emission Vehicles UK, 2013). Electrification within a vehicle's powertrain can take many forms, from mild-hybridisation (where an electric motor provides supplementary power to the ICE), to plug-in hybrids (which has an on-board battery and engine), to a full battery electric vehicle (which is wholly powered from its on-board battery) (Office for Low Emission Vehicles UK, 2013). As the ultimate form of electrification, the BEV thus provides the greatest potential for efficiency savings since at point of use it releases no emissions (Boureima et al., 2009; Helms et al., 2010; Howey et al., 2011). However, although the BEV can be described as zero-emission (Nissan, 2014), a more accurate representation can be determined by assessing the CO_2 output from the electricity which powers the vehicle (Gabriel et al., 2014). This is often referred to as a well-to-tank calculation (Torchio and Santarelli, 2010), which when combined with the tank-to-wheels figure can provide an overall emissions assessment which can be compared across vehicle types.

In their 2010 study, Torchio and Santarelli (2010) assessed data from various publications, and presented both well-to-tank (energy extraction/production) and tank-to-wheels (energy use in-vehicle) figures for a range of vehicle types. For various emissions, they compiled data into separate vehicle/fuel categories assuming an averaged figure based on the NEDC test cycle. The data which is replicated in Figure 1-8 shows the tank-to-wheels figures for each vehicle type, with CO_2 emissions represented in column 4.

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Figure 1-8 - Tank-to-wheels calculations for a range of vehicle types
Figure Source: (Torchio and Santarelli, 2010) compiled from (Concawe, 2012; European Commission, 2009, 2003)

Based on this table, BEVs offer a reported advantage compared to most other fuel types with no emissions at point of use. This is especially relevant for particulate emissions which, as described in section 1.2, can induce health problems in urban/residential areas. Once the well-to-tank calculations are considered however, the reported picture is more even. To calculate this, Torchio and Santarelli (2010) attempt to factor in many variables including the vehicle weight, and the pollution associated with fuel generation/extraction. They then combine these figures with the data in Figure 1-8 and produce a well-to-wheel index for the European Union, which is shown in Figure 1-9. Several key assumptions underpin these calculations however. Firstly, to provide an equal comparison, they assume every vehicle has a range of 600km. For the BEV, such a range is currently unavailable (see section 1.5), and the effect of their assumption means the vehicle weight is greatly increased. Thus, for a more realistic comparison they later assume a BEV with a range of 100km. In this case, the emissions output reduces by 30% (from 129 g/km in Figure 1-9 to 90.3g/km). This ranks the BEV on par with the other top alternative fuels, and ahead of conventionally fuelled vehicles. Secondly, their calculation for biodiesel assumes that some CO_2 is returned to the atmosphere in the growing process. This benefit has been questioned by Schlegel and Kaphengst (2007) however, who argue that the return of CO_2 from biofuel crops can be outweighed by emissions resulting from land clearing, fertilisation, and associated deforestation. The EEA (2006) also question the growing of biodiesel crops, suggesting that the amount of land required can be detrimental to competing food sources.

Figure 1-9 - Well-to-well greenhouse gas emissions (CO2) for various vehicle types
Figure Source: Torchio and Santarelli (2010)

Torchio and Santarelli (2010)'s findings indicate that the emissions picture for various vehicle types is complex. They also assess the fuel types for NO_x and PM emissions, reporting that biofuels perform the worst; and SO_x emissions where BEVs perform the worst due to the associated sulphur release from coal power stations. In relation to BEVs, they identify two main factors which effect their emissions output. Firstly, BEVs are at the mercy of the electricity grid from which they draw their power. Not only can this vary from country to country, but also between seasons and times of the day (Lau et al., 2014). Thus, to decrease the emissions outputs from BEVs further, it is important to decarbonise the electricity grid. Furthermore, the weight of a vehicle has a measurable impact on its efficiency. As such, from an emissions perspective, it could be more prevalent to maximise BEV utility within a restricted range, rather than to produce vehicles which can match ICEV ranges but have a greater weight.

As highlighted by Torchio and Santarelli (2010), the main factor affecting the well-to-wheel emissions of a BEV is the carbon intensity of the local electricity grid. According to Doucette and McCulloch (2011b), these variations have an effect on the environmental performance of BEVs and PHEVs. In their study, they analyse the carbon intensity of electricity grids in China, the USA, and France. In China, which produces the majority of its electricity from coal, the emissions gains for BEVs are marginal compared to ICEVs. This is highlighted in Figure 1-10 which shows the

anticipated emissions for CVs (conventional vehicles), EVs (BEVs), and PHEVs with varying battery ranges. Since the PHEV assumed by Doucette and McCulloch (2011b) (the Chevrolet Volt) has a lesser weight than the BEV (Tesla Roadster), their assumed emissions are lower at the start of a journey, since they can run in electric only mode. However, because of the high CO_2 level of Chinese electricity, the reported differences between the three technologies range only between 6-12 gCO_2/km. In France however, the carbon intensity of electricity is reportedly lower, meaning that BEVs can account for 12gCO_2/km, which is nearly 10 times cleaner than their comparable ICEV (Doucette and McCulloch, 2011b). This information is replicated in Figure 1-11.

Figure 1-10 - CO2 emissions for distance travelled in China

Figure Source: (Doucette and McCulloch, 2011b)

Figure 1-11 - CO2 emissions for distance travelled in France

Figure Source: (Doucette and McCulloch, 2011b)

Similarly, Holdway et al. (2010) calculate CO_2 emissions of BEVs and ICEVs in the US, UK, and France. They calculate the average emissions from three BEV makes, using the average carbon content of each country's grid mix. They also include distribution and BEV efficiency losses, and compare this to the existing fleet in the country (where well-to-tank calculations are also included for the ICEVs). Their results, which are replicated in Figure 1-12, suggest that BEVs can offer improvements compared with ICEVs. However, it should be cautioned that these figures are based on 2006 data (when ICEVs emissions were higher – see Figure 1-1), and an unlikely hypothetical scenario where each BEV model has replaced the entire vehicle fleet.

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Figure 1-12 - Comparison of well-to-wheels CO2 emissions between BEV fleet and existing fleet
Figure Source: Holdway et al. (2010)

Wilson (2013) extends the work of Torchio and Santarelli (2010) and Doucette and McCulloch (2011b) and compiles emissions figures for BEVs in 20 countries around the world. As well as assuming emissions resulting from electricity production Wilson (2013) incorporates a flat manufacturing emission cost of 70gCO_2/km into the calculations for BEVs. This assumed figure is uncertain, due to variability in manufacturing processes and lifetime of the vehicle (they assume a BEV completes 150,000km in its lifetime, compared to an ICEV achieving 200,000km) – however, it represents a mid-range estimate from work presented by Notter et al. (2010), Hawkins et al. (2013), and Alexander et al. (2011) who assess a number of factors including manufacturing process, extraction of battery components, and driving utility, and so can be considered valid based on currently available work). This is then compared with equivalent petrol vehicles (where manufacturing emissions of 40 gCO_2/km are assumed), and converted to an MPG figure. The figures replicated from Wilson (2013) in Figure 1-13 suggest that a BEV in the UK is equivalent to

a petrol vehicle with an MPG of 44 (currently similar to the most efficient new petrol vehicles available (Fuel Economy UK, 2014)). In countries such as India however, where electricity generation is largely fossil fuel based, BEVs could be equivalent to the worst performing ICEVs. On the other hand, in countries with a low carbon grid BEVs could represent the most efficient vehicles available (according to Wilson (2013)).

Figure 1-13 - Equivalent MPG of BEVs in 20 countries

Figure Source: Wilson (2013)

Despite the variation in stated emissions figures of BEVs and ICEVs (which are dependent on year of study, country, assumed mileages, parameters included), the importance of electricity production in relation to BEVs is apparent. Given this, their success (from an emissions perspective) could be reliant on a move towards a more sustainable grid mix – incorporating wind, wave and other low carbon sources, which according to Thiel et al. (2010) will help the emissions gap between BEVs and ICEVs grow bigger in favour of the electric car. In the UK, the decarbonisation of the electricity grid is mandated in law (part of the wider 80% reduction by 2050) (Great Britain. Climate Change Act, 2008). And, although the speed and degree of this decarbonisation appears dependent on many variables (such as government policy, oil price, wider implementation of renewables, and uptake of BEVs among others), several authors suggest at least some decarbonisation is likely, even under conservative scenarios (Anderson et al., 2008; Kannan, 2009; Shackley and Green, 2007) meaning a further improved emissions outlook for BEVs is possible.

1.3.5 Summary of emission reduction in road transport

Given the need to reduce emissions in road transport (Great Britain. HM Government, 2011b), it is likely that contributions from several technologies are needed (Automotive Council UK, 2013). As a part of this pathway, battery electric vehicles have the potential to reduce emissions in line with mandated targets and beyond (Doucette and McCulloch, 2011b). Furthermore, their impact will be boosted if a decarbonisation of the electricity grid continues (Anderson et al., 2008). For this to happen, it is key that BEVs become more widely used. Sales have increased recently; in the first 9 months of 2014, 4,500 BEVs were sold in the UK, a 148% increase on the same period in 2013 (The Society of Motor Manufacturers and Traders, 2014b). Yet, as an overall percentage of sales (<1%), these numbers remain low (The Society of Motor Manufacturers and Traders, 2014b), suggesting barriers to their uptake still exist. Given this, the following section explores the current issues limiting BEV use, and highlights the barriers that need to be overcome to help encourage their uptake and usage.

1.4 Electric Vehicle Trial Usage and Perceived Barriers to Take-up

To help pave the way for a developed BEV market, over the last few years several real-world trials have been carried out to investigate how people react and adapt to using a BEV over an extended time period. These trials have provided an early insight into the positives aspects of BEV use, and also highlighted issues which still need to be resolved if the technology is to reach the mainstream. The following section reviews these trials, describing how people adapted to BEV use, what they were comfortable with, and what they thought were continuing barriers to BEV uptake. Detailed discussions about these barriers are then provided in sections 1.5, 1.6, and 1.7. A summary of the trial information is described in Table 1-1.

Table 1-1 –BEV trials

Literature	Country	# of vehicles	Data period	Data collection
(Technology Strategy Board UK, 2011)	UK	340 (mix of private and pool users)	3 months (2009-2011)	GPS loggers, and interviews/focus groups. Collated from 8 independent trials
(Huebner et al., 2013) (Robinson et al., 2013)	North East, UK	44	13 months (2011-2012)	GPS loggers and interviews/focus groups
(Neumann et al., 2010) (Cocron et al., 2011) (Franke et al., 2012a)	Germany	40	12 months	Experience diary, questionnaires, and interviews

(Franke et al., 2012b)				
CABLED trial, summary information available from (Aston University, 2011; Bruce et al., 2012; Coventry University, 2010) with some data presented for the first time in this thesis. Key findings also presented in (Coldwell et al., 2013; Morgan, L. et al., 2014; Strickland et al., 2014)	West Midlands, UK	96	27 months (2009-2012)	GPS loggers and interviews/focus groups
(Schey et al., 2012)	USA	3,847 (collection of data from various trials across the US)	3 months (2011)	Charging information only
(Speidel et al., 2012)	Australia	11	6 months (2012)	GPS loggers
(Richardson et al., 2013)	Ireland	2 (trialed by 8 households)	12 months (2011-2012)	Charging information, and LV network data

The trails presented in Table 1-1 were operated between 2009 and 2012, with journey and perception findings based on 351 BEVs, and charging information available from 4,240 BEVs. In the UK, the Technology Strategy Board commissioned 8 demonstration trials to test and analyse usage in several market, or near-market, ready low carbon vehicles, of which the majority were pure BEVs (Technology Strategy Board UK, 2011). Each vehicle in these trials was leased to either a private individual or company (where the vehicle was typically driven by one employee) for a minimum of 12 months. Data was collected via on-board GPS data loggers, which recorded journey times/distances, odometer reading, charging events/battery state and location; and through perception surveys, which aimed to measure drivers' concerns regarding the use of their vehicle. Both the North East and West Midlands trials, listed in Table 1-1, were part of this wider program and collected data as described above. Findings from the North East trial are presented in Huebner et al. (2013), while results for the West Midlands trial were conveyed through quarterly TSB reporting with additional data analysis in sections 1.6 and 3.3, and (Coldwell et al., 2013; Morgan, L. et al., 2014; Strickland et al., 2014). A summary report commissioned by the Technology Strategy Board presents findings for the first three months of usage across the 8 UK demonstration trials.

The North East trial collected data from 44 pure BEVs from April 2010 to June 2013 – with the majority being leased to local authorities or companies for use as pool or company vehicles. Perception data was also collected via questionnaires and focus groups with more than 300 responses given throughout the trial (Huebner et al., 2013). The West Midlands trial, otherwise known as CABLED, ran from December 2010 to March 2013 and involved 96 BEVs leased to

participants for a minimum of 12 months each – of which 71% were leased to private individuals and 29% used as pool vehicles. As part of the project, all vehicles had access to a base charger (at home, or for the pool vehicles at their place of residence). Over this period, a total of ~97,000 trips were recorded. Perception data was collected by Oxford Brookes University via pre-trial and 3 month questionnaires and interviews, with all participants responding (King, 2011). A post trial survey on charging behaviour was carried out by Coventry University, again with all participant responses gathered (Berkley, 2012). The age of the cohort ranged from 23-71 (with an average age of 48.24). 80% of the participants were male, and 91% had an income in excess of £41,000. This demographic is similar to those in Huebner et al. (2013)'s trial (78% were male, 50% older than 45, and 91% in full-time work). They suggest that these profiles are symptomatic of the trial conditions, with most vehicles leased to places of work, where the employees tended to be male. The cost of the lease also demanded a high income. Although these profiles don't exactly match the wider population, they are perhaps indicative of early adoption BEV drivers, with the DfT (Department for Transport UK, 2012) reporting that 87% of those claiming the plugged-in subsidy for BEVs in the UK were male, over 40, and working full-time or retired. Comparatively, the National Travel Survey (Department for Transport UK, 2013d) reports that 55% of all surveyed car journeys were carried out by men, of which 70% were carried out by men over 40. Although women account for 45% of all car driving trips in the National Travel Survey, they only cover 36% of total miles driven (Department for Transport UK, 2013e). This indicates that males undertake more long distance trips, and as such, may have slightly higher range needs than women. Correspondingly, if BEVs become more widespread and are driven by a more representative share of the population, concerns about range may proportionally diminish.

Feedback from participants in these trials highlighted several aspects of BEV ownership, from those which they found enjoyable and convenient, to situations which required more planning, and to BEV characteristics which they disliked or felt would inhibit wider take-up. A selection of these responses is given below.

"I don't think there was anything that took me a long time to get used to at all. It was very easy to make the change from a conventional car." (King, 2011) – given during an interview after 3 months with the car

"It's been a good drive, it's been smooth, there have been no problems with it, it's nippy when you put your foot down when you need to and you wouldn't think it's any different from any other car apart from the fact it's so quiet." (King, 2011) – given during an interview after 3 months with the car

"I thought it was very, very comfortable, very easy to drive." (Huebner et al., 2013, p. 4) – post-trial questionnaire

"I found it was better than any car I've ever driven before." (Huebner et al., 2013, p. 4) – post-trial questionnaire

"I love driving that car, it's easy to drive. The braking system I think is fantastic, and I find it a lot easier that way to slow down; gracefully so to speak. It's a pleasure to drive and I find it easy to drive." (Technology Strategy Board UK, 2011, p. 15) – given during an interview after 3 months with the car

"It's been really surprising actually. I'd thought it would take a bit more getting used to, but apart from little quirks of the car, that you know wouldn't be any different if you were in a different model to your normal car, it's been quite an easy sort of relaxed transition actually." (Technology Strategy Board UK, 2011, p. 15) – given during an interview after 3 months with the car

"It's probably been better than I expected. Mostly because, I had quite high expectations, but it's been much easier, the transition's been much easier, the user friendliness and been much easier, the re-charging's been easier than I expected. It's been a very simple job to get in it and use it and I've been using it a lot. I'm trying to test what it can, so I've been using it to nip around town for meetings and things like that, so it's been better than I expected." (Technology Strategy Board UK, 2011, p. 15) – given during an interview after 3 months with the car

These responses indicate that transition to a BEV, and its general usability and performance was positive. This is further reflected in (Technology Strategy Board UK, 2011), with 95% of participants reporting after 3 months that BEV use was just as easy as in a conventional vehicle (compared to only 79% who thought it would be pre-trial). Of the concerns and perceived barriers to BEV use, a limited driving range was mentioned by the following participants.

"I'd rather be safer than sorry. The last thing I want to do is go somewhere and not be able to get back – that would just be so embarrassing having to phone the breakdown people! The inconvenience of it!" (King, 2011)

"I mean the biggest thing for me is purely the limitations of distance. If you run a diesel car out of fuel then it's quite easy to ring someone as and say "Look, could you just pop round and get a diesel can for me and we'll be on our way?" but with a vehicle like this you have to knock on the nearest person's house and say "Do you mind if I plug in my car for four hours just so I can get going? I don't think people would be quite so accommodating." (King, 2011)

For the Technology Strategy Board (Technology Strategy Board UK, 2011)'s study, participants were asked how their perceptions had changed after 3 months of driving, and what changes they had had to make to adjust from their previous car. Some of these responses described the degree to which people had to plan for longer journeys. One respondent explained:

"In terms of the practicalities, the only real thing that you have to do is bigger journey planning, you really do need to think about where you're going and plan things in advance so that you know you've got enough charge in the car to be able to use it. Not come into it an hour before you need to go out and find you haven't got enough charge to get there."

and another said:

"Well the main difference is having to think more isn't it? I mean really I have to think every day and even the night before I have to think more of what I'm doing before I know where I'm going or yeah, what I'm likely, where I'm likely to go, you know distance wise really and am I going to be able to charge." (Technology Strategy Board UK, 2011, p. 19).

These sentiments are reflected in the overall questionnaire findings after 3 months, with 74% of drivers reporting that journeys in BEVs require more planning compared to a normal car (a slight decrease from the pre-trial response of 80%). A predominant reason for planning trips more carefully in BEVs is to avoid running out of charge prior to reaching a destination. Although such situations would arise as a result of the limited driving range, it appears that users are more concerned with the fear of running out of charge and being left stranded. This phenomenon is often dubbed 'range anxiety', when drivers feel insecure completing intended journeys with the available range (Acello, 1997; Nilsson, 2011). Before the (Technology Strategy Board UK, 2011) trial began this fear was expressed by all respondents; 100% were more concerned about reaching their destination in a BEV compared to a conventional vehicle. After 3 months however, this feeling was only held by 35% of drivers. Clearly therefore, direct experience of a BEV can help alleviate some range fears. As the Technology Strategy Board (2011) point out however, a source of anxiety around the vehicle's range remains but drivers learn to adapt and become more confident managing their journey needs.

In the German BEV trial, Franke et al. (2012b) also reports similar findings. They asked their users how often they encountered a range-related stressful situation, reporting that these occurred on average 1.09 times per month. Consequently, Franke et al. (2012b) conclude that 'users experienced range somewhat more like a problem-solving task rather than a stressful encounter'. This was based on further findings which report that 90% of users felt the current range of their

BEV was sufficient for everyday use. Continuing on the issue of range, drivers across the Technology Strategy Board (2011)'s programmes were asked what range they deemed suitable for daily needs, and what was more than sufficient for all journey needs. Before the trial, private drivers on average quoted 76 miles as being adequate for daily needs. For all journeys they felt 232 miles was sufficient. After 3 months however, these figures changed to 92 and 206 respectively.

Huebner et al. (2013) questioned their participants to find out which perceived barriers were the most important for them, and which they thought would most likely hinder uptake (the results of which are replicated in Figure 1-14). Although the particular categories were provided by the interviewer, it is clear that some are viewed as more important than others. From this, Huebner et al. (2013) summarised the major barriers to BEV uptake into three categories: the cost of the vehicle, a limited driving range, and concerns about charging.

Figure 1-14 - Importance of various BEV attributes to trial participants

Figure Source: (Huebner et al., 2013)

One respondent reemphasised the issue of range by saying: *"I would say that the range must be probably the biggest barrier. If it's your only mode of transport then it probably is a problem, but not if it's for use as a second vehicle."* (Huebner et al., 2013, p. 4)

This sentiment is reflected in another questionnaire response, which asked users 'would you consider buying a BEV?' On completion of their trial, 46% of drivers said they would only

consider buying a BEV as a second vehicle, with 16% willing to purchase one as a primary vehicle, and 38% not willing to buy. Although it is unlikely that 'consideration' will translate into genuine purchase in all cases, the high incidence of those who would only consider a BEV as a second vehicle suggests that range and lack of charging availability are the biggest barriers. As suggested by the respondent above, if a household has an alternative mode of transport available (presumably a gasoline car), then the issue of range can be managed more easily. Without this back-up, owners must either use alternative modes of transport or find a way to extend the range of their BEV.

Based on Huebner et al. (2013)'s reported findings about the perceived barriers to BEV take-up and use, the following sections review the current situation for cost, range and charging, and explores how these issues manifest in reality and their possible impacts on a larger proportion of the population.

1.5 BEV Cost and Batteries

1.5.1 Total cost of ownership and price forecasts

As highlighted by Huebner et al. (2013) the up-front cost of a BEV is an important determining factor for consumers. A primary reason they are more expensive than their ICEV equivalents is due to their battery. As King (2007) pointed out back in 2007, the future success of BEVs will largely depend on battery technology and the ability to lower the cost to density ratio. Currently, batteries have a lower energy density than other fuel types, such as gasoline or hydrogen, resulting in a lesser range. Therefore, to improve this range a larger battery is needed (Thackeray et al., 2012), which results in a higher cost (Scrosati et al., 2011). This is highlighted in Figure 1-15 which shows a series of current BEVs with their stated EPA ranges (US Department of Energy, 2014) and US retail price (Ingram, 2014; Plug In America, 2015; PluginCars.com, 2014; Tesla Motors, 2015). An explanation of how vehicle ranges are calculated is provided in section 1.6. Although the prices shown are retail costs, a relationship between vehicle range and cost (of which the battery is a major constituent part) can be seen. The precise proportion of battery cost to retail price is not often declared by the manufacturers (Crist, 2012). Using an example of the Renault Kangoo ZE in 2011, Crist (2012) reported that the battery constituted 43% of the retail price for this vehicle. This is based on the fact that Renault gave the option to buy the battery separately (although this does assume that margins are equivalent for both parts).
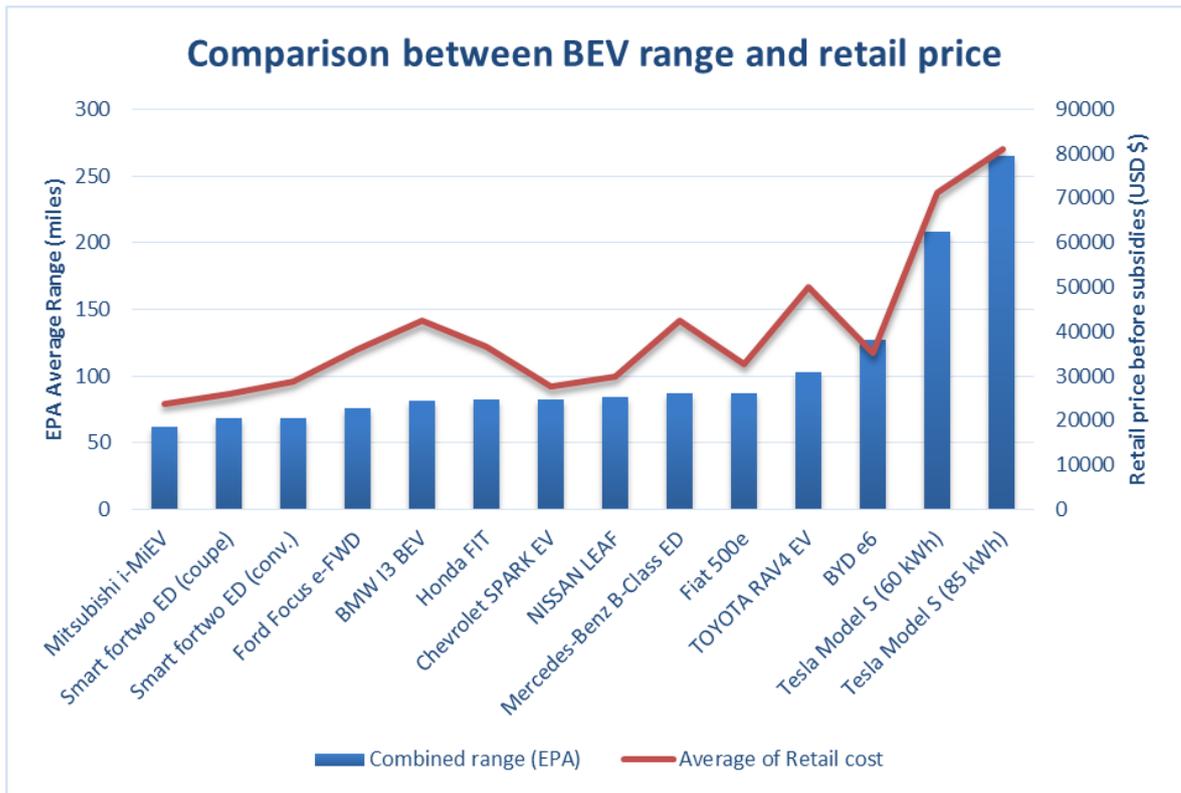
Figure 1-15 - Comparison between vehicle range and retail cost

Data Source: vehicle ranges (US Department of Energy, 2014)

Data Source: US retail prices, compiled from (Ingram, 2014; Plug In America, 2015; PluginCars.com, 2014; Tesla Motors, 2015)

Although BEVs are currently more expensive than their ICEV counterparts (Egbue and Long, 2012), King (2007) reviewed the costs of fuel production and supply for various vehicle types and identified that the BEV is often the cheapest to refuel (depending on taxes). Thus, for the consumer the cost of ownership of a BEV could be cheaper than for alternative vehicles, but despite this the total cost of ownership – which includes purchase price – is currently not in favour of the BEV, according to Al-Alawi and Bradley (2013) and Plotz et al. (2012). Over the coming years however, this could change, which would likely decrease the significance of this barrier (Egbue and Long, 2012).

Weiss et al. (2012) suggest that price parity with ICEVs might be achieved by 2032. They base this forecast on application of experience curves, which assume that costs decline based on economies of scale, manufacturing experience, and technological innovation. As a proxy for cost decline they use data and experience from the HEV market. These vehicles have been established in the market longer than BEVs, and share similar manufacturing processes (albeit with a smaller battery component). As such, they represent a useful ancillary to show how costs might decline for full battery technology vehicles. As a base, they compare prices with ICEVs by converting costs to engine power (kW^{-1}) and assume that 82% ($\pm$4) of an ICEV's retail price results from ancillary

costs (i.e. not the powertrain) (cited from Lipman and Delucchi, 2003). They also assume that ancillary costs are equivalent between vehicle types (they disapply tax costs for instance), and thus can deduce the cost of electrification in HEVs and BEVs based on the price differential to ICEVs. Historical cost data is presented for three prominent vehicle markets, the USA, Germany, and Japan from 1997 to 2010, and is shown diagrammatically in Figure 1-16, taken from (Weiss et al., 2012, p. 348).

Figure 1-16 - Historical price decline of HEVs and ICEVs
Figure Source: (Weiss et al., 2012, p. 378)

Based on the data presented in Figure 1-16, Weiss et al. (2012) show that the cost of HEVs declined between 19%-38% from 1997 to 2010, and that the price differential between ICEVs and HEVs declined between 69%-78%. These declines are principally linked to improvements in the battery technology. For instance, since 1997, Toyota managed to improve the capacity of their battery by 50% yet reduce its size by 33% and its cost by 75%. Based on the markets they study, they derive an average year-on-year learning rate for HEVs (i.e. the rate of cost decline) of 7% (±2%). This value is then converted to assume a future learning rate for BEVs. To do this, Weiss et al. (2012) attempt to identify the learning rate for the battery/electrification component only of HEVs (since a decrease in battery cost in a HEV only provides a partial decrease for the whole powertrain). Thus, they assume that the differential in learning rates between ICEVs and HEVs represents the rate of decline which can be attributed to the battery component. Thus, they calculate the assumed learning rate for the BEV powertrain as 23% (±5%). Extending these calculations, they forecast how prices may decline for BEVs, HEVs, and ICEVs up to 2036 based on vehicle take-up rates predicted by the International Energy Agency (2011). The results from the price decline forecasts are shown in Figure 1-17.

Figure 1-17 - Forecast of vehicle cost decline based on assumed technology learning rates
Figure Source: (Weiss et al., 2012, p. 382)

Weiss et al. (2012)'s work suggests that BEVs may reach price parity with HEVs by 2026, and with ICEVs by 2032 – but as indicated in Figure 1-17, there is a large amount of uncertainty with this. For instance, they cite the weakness associated with experience curves, namely that costs decline by a fixed percentage year-on-year. Over a reasonably long period, it is possible that this average rate will apply, but from year-to-year a smooth decline is unlikely. For instance, a major early breakthrough in battery technology may well accelerate this process, or conversely an improvement plateau might be reached (see section 1.5.2 for a wider discussion on battery technology). Also, Weiss et al. (2012) assume that cost of production is correlated with retail price. They perform sensitivity analyses and show that a good correlation tends to exist where pricing data is known, but often production cost data is kept confidential (Junginger et al., 2010). This may be especially true in a new market, where manufacturers may subsidise production cost to help develop a sales base (Wene, 2000). As such, current BEV production costs could be higher than assumed, meaning prices may have further to fall to reach a competitively sustainable level. Furthermore, their assumptions are based on a prediction of BEV take-up which they use to infer economies of scale, and likely technology development spending. Consequently, this adds another level of uncertainty. However, the two facets are interlinked: technology improvement, and vehicle take-up; and as such it is likely that a change in the first will cause change in the second. Whereas a slowdown in battery progress may stunt take-up rates, a major breakthrough in battery technology may make BEVs more attractive to consumers and encourage faster take-up, which in turn may help costs decline (through economies of scale), creating a snowball effect.

Despite the uncertainty that surrounds Weiss et al. (2012)'s forecast (or indeed any prediction), the recent trends they present suggest that BEV costs are likely to decline at a faster rate than ICEVs. They cite the speed of this decline to be largely dependent on improvements in battery technology, and the rate of BEV uptake – which can be linked to the overall attractiveness and viability of the vehicle for the consumer. In the meantime, government offered subsidies can help reduce the burden of higher initial costs, according to Kley et al. (2012), who suggest that initial purchase subsidies are a more effective encouragement for drivers than continuing subsidies (such as yearly tax reductions). To this end, the UK government has been offering a £5,000 upfront subsidy on BEV purchase price since 2011 (Office for Low Emission Vehicles UK, 2014). Despite this, and many similar subsidies offered throughout Europe, only subsidies in Denmark and Norway currently make the BEV cost comparable to ICEVs, according to Kley et al. (2012) who review subsidies and taxes across vehicle types in Europe.

1.5.2 Battery technology

In 2010 Kemp et al. (2010) presented a review of existing battery technologies and their relative energy densities. This work is replicated below in Figure 1-18.

Figure 1-18 - Summary of battery options, and energy density

Figure Source: Kemp et al. (2010)

Kemp et al. (2010)'s review suggests that there are many options for battery technology within vehicles, and that energy density (i.e. the capacity to size ratio) is key to the overall range of a vehicle. Given this, at a time when Lead-acid and NiMH (Nickel Metal Hydride) batteries were the norm, King (2007) recommended that advances in battery density would be needed for electric vehicles to become viable transport options. In 2015 however, Lithium-ion technology has become the prominent battery choice thanks in part to their superior energy density. This is evidenced by a review of currently available BEVs in the market which are all offered with Lithium-ion batteries (of varying sub-chemistries) - (Blanco, 2014; BMW, 2015; BYD, 2015; Chevrolet, 2015; Fiat, 2015; Ford, 2015; Honda, 2015; Nissan, 2015a; PluginCars.com, 2014; Smart, 2015; Tesla Motors, 2015). Similar to the comparison between vehicle range and purchase cost, current vehicles are supplied with batteries of varying sizes (where kWh refers to the capacity/energy potential of the battery). In relation to range there appears to be a relationship between battery capacity and the overall expected distance capability of the vehicle as is shown in Figure 1-19.
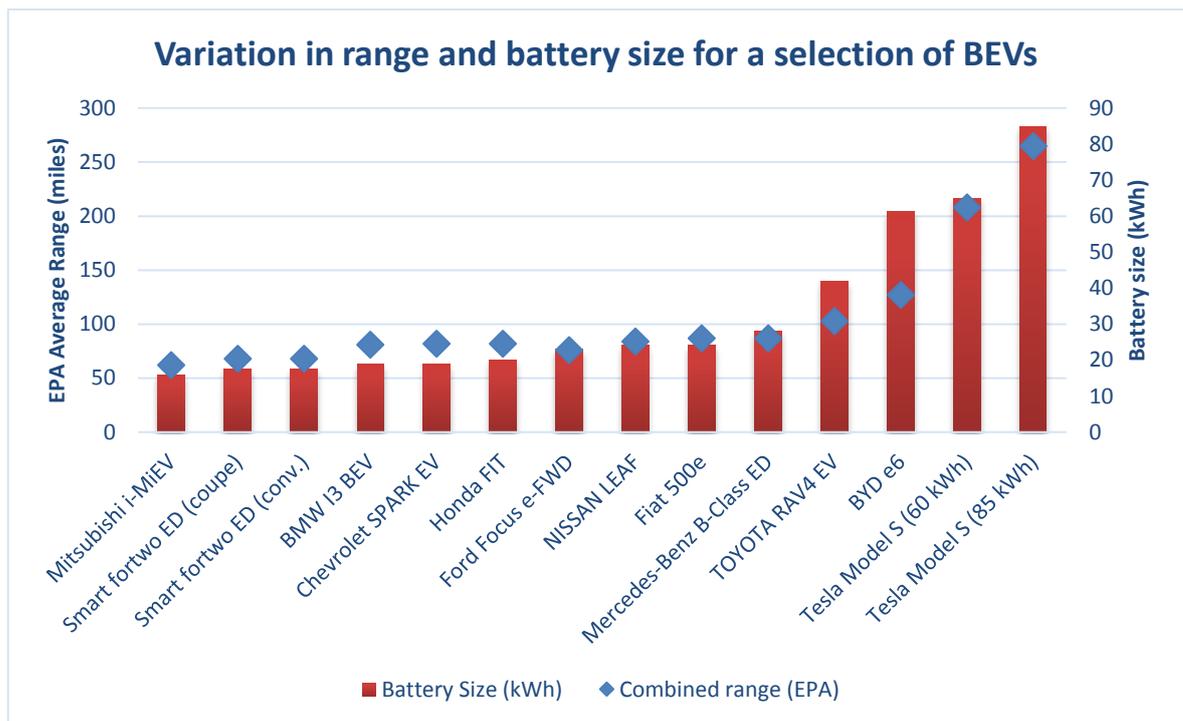
Figure 1-19 - Variation in battery size and vehicle range for a set of BEVs

Data Source: vehicle ranges (US Department of Energy, 2014)

Data Source: battery sizes (Blanco, 2014; BMW, 2015; BYD, 2015; Chevrolet, 2015; Fiat, 2015; Ford, 2015; Honda, 2015; Nissan, 2015a; PluginCars.com, 2014; Smart, 2015; Tesla Motors, 2015)

Figure 1-19 shows a set of currently available BEVs with their battery capacities shown in kWh (where various options were available for the model, the standard option is shown), and their expected ranges as stated by the EPA combined duty cycle (US Department of Energy, 2014). This data suggests that for vehicles with a larger battery, their range is greater. However, the relationship

is not perfect, with increases in battery size not directly proportional to expected range. This could be due to, as suggested by Torchio and Santarelli (2010), the additional weight that a larger battery induces. As such, it is possible that to increase range, a disproportionately larger, and thus more expensive, battery is needed. In the coming years, it is possible that technology improvements will allow for an increased energy density, and thus improved range will not be as effected by increased weight. Possible technologies which could provide this breakthrough include Lithium-air batteries, which have the potential to offer improved energy density levels since some of the catalysing chemistry is integrated from the ambient air (Park et al., 2012) (Scrosati et al., 2011) (Jung et al., 2012). However, as Gallagher et al. (2014) and McCloskey et al. (2012) point out, there are still many obstacles to overcome before the technology can be successfully implemented (such as integration of on-board air filtration systems, and risk containment of pressure and catalyst systems). Given this, in the next two sections range is discussed in reference to driver's needs, and charging provision is suggested as an alternative means to provide extended range.

1.6   BEV Range

One of the major barriers to BEV uptake, highlighted in section 1.4 is the perceived range inadequacy associated with these vehicles. To fully understand this sentiment it is firstly important to understand people's prior expectation of range, and thus why this can create a problem. A breadth of BEV ranges will then be compared with driver's actual usage habits, highlighting where possible ancillary services might be needed.

1.6.1   Description of range

Prior to a discussion on vehicle range, it is important to identify what is meant by the term, how it is calculated, and how it can vary under different circumstances. In the context of mobility, range describes the total distance a vehicle can travel when starting with a full tank or battery and driving until empty. Calculation of this figure is often derived from the fuel economy, which describes the distance that can be achieved given a certain amount of energy (and is sometimes referred to as the mpg-e, which is a conversion from gasoline efficiency to electricity) (Society of Motor Manufacturers and Traders, 2011). Using this figure combined with the battery's capacity, the full range of the vehicle can then be calculated – for instance, if 1kWh is consumed with four miles of driving then a vehicle with 20kWh of driveable capacity can be assumed to have a range of around

80 miles. The measurement of fuel economy is mandated in European legislation, requiring that each vehicle model be tested with the NEDC drive cycle before release (Barlow et al., 2009). Originally, the legislation was brought in for gasoline vehicles as a means of comparing and controlling emissions standards (André and Rapone, 2009). Basing vehicle range on such test cycles has come under criticism however, principally because an average, simulated value cannot sufficiently represent variability in real world driving (André and Rapone, 2009; Samuel et al., 2002). This phenomenon is particularly acute for electric vehicles, where a 10% change in expected range is likely to have more severe consequences than with ICE vehicles; adding another facet to the problem of range anxiety (Steinhilber et al., 2013). Thus, when determining charging provision for electric vehicles based on range, it is important to consider how potential variability in this figure will affect the solution. Several of these factors have already been explored in the literature, historically for ICE vehicles, but more recently in some cases for BEVs. For instance, on the matter of driving cycles, many authors have shown that a single and simplistic driving cycle provides a poor representation of actual fuel use. The reasons for this discrepancy are manifest, ranging from variations in driver behaviour, traffic conditions, road type/topology, ambient temperature, use of ancillary devices, and additional weight to the vehicle. Pelkmans and Debal (2006) assess emission and fuel consumption for a range of gasoline vehicles comparing the NEDC to actual driving. They report that, when compared to a series of real driving data, the NEDC underestimates fuel consumption (and thus range) by 10-20%. Similarly, Huo et al. (2011) reports that fuel economy in a real setting decreases 15.5% compared to a standard driving cycle, and Zhang et al. (2014) observes a 10% (±2%) real-world decrease in fuel economy compared to the NEDC.

1.6.2 Variation in range

A gasoline vehicle, driving in heavily congested urban areas typically consumes more fuel per km compared to highway driving as reported in (André, 2004; André and Rapone, 2009; Hu et al., 2012). For electric vehicles, the opposite tends to be true. This is largely a result of the fact that BEVs consume much less energy when idling – a scenario that is more likely in an urban setting, according to Montazeri et al. (2013) who show that 48% of time can be spent idling in congested traffic. To demonstrate how different driving condition effect range Figure 1-20 shows the ranges for a series of BEVs based on the EPA calculated rating. The EPA (US Environmental Protection Agency) implement similar legislation as the EU, requiring that fuel economy figures are calculated using a standard driving cycle (US Department of Energy, 2014). The ranges shown are the city range (based on an urban drive cycle), a highway range, and a combined range (similar to

the NEDC). For each vehicle the variation in these stated ranges is shown. In most cases the city range is greater than the highway range (on average 14% higher).

Figure 1-20 - Variation in range for a selection of BEVs

Data Source: (US Department of Energy, 2014)

Clearly, the range of different vehicles vary – but typically, the range of an individual vehicle is quoted as a fixed figure (Lintern et al., 2013). Strictly however, the achievable range in a vehicle is not fixed and can vary as a result of many factors. This is demonstrated by Walsh et al. (2010) who tested a Smart ED (original 2007 model) BEV on a test track with 6 different drivers and various driving scenarios. The scenarios tested are used to simulate variety in real-world topology, with routes designated as 'hill route', 'handling circuit', 'city course', and 'high speed circuit'. Using on-board telemetry in the vehicle, Walsh et al. (2010) study the amount of energy used by each driver over each section of the course, with their results replicated in Figure 1-21. Based on the test track results they report that both driver and topological variation can have an effect on BEV energy consumption (and consequently range).

Figure 1-21 - Variation in BEV energy consumption

Figure Source: (Walsh et al., 2010)

Given that variation is evident in energy consumption, Walsh et al. (2010) also analyse how these variations may affect overall range by studying the energy consumption of 4 Smart EDs on trial in the North East of England. Their reported findings are replicated in Figure 1-22, which show the assumed overall range of the vehicle based on energy consumption from various journeys. Although the average of this distribution is 72km, variation in journeys indicate that range could vary up to 40kms either way. Basing range calculations on an extrapolation does assume that the style of one journey would be replicated over its whole range, and that energy consumption is linear throughout the battery's state, but the results suggest that variations in real-world conditions can have an impact on the achievable range of a BEV.

Figure 1-22 - Variation in assumed range of a BEV

Figure Source: (Walsh et al., 2010)

Similar work is also carried out by Neaimeh et al. (2013) who assess the energy consumption of vehicles in the North East BEV trial (described in section 1.4). They assess a number of dynamic energy consumption parameters and devise a model to estimate the amount of energy needed for various routes (based on the anticipated speed, traffic conditions, and gradient of a route, and previous driver behaviour). They then use this information to predict and recommend a least energy cost route between Newcastle and Edinburgh, assuming various capacity, or traffic, levels on each road (15, 60, or 90%). For this test route, they show that route choice, and consequently topological, speed, and traffic conditions affect energy consumption. For instance, two possible routes are 159 and 155km in length respectively. However, when light traffic is assumed (15% capacity) Neaimeh et al. (2013) predict that energy consumption will be 15.95 and 11.75kWh respectively for the two routes (a potential difference of 17.5% in battery capacity used, assuming a Nissan Leaf with a 24kWh battery). Another variable which appears to affect vehicle range is temperature. This condition was tested by Strickland et al. (2014) using journey data from the CABLED project. Figure 1-23, replicated from Strickland et al. (2014), shows the decrease in state of charge, or SoC, for a BEV undertaking the same journey (from home to work) on several different occasions. Although topological and driving style variations are partially accounted for by selecting the same driver/route, the use of ancillary devices such as heating is not accounted for (although an attempt to limit these effects is made by focusing on temperatures between -5° and 20°). Based on this repeat journey, a trend in temperature effects on energy consumption can be observed (between 13% SoC used and 25% for the same 22km route).

Figure 1-23 - Energy consumption (SoC used) at given temperatures
Figure Source: (Strickland et al., 2014)

1.6.3 Range needs

The work presented by Walsh et al. (2010), Neaimeh et al. (2013), and Strickland et al. (2014) suggests that variation in range exists between different routes, drivers, and temperatures, while Figure 1-20 shows how range can vary between vehicle makes. But despite the fact that superior range is available within the BEV market and that range may sometimes be higher than stated, overall range is much lower than with equivalent ICEVs. This is demonstrated in Figure 1-24.
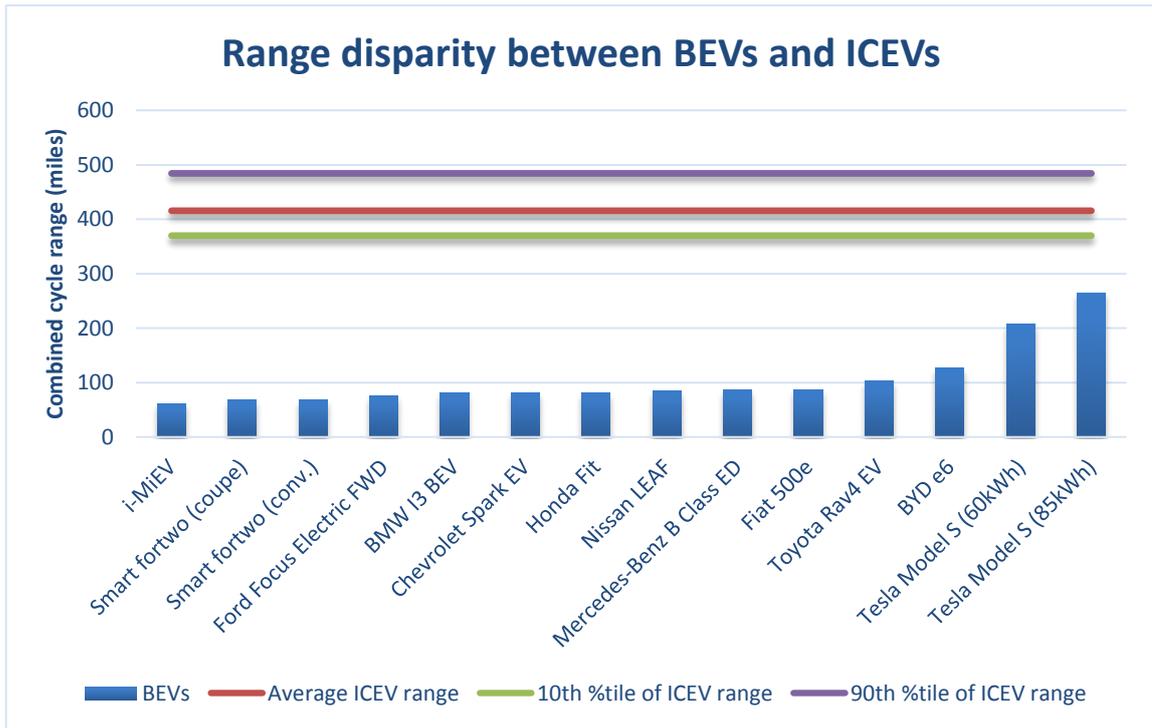
Figure 1-24 - Range disparity between BEVs and ICEVs

Data Source: (US Department of Energy, 2014)

Vehicle ranges calculated from provided combined duty cycle figures (101 ICEV set)

Figure 1-24 compares the expected ranges (based on a combined duty cycle) of several current BEVs with the average fuel tank range of a typical ICE vehicle. The ICEV ranges are based on a set of 101 current ICE vehicles, where range has been calculated using the same combined cycle as with the BEVs (US Department of Energy, 2014). From this dataset, the average (mean) value, 90th percentile, and 10th percentile of range values are shown. From this data, it is apparent that current BEVs do not offer the same single-battery/tank range capability as ICEVs. And, although the technology is likely to improve, providing more miles for a lower upfront cost, it is unlikely that battery range will be able to match ICE range in the near-future according to (Gerssen-Gondelach and Faaij, 2012; Vyas et al., 1998; Weiss et al., 2012).

The consequence of this mismatch is explored by Franke et al. (2012b) who, reporting on findings from the German BEV trial, suggest that many drivers' expectations of vehicle range are anchored by prior experience of ICEVs. Thus, when assessing a BEV's range suitability, potential drivers often desire a distance capability comparable to their last ICEV, rather than a range which would prove suitable for their journey needs. However, although BEV range is lower than with ICEVs, journey patterns may mean that a superior range is not needed in all cases. Indeed, most journey needs can be adequately satisfied with the full range of a BEV. Figure 1-25 shows the distribution of journey distances by car in England based on results from the National Travel Survey (Department for Transport UK, 2013f). Also overlaid is a typical BEV's range (median of combined range from Figure 1-24) (US Department of Energy, 2014) which highlights the proportion of trips which could be achieved with a full battery.
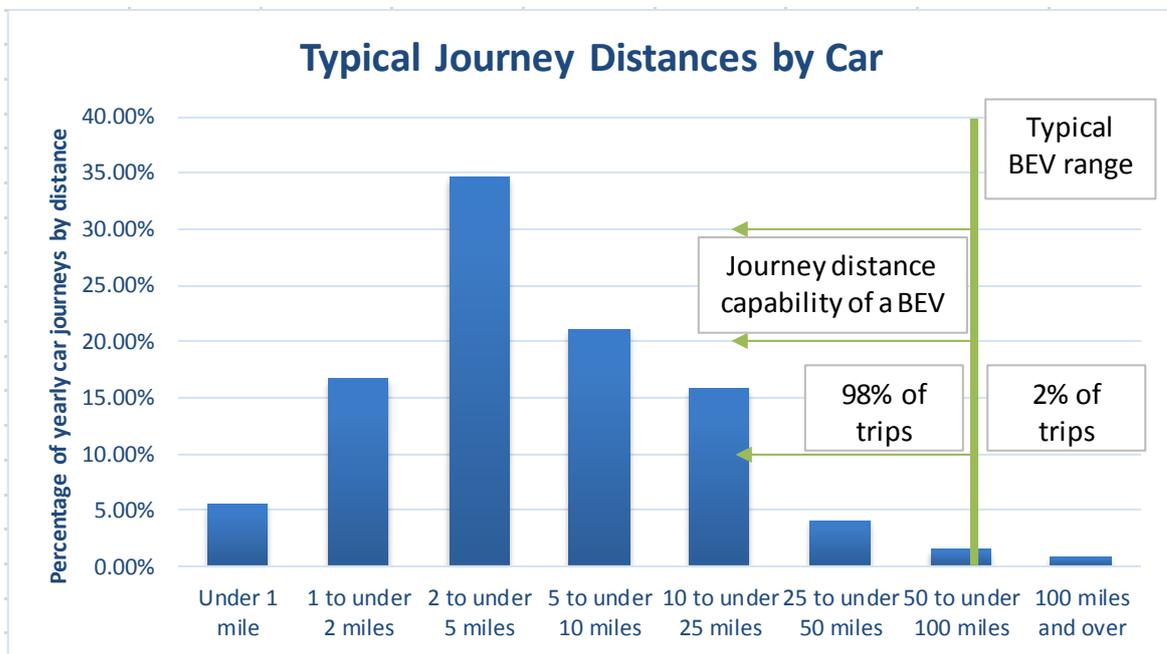
Figure 1-25 - Average frequency of car journeys by distance (England, 2013)

Data Source: (Department for Transport UK, 2013f)

Data Source: (US Department of Energy, 2014)

Typical BEV range set as median value from data presented in Figure 1-24

Figure 1-25 shows that BEVs can typically satisfy 98% of all trips, providing they are fully charged before use. Thus, for most daily journey needs the BEV can provide the same functionality as a gasoline vehicle. This idea is exemplified by reported findings from the Technology Strategy Board (2011), who report average daily mileages across the demonstration trials of 24.3, 25, and 23.3 in the first three months respectively. Car (ICEV) driving respondents to the Department for Transport's (2013a) national travel survey – which surveyed ~16,000 individuals from England about their travel patterns for a week – reported a yearly mileage between 8,100-8,300 for the same period; equivalent to a daily distance of ~22.5 miles. Findings from the CABLED trial are also

consistent with this figure – with an overall average daily mileage of 24.51. Further to this, the distribution of individual trip distances from the CABLED trial is largely consistent with the travel survey data presented in Figure 1-25. This comparison is shown in Figure 1-26, with the percentage of trip distances from each dataset shown.
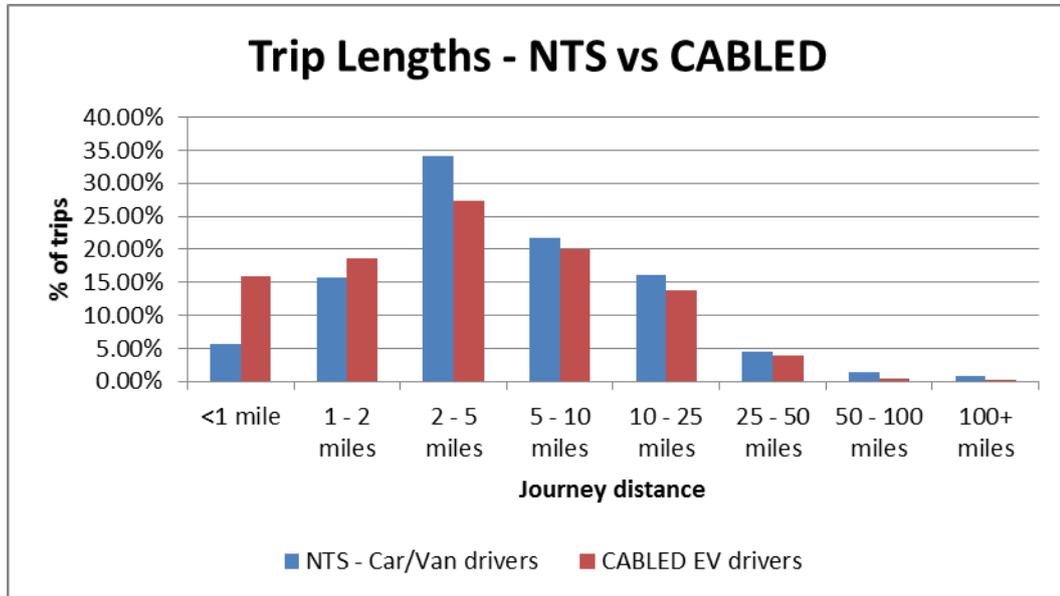
Figure 1-26 - Single trip lengths - CABLED and NTS

Data Source: (Department for Transport UK, 2013f)

Aside from a high proportion of short trips (<1 mile) in the CABLED dataset – many of which may not have been self-reported in a travel survey – a difference can be observed for journeys greater than 50 miles. Although these journeys only account for 2.22% of all national car trips, 50 mile+ trips were only observed 0.35% of the time in the CABLED data. If it is assumed that the CABLED cohort are representative of the population (their daily averages and high male proportion even suggest they travel more than the national average), then it could be concluded that they would ordinarily have carried out more 50 mile+ trips had they not been restricted by a limited range and a dearth of charging options. Given this, it is likely that the BEV drivers in the CABLED trial had to use alternative transport around 2% of the time. As pointed out by Franke et al. (2012b) based on the German trial, for BEV drivers who switch from using a gasoline vehicle, they tend to feel a greater sense of loss in functionality compared to what they might gain. For BEV owners with a second (gasoline) car, losing 2% of journey functionality is not likely to pose much of a problem, as it is likely they could easily swap to their gasoline vehicle. Single-car BEV drivers however, would have to change their travel arrangements on these occasions – an off-putting inconvenience that is observed in Huebner et al. (2013)'s reported findings – when asking if people would consider a BEV in the future. Consequently, as well as this issue being decreased if overall range is improved, options which can help satisfy these trips, such as replenishing a BEV's range en-route, may be needed.

1.7   Charging and Public Infrastructure

Trial participants in Huebner et al. (2013)'s study responded that access to quick chargers is very (40%) or quite important (40%) to BEV use, and access to public standard chargers is very important (~50%) or quite important (20%). However, comprehensive coverage and access to chargers was not available at the time of the study, and as a result, over 90% of participants responded that a 'limited availability of charge points' was an important barrier to usage. Given therefore, that charging provision is seen as key to enabling further BEV use, the following section highlights the different options that are available for charging. A review of the impact that BEVs might have on the electricity network, via public and private infrastructure, will then be given (in section 1.7.2) with a discussion on how this might affect locating capacity provision. Additionally, a summary of the current locations of chargers and the strategies used to place these will be provided (in section 1.7.3).

1.7.1   Charging options

"I found the charging very easy: plug it into the mains, put the other bit into your own electric point. That's it; that is all you have to do and walk away. Wake up in the morning and it's all done. Unplug it, take the thing out, put the cable in the boot of the car and away I go. Takes me 30 seconds in the morning to get the car up and running." (Technology Strategy Board UK, 2011, p. 29)

Yilmaz and Krein (2013) categorise charging options based on electrical supply and the rate of delivery. Based on the electricity markets in the US and the EU they define these as level 1 (which they describe as a convenience outlet, such as those available in most homes), level 2 (which they say is the predominant dedicated 'slow' charging option for private and public locations), and level 3 (intended for public/commercial locations with a three phase supply). Their summary is replicated in Figure 1-27.

Figure 1-27 - Charging options for BEVs

Figure Source: Yilmaz and Krein (2013)

Veneri et al (2012) also categorise charging options – but split them into four 'modes' based on the maximum electrical current delivered. Their summary is replicated in Figure 1-28.

Figure 1-28 - Charging current for BEVs

Figure Source: Veneri et al (2012)

Both of these works present charging times for a variety of charging options ranging from 5 minutes to 36 hours. Veneri et al (2012) cite the potential for the 'ultra-fast' 5 minute charge from Dhameja (2001) who explains that 5-15 minute charges are possible, but the high delivery of required current can induce destructive temperatures to the battery. More recently, Kang and Ceder (2009) also describe potential methods to charge in 5 minutes, but they explain that such systems are not currently commercially available and may be limited by electrical capacity constraints (180kW would be needed to recharge a 15kWh battery in 5 minutes). Such constraints are discussed further in section 1.7.2.

Analysis of real-world rapid charging times indicates that the values presented by Veneri et al (2012) and Yilmaz and Krein (2013) aren't unreasonable, but that charging times beyond half an

hour can occur. The data is based on rapid charging (43 & 50kW) usage in the Midlands in the UK, with Figure 1-29 showing the amount of time taken for each rapid charging event. A further description of this data is provided in section 4.1. Based on this, the average charging time was 24 minutes, with 95% of all charges less than 45 minutes.
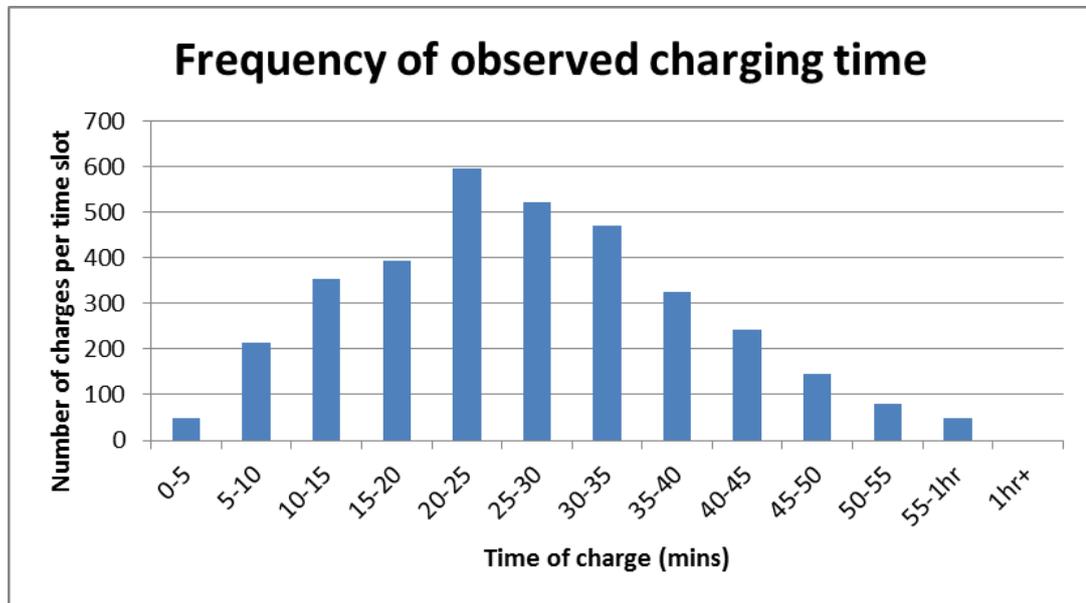
Figure 1-29 - Variation in charging time

Data Source: Cenex charging data – see section 4.1

Kemp et al (2010) define two main types of charging based on charging times: 'en-route charging', or 'charging at home or away'. For en-route charging, they describe four options which could make this possible: rapid charging, battery swapping, charging at a destination, and use of a gasoline engine through hybridisation. Rapid charging – which for the purposes of clarity is taken to describe level 3 or mode 4 charging from above – can replenish a battery by delivering a high level of current in a short time (as shown in Figure 1-27 and Figure 1-28). For instance, a top-up in 15-45 minutes is currently achievable (Botsford and Szczepanek, 2009; Chan, 2007) and could allow a BEV driver to stop off, recharge and continue onto their destination much as they would in a conventional ICEV.

Another option highlighted by Kemp et al (2010) for 'en-route charging' could be not to charge at all, but instead exchange a near empty battery for a fully replenished one. This method, pioneered by Better Place (Better Place, 2011), enables the BEV to be driven into a specialised battery exchange station, have its depleted battery robotically removed and then replaced with a fully charged new one. This whole process can take as little as 3 minutes – a time akin to, if not less than, refilling a petrol tank. This method of 'recharging' has several advantages as well as disadvantages compared to conventional charging. Firstly, the battery is not inherently tied to the

vehicle and could potentially be owned on a lease basis (Kley et al., 2011). This may avail a cheaper purchase price, since the battery forms a significant cost of any BEV; but it also means that any maintenance, upgrade or replacement is the responsibility of the battery provider. However, as Kemp et al (2010) point out the logistical efforts needed to provide a sufficient battery swapping provision may be difficult to implement. Positively, this option may mean multiple battery recharging could also be managed more effectively, from a grid perspective, providing the operator with an additional revenue stream (Coldwell et al., 2013; Kempton and Tomić, 2005). As an alternative to rapid charging, battery swapping offers similar challenges regarding infrastructure provision. Given this, the work in this thesis could also be applicable for the provision of battery swapping, albeit with different practical considerations, so for the purpose of this thesis battery swapping is regarded as synonymous with rapid charging.

The other options mentioned by Kemp et al (2010) for en-route charging are also likely to play a role in enabling electric vehicle use, however, for the purposes of this study the provision of recharging is seen as more important for BEVs (as they do not have an ancillary engine to extend range as in a PHEV). Destination charging can also be described as being similar to charging at home or work or where a long stoppage en-route occurs (e.g. an overnight stay). Since many of the long journeys that this thesis is concerned with are completed within the course of a day, these options along with slow charging are not considered as part of this work.

1.7.2 Capacity for charging stations

Given that charging stations are connected to, and rely on, the electricity Network, it is important to consider the impacts BEVs might have in this regard, and what constraints may be applicable. In this field, there have been a number of studies and subsequent reviews on the impact of electric vehicles on the distribution grid system (Cheng et al., 2014; Papadopoulos et al., 2012; Yilmaz and Krein, 2013). Impacts of vehicle charging on the electricity Network could include: exceeding ratings of equipment (transformers and cables) and going outside of statutory limits (voltage and harmonics). Due to the low penetration of electric vehicles to date these impacts have not been validated through the use of real world data and, as such, authors have had to use modelling tools to hypothesise these impacts. Modelling in this area can be split into four main areas as shown in Figure 1-30. Here, Network is referred to as the electrical grid network, as opposed to an OD network.

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┌─────────────────────────────────────┐
│    Modelling Impact of BEVs on the   │
│    distribution network in relation to│
│       charging site capacity         │
└─────────────────────────────────────┘
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Small scale modelling using practical scenarios at pre-determined locations	IEEE test network modelling	"Typical" distribution network modelling using a generic model	Economic/Carbon modelling
For example; Single charging station (Bae and Kwasinski, 2012) Shopping centre (Ghiasnezhad Omran and Filizadeh, 2014)	For example; IEEE34 model (Clement-Nyns et al., 2010, 2009) Feeder model including IEEE models (Moses et al., 2012)	For example; Typical feeder model (Qian et al., 2011), (Shao et al., 2009) Typical Feeder Network (range 10kV to 15kV) (Farmer et al., 2010; Lopes et al., 2011; Pollok et al., 2009; Valsera-Naranjo et al., 2011; Zhao et al., 2010)	For example; Effect on generation dispatch (Lojowska et al., 2012), (Coldwell et al., 2013) Effect on CO_2 levels (Robinson et al., 2013) EV Charging location (Meng and Kai, 2011)

Figure 1-30 - Capacity impacts of electric vehicles on the distribution Network

Within the Network modelling (IEEE or "typical" distribution modelling) fields, the location of the BEV charger on the Network has been pre-determined. This location is chosen through probabilistic or deterministic methods where no pre-assumed impacts of the physical charger location within a real world situation are taken. Results from these studies need to be treated as indicative and in many cases results are alluded to through numerical examples. Impacts from studies with between 10% and 30% penetration of BEVs using uncontrolled charging result in the following prediction of issues: cable and transformer overloads (Farmer et al., 2010) and harmonics and voltage levels (Putrus et al., 2009) at higher levels. Those that consider fast charging, such as Shao et al. (2009), and Pollok et al. (2009) indicate that the effects might be felt earlier and that up to 2.5% penetration could result in problems, again if charging is uncontrolled.

The small scale modelling examples each consider a specific physical location (which is pre-determined). Given they are based at just one location, the results are localised and the constraints are mainly due to the demand determination at that location studied. Thus, these examples are constrained based on the specific fixed transformer rating (to which they are connected) as opposed to effects on the broader Network. Examples from the 'Economic/Carbon modelling' section, where cost and location are used, primarily consider generation or renewable costs, for example, the impact of a high BEV penetration in a country and the effect on generation dispatch across

Europe (Lojowska et al., 2012). Similarly, the effects on generation dispatch have been studied in a UK context using charging profiles from the CABLED trial (described in section 1.4) (Coldwell et al., 2013). Additionally, the carbon content of electricity has been calculated based on the charging behaviours of drivers in the North East trial (Robinson et al., 2013). This highlighted the importance of measures to encourage off-peak, or low carbon, charging – patterns which weren't observed in an uncontrolled charging situation. An example where the impact on the electricity network is used to help determine BEV charging locations from a set of sites is based on a game theory approach (Meng and Kai, 2011). A set of relevant factors are chosen such as: government planning, views of surrounding residents, distribution of electric vehicles around, land use situation, traffic conditions, geographical conditions, weather conditions, fire-proof and explosion proof conditions, station harmonic pollution problem, electricity network situation, station load and charging pattern, total investment and management costs. Game theory is applied such that a hierarchy analysis based on these factors and a number of pre-determined charging stations allow a 'pay off' strategy to be formulated and used to determine the solution set. This method relies on pre-determining a set of charging stations prior to undertaking this analysis. Although not explicit, the strategy for deciding electric vehicle demand is based on a median model, where locations are preferred near BEV drivers' homes (the impact of this approach is discussed in section 2.1). Results are generated based on simulated parameters, so it is currently unclear how this strategy may be used to help determine sites based on Network constraints.

As well as electrical capacity, there is also likely to be temporal capacity constraints. Part of this issue is highlighted in Figure 1-29 in section 1.7.3.2 which shows that rapid charging times can be 45 minutes or longer, even if the overall average charging time is 24 minutes, or 30 minutes quoted in section 1.7.1. Given this, it is possible that – without sufficient provision or prior knowledge of availability – queues could form at charging stations. The likelihood of more than one driver requiring the same charging point is likely to be dependent on demand throughout the day. This can be exampled in Figure 1-31 which shows the frequency of rapid charges that took place in the Plugged-In Places Midlands network throughout the day (a description of this data is given in section 4.1). As a comparison, the frequency of journeys in progress from the National Travel Survey (Department for Transport UK, 2013f) is also shown. This is based on 'long journeys' in cars/vans that were in progress by time of day. In the Plugged-In Midlands data, there is a clear peak in the afternoon and early evening. As pointed out by Pollok et al. (2009) this could have implications on the distribution network – but only if, as they suggest, BEV penetration exceeds 2.5%. As a means of handling queues at charging stations, scheduling systems like those suggested by Gerding et al (2013) and Stein et al. (2012) could be used to handle multiple demands, which would require BEV drivers to 'pre-commit' or book a slot to use the service.
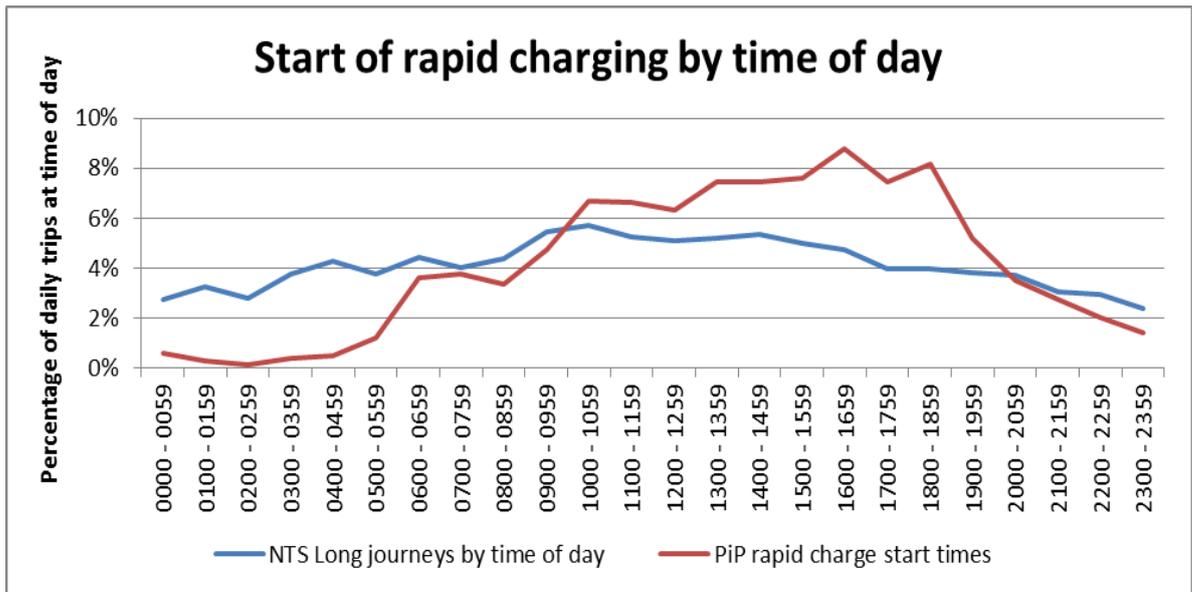
Figure 1-31 – Rapid charges by time of day

Data Source: (Department for Transport UK, 2013f)

Data Source: Cenex charging data – see section 4.1

The evidence presented based on capacitated Network constraints suggest that noticeable effects on the overall distribution Network are unlikely to be observed with <10-30% BEV penetration. For rapid charging, issues may be observed with a lesser penetration, but this will be dependent on overall Network demand, times of rapid charging usage, and peak load management. At an individual site level, constraints are sensitive to the particular rating of the local transformer, meaning that capacity can vary from site to site. Additionally, demand may vary throughout the day and by location. Given this, it is likely that a site specific capacity constraint will have to be considered, rather than a network average. This detailed analysis of electricity Network constraints in conjunction with charging location is considered outside the scope for this work due to the difficulties of getting suitable data across the whole Network, but is considered an area for further work in chapter 6.

1.7.3 Current charging infrastructure

Based on the discussions in section 1.7.1, two types of battery replenishment for BEVs can take place: those which are non-time critical, such as slow home or work charging, or destination charging (where there is not an immediate need to start another journey), and those which are time critical, such as rapid charging and battery swapping. In the following two sections, a discussion on the current and potential provision for these two types of charging (referred to as slow charging, and rapid charging), is given.

1.7.3.1 Slow charging

In the UK, there are currently 8259 public charging posts – split across 3183 sites, according to Zap-map.com (Lane, 2015) who have compiled a comprehensive database of the UK's charging infrastructure from the National Charge Point Registry (NCR, 2015) and Open Charge Map (Open Charge Map, 2015). The number of posts that have been installed in the last two years in the UK – including the type of charger (where fast is equivalent to level 2 charging as in Figure 1-27) is shown below in Figure 1-32.

Aston University

Illustration removed for copyright restrictions

Figure 1-32 - Number of charging points in the UK

Figure Source: (Lane, 2015)

As suggested in section 1.7.1, slow charging is likely to play a key role in enabling BEV use. These figures show that this is currently the most populous form of charging provision (if 'fast' is included in this category) – with only about 1 in 8 being rapid chargers. As well as the number of public chargers available, many charging points have been installed in private locations, such as homes or workplaces (OLEV, 2013). Robinson et al. (2013), reporting on findings from the North East trial (see section 1.4), reports that private BEV owners predominantly charged at home overnight. However, they also reported that most pool vehicles (usually parked at a workplace) tended to be charged throughout the day – which could have implications on the electricity network (see section 1.7.2). In the North East and CABLED trials, most private BEV drivers had access to a home-based charger – and for these users it was found that this was their predominant charging location. However, access to a home-based charger may not always be possible for all future BEV drivers. In such circumstances, these drivers may have to rely on regular top-ups at work, or at public locations (for which rapid chargers could feasibly be used). The use of home-based charging however was seen as a positive convenience for BEV drivers (see example statement at start of

section 1.7.1). Given this, a primary consideration for potential BEV consumers may be whether or not they could have access to a charging post at home. In the US, Axsen and Kurani (2012) conducted a web-based survey in 2007 of 2373 new car buying households and reported that half of the cohort have potential access to a dedicated level 1 charging outlet. In the UK, the English Housing Survey (Department for Communities and Local Government UK, 2012) carried out a physical inspection of ~16,000 homes (and a further ~16,000 by interview) to determine the state of the housing stock in the country. They report that 40% of dwellings had access to a garage, and a further 26% off-street parking. Given the requirements for charging, it is feasible that these locations could constitute suitable slow charging sites for future BEV drivers. When split by tenure type, the percentage of homes with a garage or off-street parking is greater in owner occupied home (see Figure 1-33 below).

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Figure 1-33 - Parking provision by tenure
Figure Source: (Department for Communities and Local Government UK, 2012)

Based on these figures it is likely that home-based charging could be made available in the majority of cases (potentially 66% or more). For people who do not have access to a home charger, BEV ownership may be more difficult (although, based on the trials reviewed in section 1.4 this is largely untested). Given this, it is possible that future BEV owners may self-select themselves depending on their circumstances. Analysis of Census data carried out by Campbell et al. (2012) in Birmingham, UK suggests that the early adopters of BEVs are more likely to have a higher income, be owner occupiers, and have access to a garage/off-street parking. Given this, a solution which allows BEV drivers – like those in the trials reviewed in section 1.4 – to extend their range occasionally, whilst being able to recharge at home is seen as a key need.

1.7.3.2 Rapid charging

There are currently 1074 rapid chargers in the UK, according to Zap-map.com (Lane, 2015) who have compiled a comprehensive database of the UK's charging infrastructure from the National Charge Point Registry (NCR, 2015) and Open Charge Map (Open Charge Map, 2015).

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Illustration removed for copyright restrictions

Figure 1-34 - Locations of current UK rapid chargers

Data Source: (Zap-map.com, 2015)

The majority of the rapid charging locations shown in Figure 1-34 have been funded through regional infrastructure bodies, coordinated by the UK government's Office for Low Emission Vehicles (OLEV, 2013). The regional schemes that have been funded are:

- The East of England (Source East, 2015)
- Greater Manchester

- London (Source London, 2015)

- Midlands (Cenex, 2015)

- Milton Keynes (Milton Keynes Council, 2013)

- North East England (Charge Your Car, 2015)

- Northern Ireland (Department for Regional Development (Northern Ireland), 2013)

- Scotland (Greener Scotland, 2015)

According to OLEV (2013), these schemes have match funded the installation of over 4,000 charging points (of which 65% are publically accessible). However, given the funding mechanisms in place, the location planning coordination of the network has mainly been ad-hoc in nature – since funding was supplied to businesses/public consortia based on those who applied/wanted a provision of charging points in their locale (Cenex, 2015). Given this, it is possible that provision for BEV journey purposes has not been strategically considered. Additionally, since the schemes have largely been coordinated at a local level, it is likely that the strategic location planning for a national network has been piecemeal.

1.7.3.3 Feasibility for future rapid charging sites

Given the constraints of installing a rapid charger (electricity network, land availability/cost), it is likely that detailed planning will be required for the provision of future sites. However, it is also likely that there is still plenty of scope for the expansion of the network, even with these constraints considered. For instance, in the UK there are currently ~1,000 rapid chargers compared to an estimated 11,000 petrol stations (RAC Foundation, 2013). Furthermore, within the current layout of sites, there are certain locations which have more charging options than others. Consider Figure 1-35 and Figure 1-36 below which show the current provision of rapid charging stations in the Milton Keynes area, and the Birmingham area (both are shown at the same scale and are replicated from (Zap-map.com, 2015)). Within the Milton Keynes area, there are currently 34 rapid charging sites – yet in the Birmingham area there are only 12, indicating that a further provision of sites could be possible, given locating constraints.

Figure 1-35 - Current rapid charging sites around Milton Keynes
Data Source: (Zap-map.com, 2015)

Figure 1-36 - Current rapid charging sites around Birmingham
Data Source: (Zap-map.com, 2015)

1.8 Summary

Given the need to reduce emissions in road transport as set out in section 1.3, alternatives to the status quo are needed. One such alternative, the BEV, has the potential to contribute towards reduction targets in line with a decarbonisation of the electricity grid (Doucette and McCulloch, 2011b) (Anderson et al., 2008) (Shackley and Green, 2007). Currently however, despite the fact many models are available in the market (US Department of Energy, 2014), sales are still low (The Society of Motor Manufacturers and Traders, 2014b) suggesting barriers to their uptake exist. Based on the reported findings from several real-world trials (section 1.4), the main barriers to uptake and usage were identified as cost, range, and charging (Huebner et al., 2013). As described

in section 1.5, the upfront cost of any vehicle is a important determining factor in its purchase (King, 2007). And, although BEVs are operationally cheaper than ICEVs, a greater upfront cost – stemming from high battery costs (Scrosati et al., 2011) – means they are not cost competitive, even if the total cost of ownership is taken into account (Alawi and Bradley, 2013; Plötz et al., 2012). Thus, for BEVs to become a viable alternative it is seen as key that their relative cost comes down (Egbue and Long, 2012). Forecasts suggest that this is likely to happen over the coming years – with cost competitiveness perhaps being achieved by 2032 (Weiss et al., 2012). Given this, it is important that the other barriers to BEV use are addressed by this time. Although the range of a BEV, and the availability and ease of charging are described separately, the two are intrinsically linked, since a vehicle's range dictates the frequency with which it must be recharged. Thus, an improvement in either vehicle range, or charging provision, will likely minimise the problems of both. As described in section 1.5 increases in battery capacity would help, but currently this comes at a higher cost (as illustrated in Figure 1-15). This is particularly relevant given that the actual usage of this additional range is likely to be minimal (based on current travel patterns observed in the National Travel Survey – see Figure 1-25). Furthermore, if an improvement in range increases the weight of the vehicle then the emissions benefits of BEVs may be reduced (Torchio and Santarelli, 2010). Given this, an expansion in charging offers an alternative method to enabling greater BEV use, and might negate some of the need for larger batteries, and in turn make BEVs a more cost-effective alternative.

In the context of charging and journeys, two main needs exist. The first can be classified as non-time critical replenishment (such as at home or work). This form of charging could be sufficient for 98% of journeys (Department for Transport UK, 2013f) (and Figure 1-26), and so is likely to represent the most frequent type of charging activity. However, a need exists to satisfy the other 2% (or more), such that BEVs can reach utility levels nearer current ICEVs. One form of charging which could satisfy these journey needs can be classified as range extension. This describes the need for recharging when the immediate range of a BEV is insufficient to carry out a long journey. Solutions which allow for this include rapid charging and battery swapping as they can provide additional range capacity in a short period of time (Kemp et al., 2010).

1.9   Research Aims and Objectives

Current UK charging locations, as shown in Figure 1-34, have largely been match funded through public grant schemes and business and public sector consortia (OLEV, 2013), and arranged through

regional bodies such as Cenex (Cenex, 2015). To date minimal location co-ordination between installers and/or regions has occurred through OLEV (OLEV, 2013), and this has mostly been ad-hoc in nature due to the funding mechanisms provided. To maximise the benefits of public spending in this area, it is desirable to locate rapid chargers as part of a more cohesive strategic plan so that investment is tied to locations which will offer high utilisation and value for money (Lumsden, 2012), (Arup, 2012). To do this it is necessary to determine a method of locating rapid chargers that is relevant to current and future BEV drivers' usage patterns, and is expandable to cover national areas. The focus of this research is based on the need to extend the immediate range of BEVs. As described in the previous section, the provision or availability of non-time critical replenishment is also seen as critical, however, due to the differences in habitual patterns between these two forms this is considered outside of the scope for this research.

Given this, this research addresses the issue of determining an appropriate location strategy for the needs of BEVs with the following **aim**:

- Determine a method for locating a network of rapid chargers to enable extended BEV journeys in order to assist research and development into encouraging uptake and usage of BEVs.

Based on the needs of this aim, the developed method should incorporate the following features:

a) Be geographically representative
b) Expandable
c) Take into consideration range and habitual journey patterns of BEVs
d) Be realistic and applicable to real-world networks

To achieve these aims the following objectives need to be met:

Objective 1: Understand how location modelling has previously been applied for similar purposes, and identify the assumptions and short comings inherent in these methods.

Objective 2: Develop a model and appropriate methodology to recommend sites for a charging network, and overcome issues with previous work in this area.

Objective 3: Apply this model to a real world network and analyse its outputs against current charging usage.

Objective 4: Demonstrate differences in modelling outcomes based on comparison between national infrastructure plan and a smaller regional like plan.

To meet these objectives it is necessary to conduct original and novel research, especially in regards to objectives 2, 3, and 4 where the following key areas of contribution to knowledge include:

- Development of a location model specific to battery electric vehicles
- Development of a methodology to allow the location model to be applied in a practical context
- Validation of the model and method using empirical data
- Understanding scaling issues between regional and national size models

Chapter 2 deals with objective 1 and investigates the advantages and disadvantages of previous location models in this field. Based on this a set of more specific modelling objectives are proposed and described in section 2.7.

Chapter 3 proposes and describes methodologies and options to deal with objective 2.

Chapter 4 describes a novel process of real world data validation.

Chapter 5 demonstrates the methods on a large scale and compares this to a smaller area to meet objective 4.

Chapter 6 discusses the implications for this work, the context in which it can be applied, and directions for future work; and Chapter 7 provides a conclusion and summary to the findings from the research.

2   INFRASTRUCTURE MODELLING

Objective 1: Understand how location modelling has previously been applied for similar purposes, and identify the assumptions and short comings inherent in these methods.

A key issue for infrastructure strategy and planning is that of location determination (Hickford et al., 2015), and the ability to answer questions such as 'Where can we locate our infrastructure provision to help achieve our objective?'. On this basis the field of location modelling exists to help an infrastructure planner determine where to *'site (their) facilities in some given space'* (ReVelle and Eiselt, 2005). Location modelling therefore can be used to represent the real world and help provide location-based decisions. As such, an important step for any location plan is to determine how to represent complex spaces and behaviours in a form that can be modelled, manipulated, and analysed (Church, 2002; Murray, 2003). Given this, a trade-off between realistic representation and problem complexity must be made depending on the needs of the study. This is highlighted below, where a series of location modelling decisions are defined based on the inherent complexity of representing a real-world space.

Non-spatial networks		Realistic, continuous space
Small problem scale		Large problem scale
Single facility	Complexity →	Multiple facilities
Static demand		Variable demand
Single decision variable		Multiple decision variables
Fast/dynamic implementation		Slow, one-off implementation
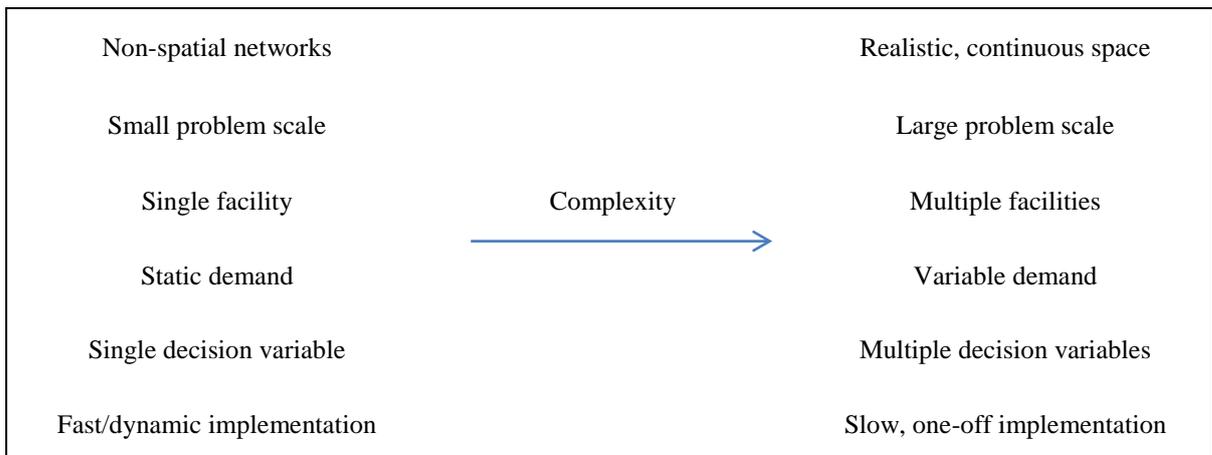
Depending on the requirements of the study, some conditions may be simply defined, leaving room for greater complexity in other areas. For instance, it may be desirable to determine the most appropriate warehouse site from two possible options. Given the requirements of this problem, there is no need to model the facilities in a continuous space, at a large scale, or to choose the best set of multiple facilities. As such, a factor rating system may be appropriate (Ertuğrul, 2011). This approach is not necessarily location orientated, and involves tabulating and assessing each site on a defined set of parameters, applying a score to each element, and then weighting the parameters to determine which site is more suitable. Given that many elements of this approach are simple, complexity can be introduced in one area – in this case involving multiple decision variables.

In other approaches, such as agent-based modelling (which is described further in section 2.1.6), the use of complex aspects such as assigning multiple decision variables to each agent, may mean that simplicity is needed elsewhere (to make the model computationally manageable), such as using a non-spatial network and applying it to a small study area only. For this study, the aim is to 'determine a method for locating a network of rapid chargers to enable extended BEV journeys'. As such, two basic requirements of the model are to: represent a road network (on which BEVs can be assumed to travel), and recommend locations for a set of facilities (which could allow BEVs to recharge). Given this, the next section reviews a series of location models which share one, or both, of these requirements. For road representation most previous models have been built using an Origin-Destination (OD) network. An OD network can provide a representation of roads, and travel, by assigning to a space a set of nodes (origins, destinations, road junctions) and arcs (road sections) (de Dios Ortúzar and Willumsen, 2011). In the context of representing range-limited vehicles, an OD network can be used to determine the distance from one location to another, and can thus help determine the amount of range that is needed for each route. A more in-depth discussion on OD networks and how they can be constructed is provided in section 2.2.

2.1   Facility Location Modelling

Location models are built to assist a planner in their decision process and help them find the best location or set of locations for a facility, given their particular needs and constraints (Hamacher and Drezner, 2002). In this research the aim is to 'determine a method for locating a network of rapid chargers to enable extended BEV journeys'. Based on this, the field of facility location modelling is deemed appropriate for this study. Church (1999) states four main categories in facility location modelling; median, coverage, capacitated and competitive. Since then another form of modelling, flow-based, has become particularly relevant for siting alternative fuel networks – an idea initiated by Hodgson (1990), applied to refuelling networks by Kuby and Lim (2005), and compared to traditional models by Upchurch and Kuby (2010) and Nicholas (2010). The definitions of these five model types vary by how demand is attributed and satisfied, although it should be noted that more complex models can use a combination of the above and often employ more than one objective. Also, as noted by Current et al. (2002), location models are typically designed to solve a particular problem. As such, throughout the literature many models exist which are similar in design, but vary slightly in their objective or application (Hamacher and Drezner, 2002). The following review therefore, identifies models which broadly fit into the five categories mentioned

above and assesses their relevance for the specific challenge of siting recharging points for electric vehicles. A summary of this information is provided in section 2.1.7.

2.1.1 Median models

Median models, like the p-median model initially described by Hakimi (1964), locate a given number of facilities that minimise the total distance, or cost, travelled by customers to facilities. These models are particularly relevant for analyses such as warehouse location, where it is desirable to place a depot that minimises the distance to a set of delivery points. It has also been used in the context of locating, or rather vindicating the location of, gasoline stations (Goodchild and Noronha, 1987) based on the assumption that they are preferred near customers' homes – an idea adopted from (Kitamura and Sperling, 1987). In this case, the median model is used to evaluate the location of gas stations by calculating the distance a set of customers have to travel to refuel from their homes. Since it is assumed that people choose the closest station, it follows that the highest ranking stations are located in areas of high population and where there is less competition.

In their (2011) paper, Fang and Torres use a median-type model, adopting the premise that drivers wish to refuel near their home, to test a design strategy for a possible hydrogen refuelling network. Initially, they place a set of 248 candidate refuelling stations throughout the study area. They are placed based on three criteria: at 10 mile intervals on highways where traffic count is greater than 50,000 vehicles per day, in metropolitan areas with a population density greater than 1,000 people per square mile, and at locations where current hydrogen refuelling exists. The study area, Connecticut in the US, is populated from Census data; and citing computational efficiency they aggregate the initial 2000 Census zones into 275 TAZs (Traffic Analysis Zones). They then apply a median model to minimise the total vehicle miles to hydrogen stations across the region. They report that hydrogen stations tend to be recommended in urban centres (reducing travel times for the majority). This approach thus assumes that people prefer to refuel near their homes – a concept that was initially tested by Kitamura and Sperling (1987), who reported that refuelling near to home was a stated preference of gasoline drivers.

Chen et al. (2013) apply a median type model to determine suitable sites for BEV slow charging. For this, they identify TAZs where parking demand is currently high and combine it with household travel survey data (for which they also have trip purpose information) in Seattle, USA.

They use this data to determine public parking duration times based on instances of consecutive trips (that end and start at the same location), and exclude instances where duration is less than 15 minutes (which they deem an insufficient time to slow charge). To recommend charging sites they implement the median model to minimise the walking distance of BEV drivers from a charging station to their destination. In their test case, they recommended sites for 80 chargers (throughout the 900 TAZs in Seattle) and report that recommended locations are correlated to trip purpose (work and education). They additionally apply a constraint that chargers must be placed at least 1 mile apart (to avoid cannibalisation, which is further described in section 2.1.5). Based on this, their model assigns chargers to locations with the highest parking demand/duration (and where walking distance is minimised). However, this approach assumes that BEV charging demand is directly correlated with parking demand (i.e. a driver always needs to charge whenever they park). As such, it does not account for the battery state (i.e. how many miles range it has left) and whether the driver has genuine recharging need. Additionally, by spacing stations 1 mile apart, they assume that where demand is high, BEV drivers are willing to drive to the next station if needed.

2.1.2 Coverage models

Coverage models aim to maximise the total number of customers served by a facility within a given maximum distance (Church and ReVelle, 1974). This model is useful in emergency service planning where it is desirable to serve a proportion of the neighbourhood within a given time frame. Unlike median models, which 'prefer' to capture customers close to facilities – i.e. minimise the total distance travelled - coverage models are concerned with capturing as many customers as possible, as long as they fall within a facility's range. With coverage models therefore, all customers can be described as either captured or uncaptured, with a demand point on the outskirts of a facility's range as important as one much closer. This type of model might be pertinent if locating slow BEV chargers. For instance, it would be possible to place a charge facility so that the number of BEVs within a vehicle range from the facility is maximised. In this case, the coverage distance is determined by the range of the vehicle. Thus, the facility could be accessible for every BEV within a given range, but not necessarily accessible to those beyond a BEV's range. The complication however, when treating BEVs as demand points is that the vehicles are not always stationary, and thus could have shifting ranges which must be modelled.

Lam et al. (2013) used a coverage type model to devise a network strategy for charging points (the type of which is not mentioned) in Hong Kong, China. They construct their model to maximise the

number of BEVs that can be served within a maximum distance (the vehicle range). Furthermore, they set a condition that means that every charging site is reachable to and from every other site by the range of a BEV. This approach ensures that an even coverage of points is available throughout the island city, and that all journeys to and from a charging site to another are possible. However, the approach ignores the direction of journeys that might take place. Thus, although all journeys can be completed, the deviations involved might be considerable (since it may be necessary to travel from one charging site to another just to recharge, even if it is a long way out of the way for the driver).

Wang and Lin (2009) apply a coverage type model to the island of Taiwan. Their approach mimics many of the range constraints developed in alternative flow-based models (described in section 2.1.5) – but unlike these approaches, where the objective is to maximise the number of trips that could be made, Wang and Lin (2009) set their objective to minimise the installation cost of the network. Their approach then finds the minimum cost of a network which can service 100% of the island (based on several ranges). Although their approach services 100% of their network, this is more likely due to the network composition of their representation of Taiwan. The road network they choose is elliptical – with no cross island routes modelled. This means that routes from most nodes can only go in two directions (either clockwise or anticlockwise). Given this, a facility only need be placed so that nodes in either direction can access it – and so an even spread of facilities, approximately every 100km (or the equivalent range of the BEV) is sufficient to service the network in this case. However, it is unlikely that this approach will work on more complex networks (where route choices are more diverse). They do report that cost can have an impact on the location of facilities – but effectively variation in cost just means that the configuration of recharging sites is shifted round in either a clockwise or anticlockwise direction.

2.1.3 Capacitated models

Capacitated models are often applied to maximal covering models or median models, with the addition of placing a limit on how much service can be supplied from a facility (Current and Storbeck, 1988) (Hamacher and Drezner, 2002). This could describe a limit on the number of customers a facility can serve, or a limit on its production output, i.e. from a factory or warehouse. Typically, capacitated models then follow a median model whereby the objective is to minimise the distance to each facility given a supply limit, or a maximal covering model where the objective is to serve as many 'customers' within a given distance, and an upper limit of service capability

(Toregas et al., 1971). Upchurch et al. (2009) considered capacity at hydrogen refuelling stations by setting a limit on the amount of hydrogen available in each refuelling tank, and applied this constraint to a flow-based model (discussed in section 2.1.5). If demand outweighs capacity at a certain station then additional customers are assigned to the next-best facility in the network. In the context of electric vehicle charging infrastructure, capacity could be determined either by localised network constraints, or temporally defined queueing and dual demand for service. These issues are discussed in detail in section 1.7.2.

2.1.4 Competition models

Competition models consider scenarios where there are several stakeholders competing against one another (Eiselt et al., 1993). Often therefore, the objective is to maximise a share of the market with facilities placed to target an unsupplied region or directly compete with other facilities to acquire some of their customer base (Daskin, 2011). Unlike the capture of customers in median or coverage models, the assignment of customers to a competitive facility is not necessarily exclusive. Customers can be assigned proportionally, either based on where they live (i.e. half of a population zone might go to one facility, and the other half to another) (Tobin and Friesz, 1986), or temporally (i.e. at a certain time of the day, one facility might be more attractive that another), representing the fact that people's choices may vary depending on circumstances (Berman et al., 1995; Huff, 1964). In an immature market, such as a recharging network (OLEV, 2013), direct competition is less of an issue with the priority being to provide for new, rather than existing, portions of the market. Fang and Torres (2011) and Chen et al. (2013), for instance, used this idea to deliberately avoid competition between facilities. However, the awareness of potential future competition might be important, since it is possible that an initial infrastructure provider who starts out with an 'optimal' network could have their market share subsequently eroded by future competitors (Redondo et al., 2008).

2.1.5 Flow based modelling

Most classic location models deal with satisfying demand based at fixed nodes, because in most cases demand is assumed to be resident in one location for a long period of time (Hamacher and Drezner, 2002). This implies that the purpose of a trip from a demand node to a facility is exclusive. However, in some cases this may not always be true. For instance, an ice-cream

salesperson does not always wish to set up at a location which minimises their average distance from a group of customer homes (i.e. fixed demand points), rather, they wish to find a location that is *near* to or *on the way* to a more prominent attraction. This phenomenon can also be observed in the usage of convenience stores or gasoline stations, where passing demand is more relevant than fixed demand (Berman et al., 1995). In his 1990 paper, Hodgson introduced the Flow-Capturing Location Model (FCLM) which was designed to 'capture', or assign to a facility, demand as it passes by as flow in a network. The structure of this network relies on an Origin-Destination matrix. Each Origin represents the starting point for a vehicle on the network, and each OD pair is connected along its shortest path via a series of arcs and nodes, which are usually assumed to be candidate sites. Since each OD pair generates a separate demand, or flow, the route can subsequently be considered captured if a facility is located at any node along its shortest path. The overall objective of the FCLM is to locate a given number of facilities such that the amount of flow captured is maximised. This is achieved by quantifying the passing flow at every node, or candidate facility, in the network and choosing each site in a greedy manner. In effect, this equates to choosing the node with the greatest *through* flow, as opposed to one that lies in, or near to, a population centre (Church et al., 2004). After each site has been chosen, and since demand can be spread across many nodes, the total linear weight from each serviced OD pair must be removed from the whole network. This avoids the problem of double-counting, or cannibalisation, since an OD pair can be fully serviced with just a single facility. Thus, each subsequent facility is chosen from the continually updated set of uncaptured flow, rather than from the initial flow network.

Berman (1997) also adopts a flow-intercepting model and combines it with a more classical fixed node model. This is applicable for cases where the visit to a facility may sometimes be exclusive (i.e. to a supermarket), or occasionally, en-route to another destination. The idea is developed further in Berman and Krass's (1998) paper where they propose a flow-intercepting spatial interaction model that considers demand arising from nodes on the network and connecting paths between nodes. They also incorporate facility attractiveness into the model, an attribute commonly used in competition models. This process applies a weighting to each site based on an attractiveness measure (which could include the convenience of its ancillary services). Customers are therefore assigned proportionally to a facility based on both its desirability and travel distance from a node or path. Additionally, Berman and Krass (1998) assume that customers are prepared to deviate from the shortest path, and use an exponential decay function to express the proportion of customers willing to do so, an idea first utilised in (Berman et al., 1995).

Hodgson (1990) and Berman and Krass (1998) assume that an OD pair's flow is captured by a single facility placed anywhere along the route. Whilst this is acceptable in many situations, it does not always hold true for the case of alternatively-fuelled vehicles (AFVs), which includes BEVs. Since AFVs are range limited, refuelling only once on a journey may not be sufficient. Additionally, the spacing of a refuelling station along a route is important; a facility at the mid-point of a path is more likely to be appropriate than one at either end. Thus, Kuby and Lim (2005) identified the applicability, and limitations, of previous flow capturing models and created the Flow Refuelling Location Model (or FRLM) to specifically consider the refuelling needs of range-limited vehicles. Similar to the approach of Hodgson (1990), the FRLM is designed to optimally place facilities at nodes on an OD network, with each OD pair representing the travel, or flow, of AFVs between two locations. The FRLM does not consider single purpose trips and thus assumes that refuelling is a necessary part of, but not the sole purpose for, long range journeys. Unlike the models discussed above, Kuby and Lim (2005) define an OD pair as representing a round trip. This is relevant because there may not always be a refuelling point at the destination, D. In such cases, it is necessary for the driver to arrive at their destination with at least 50% fuel remaining so that they have sufficient range to return to the last refuelling point which they used on their outward journey. Furthermore, they assume that all vehicles start new journeys with a half tank, thus guaranteeing that an adequate refuelling service is provided in all cases. This is acceptable in circumstances where all refuelling points can be accounted for and incorporated into the model. However, assuming a range that is half of what can be achieved may mean that an overprovision of service is recommended.

The formulation of the FRLM begins by creating a set of all combinations which can refuel each path, given the limited range of the vehicle (which they define algebraically, rather than numerically) and the need to be able to return to the origin and complete a round trip. It is important to note that each route combination (which is defined as routes with sufficient refuelling provision) is made up of a discrete set of fixed nodes, or candidate sites, which must be pre-selected by the model implementer. The process is constrained so that no combination contains more refuelling points than necessary; however it is possible that one path may have many different combination possibilities. On routes where it is necessary to refuel more than once, Kuby and Lim (2005) note the importance of considering the set of facilities that is needed to refuel a route. Where more than one refuelling point is needed, the flow on that route cannot be considered 'captured' until two or more sufficient points have been placed. Therefore, when using a greedy algorithm which places points sequentially, the flow from a long route can only be counted as 'captured' once both points are in place. In the case of a large or complex network, and if every node is considered a candidate site, the number of combinations of facilities for each OD pair could

be large – a problem that is discussed in Capar and Kuby (2011) who devise a heuristic approach to determine the set of all combinations for the FRLM.

An argument for using flow-based modelling rather than fixed-point modelling to capture as many en-route journeys is presented in Upchruch and Kuby's (2010) paper. They compare results between the flow-based FRLM and a fixed demand p-median model (like those described in section 2.1.1) and report that, in the context of providing refuelling services to range-limited vehicles, the FRLM performs better. They measure this as the amount of journeys which can be provisioned given a fixed number of facilities placed. When used in this context, they report that the p-median model places points within large population centres but not along highways to capture intercepting flows. By contrast, since the FRLM allows demand to exist at one of many nodes along a path, it tends to place facilities in more network central locations (rather than population centres). Thus, successful facilities serve flow from many different routes which intercept at common points. However, this process is only carried out as a comparison on a small simulated network, and so it is unclear how this may apply in realistic settings.

In the formulation of the original FRLM an algorithm is implemented which identifies all possible refuelling combinations for an OD pair. Each combination describes a distinct strategy for an AFV to complete the route via one, or more, candidate refuelling sites. Whilst it is possible that several combinations can refuel a single path, the FRLM only considers sites which fall directly on the shortest path. Thus, even if a site is close to the shortest route, it will not be considered. To address this limitation, Kim and Kuby (2012) developed the Deviation Flow Refuelling Location Model (or DFRLM). This model inherits the basic design of the FRLM but accommodates the assumption that drivers can deviate from their shortest path, similar to Berman et al. (1995). They constrain possible deviations by ensuring a path can still be traversed within a vehicle's range, and by setting a maximum deviation threshold to limit the extent of detours. This bound can be varied by the modeller to represent the maximum distance drivers are willing to deviate. However, although all the set of all deviation paths are feasibly considered, Kim and Kuby (2012) limit the DFRLM to only generate one deviation path for each OD pair. This moderates the computational intensity required to generate and store every combination – a factor which would be exacerbated in a complex network. Yet, in doing so many other potential paths and facilities, which could help improve the network performance, are ignored.

Once the set of deviation paths has been generated, Kim and Kuby (2012) apply a decay function to represent the loss in flow likely to occur on a deviation path. Without access to information about the willingness of AFV drivers to deviate from their route to refuel, they propose four different decay functions which they use to assume deviations patterns: linear, exponential, inverse distance, and sigmoid. Each function allows the modeller to adjust the rate at which flow is likely to drop-off in relation to deviation distance. In all cases, this task necessitates the consideration of partial flows – whereby a certain number of drivers are considered willing to deviate to refuel, and a certain number are not. Thus, the partial provisioning of routes – which might not have been serviced at all – extends the flow-capturing capabilities of the DFRLM in comparison to the FRLM.

The models presented in this section have been built on representative networks and either evaluated individually or compared to previous work. However, the models are untested against empirical data which could mean their approaches are not representative of realistic behaviours or are not scalable. The methods that are used to solve these models and/or mathematically validate their approach are presented in section 2.6.

2.1.6 Alternative models

As well as models broadly fitting the categories defined in section 2.1, alternative models have also been produced to develop infrastructure recommendations. Tan and Lin (2014) introduce the idea of stochastic flow into their OD network. This assumes that flow between the same OD pair can vary over time – and thus more realistically represents traffic patterns. However, they base their model on a coverage type problem, which as described in section 2.1.2 does not always necessarily enable feasible trips. This is illustrated in Figure 2-1, which they use to describe their model. For every facility, they construct a 'covering' circle around it, which is equivalent in radius to the range of a vehicle. They then suggest that a route from A to Z1 can be serviced, by a deviation to B – but a route from A to Z2 cannot because a facility does not overlap this route. However, this approach ignores the fact that a vehicle's range reduces as it travels. Thus, by the time the vehicle departing from A reaches the radius of B it may not have enough charge/fuel to actually reach B. Nonetheless, their approach to consider stochastic flows could have validity. To account for these, they initially implement the model once assuming a fixed flow for each route. They then alter the flows based on random scenarios and run the model again and see if the solution set can be improved. This approach therefore, requires that the model can be optimally solved and run many times without computational intractability. In their solution, they test the approach on a small

simple non-spatial network. As such, based on this demonstration it is unclear whether their approach is scalable.

Figure 2-1 - A coverage modelling approach

Data source: Tan and Lin (2014)

Another approach that has been used is agent-based modelling (Sweda and Klabjan, 2011), (El-Banhawy et al., 2012). Similar to modelling stochastic flows, this type of modelling creates 'agents' who travel throughout a network based on a defined set of behaviours (Brown et al., 2005). These agents can be defined to represent individuals or aggregated groups of people. These models can therefore be more detailed that a discrete approach and can reflect human behaviours more realistically at a micro level (Grimm et al., 2006). Sweda and Klabjan (2011) assign groups of agents who behaviours are defined by a set of errands (local trips, work trips, and distant trips). In this approach they assume that BEVs can recharge at home, and choose to do so whenever is convenient. For longer trips BEVs can charge where facilities are available – but in their scenario the network is small (4 boroughs of Chicago) and does not consider the need for range extended journeys. As such, charging facilities (which they load into the model as existing and proposed sites) are assessed based on the inconvenience of making special-purpose trips to recharge. Although they do not provide an evaluation of the current recharging network, it is feasible that this approach could be used to determine which set of potential charging facilities are likely to receive the most usage. However, for a national scale model it is not clear if this approach could be implemented given the computational power that would be needed to model interacting behaviours of potentially thousands of agents – a reason most agent based models have currently been applied to micro level networks (Heppenstall et al., 2011).

El-Banhawy et al. (2012) suggest an agent-based approach that could be used to assess the provision of an existing infrastructure (in the North East of England). They suggest that the agents' behaviours could be modelled based on historic behaviours of BEV drivers collected through travel

survey, and that BEVs could have charging needs at home, at work, or at on-street locations in public (slow charging). However, they do not present any results based on these suggestions, so it is unclear if this approach would be applicable at a larger scale. Given the inherent complexity in the models reviewed in this section – they have currently only been tested on small simulated networks – their applicability to larger networks (as required in the objectives) is unclear. On the subject of using models with stochastic flows for facility location, Berman and Krass (2002) state that the '*problem combines the complications of 'classical' location problems (most of which are known to be NP-complete) with the complicated dynamics of queueing systems – resulting (nearly always) in 'intractable' models.*' (Berman and Krass, 2002, p. 329). Despite this, stochastic or agent-based approaches may have applications for city wide infrastructure provision, or for larger networks if computing power increases or efficient heuristics can be developed.

2.1.7 Summary of model types

The models reviewed in this section vary based on whether demand is assumed fixed (such as with median models), or moving (such as with flow-based or agent-based models). In relation to the aim of this study, an approach is desired which can enable long range BEV journeys where charging is required en-route. As such, median models are not deemed suitable given that trips to recharge are assumed to be exclusive, and that distances are minimised for travel from home/work regardless of direction. For BEV drivers who can charge at home, as discussed in section 1.6.3, it is unlikely that non-time critical charging near their home will be necessary. However, for BEV owners who cannot charge at home, median models could be used to provide service for every day needs. For instance, a rapid charger that is placed in a neighbourhood with many flats (that might not have charging facilities) could provide a lot of service with minimum inconvenience to the drivers. Alternatively, slow chargers could be placed near to customers' homes so that overnight charging could take place. In this scenario, it would be desirable to minimise the walking, or perhaps cycling distance that drivers would have to cover to get home.

Coverage models have also been proposed as a means to provide service for recharging. These assume that a facility has a service buffer, which can ensure that another charger could be reached if it falls within this area. This approach might be suitable in some circumstances – such as a 'circuit' type network like Taiwan – but in most, coverage models ignore the fact that vehicle range can decrease throughout a journey, and that the direction of the nearest charger may be out of someone's way. Flow-based models assume that traffic moves throughout a network, and as such

that routes could be serviced on-the-way to a destination. An awareness of changing vehicle range can also be incorporated to determine where on a route a vehicle needs to charge. As such they provide a means to model service that is applicable to the needs of this study. Advances on this type of model include agent-based and stochastic models, where demand is assumed to be dynamic and can have varying behaviours other than just charging needs. However, as described in section 2.1.6, these models have not yet been tested at a relevant scale due to their inherent complexities. Given this, a flow-based approach is deemed appropriate for the needs of this study, given that it has been shown to be expandable. The following sections therefore describe in more detail the choices made in the construction of these models, with a review of the current gaps and shortcomings, and a proposal for new objectives provided in section 2.7.

2.2   Network Choice

For the purposes of location modelling, network construction can either be non-spatial and/or simulated, or based on realistic geographies (Melo et al., 2009; Taniguchi et al., 2001). If the purpose of the model design is purely theoretical then it may be sufficient to use a fictitious or simulated network. This option was chosen by Hodgson (1990), Kuby and Lim (2005), and Kim and Kuby (2012) – using a simulated 25-node network originally presented by Simchi-Levi and Berman (1988). As described in section 2.1.5, this allowed the authors to simply demonstrate the fundamentals of their model and highlight differences in the outputs based on the design of the network. However, since the network does not attempt to represent the real world, the results produced cannot be used in a practical sense, and thus only theoretical conclusions can be drawn. Furthermore, the design of a model on a simple network may not account for issues which become more pronounced in a complex network. Thus, if the model is later applied to a realistic network, issues of intractability may arise. This was a problem encountered by Kim and Kuby (2012) who initially developed their DFRLM model on a small simulated network. Their theoretical approach allowed the set of all deviation routes to be considered for each OD pair, increasing the locating feasibility in the model (see section 2.1.5). However, when applied to a full scale network they reported that the complete viability of this method was not tractable. Thus, to manage the increased complexity in the realistic network they restricted the model to only choose one deviation path, instead of the full set. This proposal offered a reported improvement over a non-deviating model – in terms of locating options in a comparative modelling setting – but not to the same extent as had been possible in the simplified model. Thus, the use of this type of network allows a model to be developed and tested theoretically, however further developmental work may be required to make it practical in a realistic sense.

Another option for network choice is to build a network based on representative road and geographical data for a particular area. This allows researchers to test their model in a realistic environment, and draw conclusions that may be applicable for infrastructure planning decisions in that region. This approach has been used by Chen et al. (2013), who developed a model to recommend slow-charging locations in Seattle, USA; Lines et al. (2007) who developed a network for Florida to test the FRLM; and Wang and Lin (2009) who demonstrated their model on a representation of the island of Taiwan. As employed by Lines et al. (2007), the first stage of realistic network development is to obtain road, and population, or traffic, data for the geographical region – given that this is a road transport problem. Lines et al. (2007) developed their network for the state of Florida and obtained population data from the 67 administrative counties, and a GIS layer of the highways in the state. From these 67 counties, they disaggregated (split up) those with large urban areas into separate zones and also aggregated (joined together) a few small rural counties together. They then assigned Origin-Destination nodes to each of the zones to coincide with major junctions in the road network (although the precise methodology for how this was achieved is not presented). Their resulting network is presented in Figure 2-2, showing the 74 node and highway network they used to represent Florida. Thanks to the initial layout of the counties, which were all of a fairly even size, and the further aggregations employed, this design created an even spread of OD locations across the regions. Although Lines et al. (2007) did not calculate the aggregation distances for each OD point, the even dispersal of the network ensures that these distances are unlikely to be too high. However, depending on the layout of the input data, an even spread of OD locations, and thus a network with minimal aggregation distances, may not always be immediately available. This issue is explained further in section 2.3.

Aston University

Illustration removed for copyright restrictions

Figure 2-2 - OD network design for Florida

Figure Source: Lines et al. (2007)

As well as choosing the locations for a network of OD points, it is also necessary to assign traffic flow for each route. McNally (2008) describes this process via the widely used four-step model, (initially described in Manheim (1979) and expanded upon in Florian et al. (1988)). The four-step model involves assigning a trip generation rate for each origin location (1), assigning a trip attraction for each destination location (2), defining the modal split of traffic (3), and generating travel flows for each route based on a traffic assignment method (4). This process assigns traffic flows throughout a network by assuming each location has a trip generation and trip attraction rate. From this, traffic flows can be modelled across the network to describe the expected number of people who will travel from A to B. The first two steps, generating trip generation and trip attraction rates, can be derived from known behaviours, travel surveys, or population data (Purvis, 1997; Ruiter and Ben-Akiva, 1978). The modal choice step involves filtering the assigned data travel mode (McNally, 2008). The final step of traffic assignment defines the route choice (and magnitude) between an origin and a destination and throughout the network. The first aspect of this is to define how people choose a route. In most transport applications, it is expected that people take the least-time route (de Dios Ortúzar and Willumsen, 2011), which can be calculated using

Dijkstra's algorithm (Dijkstra, 1959). Other behaviours can also be assumed for people who may take the least-distance path (Zhan and Noon, 1998), the most scenic route (Colenutt, 1969), or the most efficient route in a BEV (Neaimeh et al., 2013). The next choice is to define whether people always take the same route (between the same points) – which is known as all-or-nothing assignment (Spear, 1996), or whether route choice varies between drivers, time of day, or traffic conditions etc (Fisk, 1980). A common dynamic approach is the equilibrium assignment (Sheffi and Powell, 1982). This method attempts to minimise the travel time in the network by assuming that drivers take the least time route, given the set of all other vehicles that may cause congestion and so increase travel time on a route. In facility location, or transport planning, this can help avoid a facility *causing* congestion once it is put in (which may happen with the all-or-nothing assignment). However, for this research problem, most previous authors assume, at least initially, that BEVs are only likely to represent a small portion of the overall traffic and as such will not create their own significant source of congestion (given that in the UK, BEVs represent <1% of passenger vehicles (The Society of Motor Manufacturers and Traders, 2014b)). Finally, it is also necessary to define the proportion of trips from each origin to each other destination. As well as the equilibrium assignment, a typical approach in transportation forecasting is to use a gravity model (Erlander and Stewart, 1990; Evans, 1976; Wills, 1986), which assigns vehicles between an OD pair based on their relative production, attraction, and distance apart. For infrastructure modelling demonstration, this approach has also been used by Lines et al. (2007), Kuby and Lim (2005), Hodgson (1990), and Wang and Lin (2009).

Another approach for traffic assignment can involve the use of empirical traffic count data (Bera and Rao, 2011; Cascetta and Nguyen, 1988; Cascetta and Russo, 1997; Yang et al., 1992). These methods involve assimilating traffic link counts (often recorded via major road cameras or sensors) and assigning the data throughout the network based on either gravity-type models, least squares methods, or Bayesian estimators (Cascetta and Russo, 1997). Although traffic count data can be used to estimate route assignment (if trip generation and attraction rates are known within the four-step method), it is often used as an corroborating technique, where prior assignments have been derived using other methods (Cascetta and Russo, 1997). A more advanced alternative to the four-step model (also known as trip-based models), is the activity based model (Bowman and Ben-Akiva, 2001; Dong et al., 2006). Activity based models, are often constructed in a similar manner to the four-step model, but at a more disaggregate level (often at an individual level rather than zonal level) (Kitamura, 1988). As such, rather than a single trip generation rate, journeys can be modelled to originate based on activity purpose and by time of day, often based on information from travel diaries (Axhausen and Gärling, 1992).

Several of the approaches mentioned in this section and the previous one tested their model on a realism-based OD network – but the addition of this meant that several other factors had to be considered, such as the modelling scale (described in section 2.3), platform choice (described in section 2.4), and candidate site selection (described in section 2.5).

2.3   Modelling Scale

One of the fundamental challenges for location modelling is the problem of digitally representing spatial data (Church, 2002; Murray, 2003). Traditionally, location modelling deals with demand and facility data by representing them as fixed points. Thus, questions such as 'how many households are there within 5km of this retail store?' are easy to answer. For vehicles however, this representation can be more problematic. Because they are mobile, they cannot always be represented by a fixed point. To combat this, models like the FCLM (Hodgson, 1990) and FRLM (Kuby and Lim, 2005) treat demand as moving flow, which can be represented by a single linear feature. This enables the quantification of demand to occur at many points/nodes – rather than just one. Thus, questions such as 'how many vehicles are passing by (through) this retail store?' can be answered. Kim and Kuby (2012) introduced the idea of deviation of travel to the FRLM. This implies that many alternate routes are feasible between two points – meaning the representation of demand as a single linear feature is no longer applicable. Instead, they devise a methodology to choose one alternate deviation path – and thus store demand as two linear features. However, as described in section 2.1.5 and since this approach cannot represent all demand in one feature, computing, storing and analysing every possible route becomes more complex as the size of the network increases. To maintain ease of spatial representation therefore, the only way to store all feasible routes in one feature is to extend the representation of demand to the next spatial level: areas. Figure 2-3 below illustrates how this might be achieved.

A

B
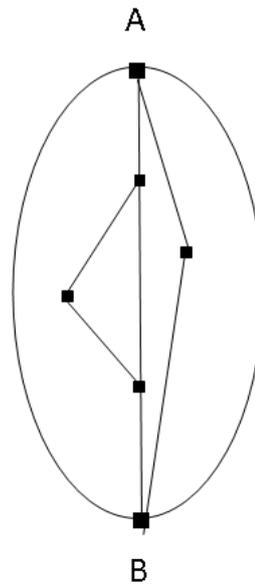
Figure 2-3 - Representing multiple routes with one feature

Typically, areas are used to represent continuous features, such as land cover, where the same attribute is assumed at every internal point. For routing options, however, this would not be the case. Instead, the area could be used as a holding feature which contains underlying demand, observable as lines (any contained road), or points (any network node). Representing a series of individual data points as a single areal unit, is well established in the literature (Church, 2002; Murray, 2003) – notably as a means of storing and representing Census data.

Another factor when transforming the real-world into location modelling, is the problem of spatial aggregation (Current et al., 2002; Murray and Tong, 2007). For features such as Census blocks, this has particular relevance. As described in section 2.1.1 (regarding TAZ generation from Census blocks), a Census unit may consist of several thousand individual households. Thus, answering the question 'how far is it from each household in Census district A to each household in Census district B?' could be computationally exhaustive. If households are therefore represented by a single areal unit, then the question becomes 'how far is Census area A from Census area B?' Although the problem is easier, the ability to answer it is not, since the distance between two areas is multivariate (edge of A to centre of B, centre of A to internal point of B etc.). Thus, to realistically answer the question, it is necessary to aggregate the area into a single point (Church, 2002; Murray, 2003). This could be achieved by aggregating to the geographic centroid. Hence, the answer to the question would be found by determining the distance from the centre of A to the centre of B. By consequence however, an aggregation error would be introduced (Francis et al., 2009). Thus, when considering a location model over a large scale, it is important to note the spatial and aggregation errors that are present and understand their effect on the outcome.

If the aggregated space is exactly circular, like in the p-median problem (Current et al., 2002), then the error can be taken as the radius of the space aggregated. However, for non-regular shapes, determining the aggregation error is problematic. As a result, analysing data which is non-regular in shape, such as Census districts, can be difficult. This is typically referred to as the modifiable areal unit problem (MAUP) (Openshaw, 1983). Occasionally therefore, it is beneficial to reassess the underlying data in complex shapes and, where possible, re-aggregate to a more manageable composition.

For the infrastructure provision models reviewed in section 2.1, aggregation scale has not been explicitly considered. For small networks the unconsidered aggregation error may be negligible, however, as the size of the problem increases the aggregation errors are likely to increase (Francis et al., 2009), meaning that the disparity between what is modelled and what is real also increases. Additionally, in previous infrastructure provision models, demand has only been quantified at fixed points. Given this, Capar and Kuby (2011) report that, in a large network, the number of fixed locations where demand is represented can be large, and that the storage and computation of these combinations could be intractable. As such, representation of this demand could be better managed if stored in a higher spatial level (as described in Figure 2-3). This option is discussed further in section 2.7.2.

2.4   Platform Choice

For location modelling there are two main options regarding the platform, or software choice, in which to construct and solve a model: non-spatial networks and graph structures, and spatial databases, which allow for a geographical representation of data (Hamacher and Drezner, 2002).

Typically, spatial databases are referred to as Geographical Information Systems (GIS), which allow a user to store, edit, analyse, and visualise spatial data (Church, 2002). Thus, data which has been registered to specific locations or areas can be combined with other spatially-referenced data and analysed using a consistent geographical reference system. As such, a GIS provides a platform for the implementation of location models. Unlike non-spatial networks and graph structures, data in a GIS can be represented in the context of its spatial surroundings, as it is embedded in the plane – i.e. a continuous surface. This feature has many advantages, and in the case of this research, allows candidate sites to be considered anywhere – not just at specific points on a network. Data

within a GIS can be stored in two principal formats: raster or vector. A raster model divides a space into a continuous grid of equally sized squares (Maguire, 1991) and typically represents a space which can be defined into binary categories (i.e. suitable candidate site, or not). Vector data on the other hand can represent data as points, lines or areas which are stored as separate features (Church, 2002). This format is particularly relevant for the construction of networks – which are made up from a series of points/nodes (junctions), and lines/arcs (roads). And, although areas are not implicit in networks, they can be used to define the limits of certain sections of road, i.e. a zone can be extended around a road to identify all other roads within a 5 minute drive-time. Once inside a GIS, spatial relationships can then be used to carry out queries, such as 'how far is node A from node B as the crow flies?', or 'how many routes fall within this geographic area?'

2.5   Candidate Site Selection

In facility location science, GIS can be applied to choose the best site, or set of sites (Brandeau and Chiu, 1989). Often, this is done using a top-down approach, excluding candidate options from an initially wide choice. Several layers, with specific criteria, can thus be integrated into a GIS and used to reject inappropriate sites (Church, 2002). For instance, if it is necessary for all sites to be located within 1km of a road, then a GIS road layer can be used to filter out sites which do not match this criterion. This type of analysis represents continuous space methods, where potential sites can be considered anywhere in the study area (Murray and Tong, 2007). Discrete methods, on the other hand, represent cases where a finite set of potential locations is already known. In such cases, the best set of sites is selected, typically based on a scoring strategy, from a restricted input list. When locating facilities for AFV refuelling, decisions should be made depending on whether the model will be used to solve particular instances (i.e. choosing sites from the set of all land space owned by a particular supermarket – discrete), or used to support wider strategic decision-making (continuous). In some situations the approach used depends on the stage at which the model will be implemented. For instance, most of the location models reviewed in previous sections utilise a discrete candidate set (Hodgson, 1990; Kuby and Lim, 2005). This could be the prevalent choice when siting gasoline or hydrogen stations, where locations are particularly restricted (i.e. a site must be found in a location where it is appropriate to submerge, and transport, a flammable and toxic fuel) (Nicholas, 2004; Shinnar, 2003). Given this, by the time a facility location model is run, it is assumed that a degree of 'pre-screening' has already taken place. However, such a process may restrict the later facility model to only choose from a handful of appropriate sites. For the FRLM (Kuby and Lim, 2005), the nodes of the network are initially considered adequate locations for facilities, since a flow can be captured anywhere on the shortest path. However, as pointed out in

Kuby and Lim (2005) and Kuby et al. (2005) this set of candidate sites may not always be sufficient. Consider the route in Figure 2-4.

Figure 2-4 - Refuelling a Network path

Figure 2-4 shows an OD path which is 180km in length. There are three existing nodes on the path a, b and c which are considered candidate sites. Assuming a vehicle has 100km range and sets out from O fully charged, it is clear that it will not be able to reach D via any of the existing nodes on the path. Even if a top-up charge is carried out at a, the vehicle will run out of charge 20km before it reaches b. Thus, if this path is to become viable, the addition of further candidate sites is necessary.

In their (2007) paper, Kuby and Lim seek to address this problem by adding candidate sites onto arcs on the network. They propose three methods for doing so, but note that they are not able to find a finite dominating set of candidate sites, or a method to solve a continuous network location version of the FRLM. Their first method adds candidate sites to the mid-points of path segments and the other two add sites based on the Added Node Dispersion Problem (ANDP) (Kuby et al., 2005). The algorithms they develop identify relevant segments where an additional point is needed. Firstly, their mid-point method adds candidate sites to segments which cannot otherwise be traversed (there and back again) without at least one more refuelling point. Candidate sites are subsequently added into the network at the mid-point of these segments. They also propose minimax and maximin methods such that the longest arcs in the network are minimised (minimax), or the shortest arcs are maximised (maximin). These additions ensure that every route is traversable, but in all cases, the finite dominating set of candidate sites cannot be achieved, meaning alternative placement may yield better results (see Figure 2-5). Furthermore, the procedure of adding new candidate sites requires the modeller to spend time pre-processing their network, possibly without the knowledge of whether or not the additional candidate sites are viable. This is an important consideration for planners since they are restricted by many real-world constraints. For example, land price, planning restrictions or infrastructure availability may disable them from carrying out the initial model suggestions. If this is the case, then the results from the model could be void, since it would not be possible to move sites in the network without re-running the solution.
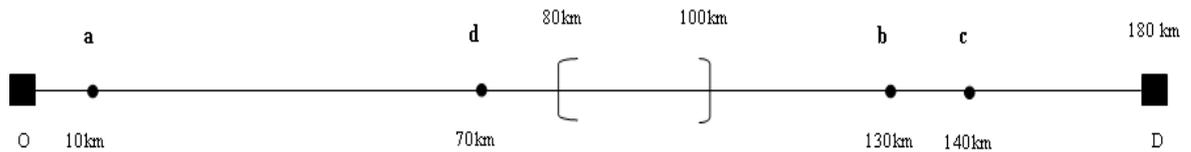
Figure 2-5 - Refuelling a path using a Segment

Figure 2-5 shows an OD path of length 180km where facilities exist at points O and D and candidate sites exist at a, b, c and d. Unlike in Figure 2-4 this route is feasible – via d and b, or d and c. It would not therefore be considered for further added nodes in Kuby and Lim (2007). However, an alternative option is available which allows the route to be traversed via only one facility. This can be achieved if a facility is placed anywhere in the segment from 80 to 100km, since a BEV with a 100km range could reach the 100km limit on the way out and the 80km limit on the way back. Thus, as long as a facility could feasibly be placed anywhere in this range, the infrastructure planner could service the route for half the cost (assuming all site and facility costs are equal). Furthermore, the provision of a range of siting options provides the planner with greater locating flexibility, a key attribute when siting facilities in the real-world.

When considering feasible sites for rapid charging a planner has two main constraints: land availability/cost and access to electricity supply (Arup, 2012). A description of the electrical network constraint is given in section 1.7.2, while the consideration of land availability is considered outside the scope for this research. Given these unknowns therefore, it may be preferential to adopt a continuous candidate approach such that a modeller can visualise universal demand, from which specific sites could be reviewed after suggestion by the model – rather than the other way round.

In this section two types of candidate site selection were considered: discrete, and continuous. The benefits of using a discrete set mean that the size of the problem space can be much smaller, and the number of feasible solutions to the model can, in small networks, be manageable. However, the input of a discrete set relies on the planner having pre-assessed every option. And, since the input candidate set must be larger than the planned number of facilities (Current et al., 2002), the number of sites that must be reviewed could be large. A continuous approach on the other hand, does not necessarily require an input candidate set and as such can be considered a valid approach when precise data about land availability etc. is not known. This option was also considered appropriate for similar location models by Redondo et al. (2008), Redondo et al. (2012), and Brimberg and Drezner (2013), albeit not for flow-capturing purposes.

2.6   Solving Models

Most of the location models discussed in sections 2.1 are deterministic in nature. This implies that the input data is fixed and believed to be accurate and representative of most cases. This process is typically utilised as a way of representing the natural world in a more simplified manner, enabling large-scale location models to be formulated without overly intensive computing power required (see section 2.1.5). In turn, this allows models to be run and have solutions generated in a short time-frame. The following section therefore describes how the location models in section 2.1 are solved and, where applicable, describes the implication of the result. However, it should be cautioned that since location models are typically used as forecasting tools, the ability to validate the outcome is often difficult (Murray, 2003; White et al., 1999) Thus, even if a model provides mathematically optimised results, its affect in practice may not be, due to variations in input data accuracy, unrealistic modelling assumptions, or an inefficient processing time.

As described in section 2.1.5 Hodgson's (1990) Flow-Capturing Location Model is solved by choosing sites in a greedy manner. This implies that the first point chosen corresponds to the location with the highest demand (Benati and Laporte, 1994; Daskin, 2011). Because it is additive in nature, the algorithm only consults the information which it is presented with at time of choice. Thus, by definition, it is not forward thinking, and instead takes the greedy choice at each step. Since Hodgson (1990) defines that a single site can satisfy the flow from a whole route, the resultant captured flow is removed from the model at each stage to avoid the same site, or nearby site, being chosen. The network is then reassessed and the process continues until the required number of facilities has been placed.

For the FRLM (Kuby and Lim, 2005), once the set of combinations has been tabulated, the model attempts to solve the problem so that captured flow is maximised, given a prescribed number of facilities. Each candidate node in the network is effectively assigned the weight from each flow route passing through it. For longer routes, the flow can only be considered captured if all nodes in the combination are open – i.e. serviced. To solve the FRLM, Kuby and Lim (2005) define a mixed-integer linear program (MILP). This process effectively scrolls through every combination of p-facilities and evaluates it against the objective function. Thus, if it is beneficial to service a multi-stop route because it offers greater flow than two individual routes requiring one-stop, then it will do so. Within the framework defined, this solution provides the optimum solution, given that every feasible combination is compared to every other. However, as they note, as the size of the network increases, the number of combinations which must be evaluated also increases. Thus, in

large (i.e. real-world scale) networks this process is considered intractable. As a result, they also test a greedy-adding heuristic which is capable of solving large instances of the problem. Similar to the approach used by Hodgson (1990), facilities are chosen greedily one-by-one and flow is removed after each step. They report that this approach performs sub-optimally in relation to the MILP procedure and cite the fact that unlike the FCLM, the consequence of having multi-stop routes introduces problems. Specifically, because these routes require two or more facilities, the greedy-adding approach struggles to link them up in combination. Indeed, the flow from these routes cannot really be considered in the model until all but one of the required facilities has been placed. At this point, one additional facility will service the route, and thus add to the objective function, but the probability of this happening is not guaranteed. Thus, there is a reliance on initial facilities being placed conveniently, albeit without knowledge, to help enable multi-stop routes.

To evaluate their model, Kim and Kuby (2012) test the DFRLM on the same 25-node network presented in Kuby and Lim (2005). Because the number of paths, and the number of refuelling combinations are stored separately, the problem size of the DFRLM increases dramatically compared to the FRLM. This is especially evident as the vehicle range and maximum deviation distance increase. Thus, they conclude that the DFRLM may be limited to small networks – unless efficient heuristics are developed. However, solving of the DFRLM on the 25-node network produces an improved solution in comparison to the FRLM. In most cases, when placing up to 25 facilities, the DFRLM can service the same amount of flow with one or two fewer facilities. The rate at which flow is captured is dependent on the parameters specified; for instance, there are marked performance improvements if the deviation threshold is increased from 10% of the shortest-path distance to 50%. As in the FRLM, the greater the vehicle range, the faster the rate of flow-capture. In conclusion, their results show how the consideration of deviations – even if small – can improve the flow-capturing gains of a prospective refuelling infrastructure. They also cite the importance of determining driver deviation habits with empirical data.

In their 2010 paper, Lim and Kuby developed several heuristic approaches to solve the FRLM and improve the results of the greedy-adding approach. As such, they propose two methods and compare the results against the greedy-adding technique and the optimal solution (generated by the MILP formulation). Firstly, they implement a greedy-adding with substitution method. This process initially chooses a site greedily, but after each addition attempts to find a better solution via substitution. Specifically, each current site in the solution set is removed individually and replaced with the greedy optimum identified at that point. If the overall objective is improved, the heuristic moves onto the next substitution. This process continues until the user-defined number of

substitutions has been implemented, or if no substitution improves the solution. Furthermore, they generate and implement a genetic algorithm. As the name suggests, this approach is inspired by genetic variation – with the idea being to generate and manipulate a suitable 'gene pool' (Jaramillo et al., 2002; Koyonagi et al., 2006). In application for the FRLM, the genetic algorithm is designed to create an initial population of facilities and then vary this solution through genetic, specifically chromosomal, diversity (Lim and Kuby, 2010). Mutations of the solution are run and cross-overs are implemented until the problem converges towards the optimum. Finally, comparison of all three results is presented based on a 25-node test network and a 302-node (74 OD) network of Florida. These show that the genetic algorithm performs optimally on the test network at every stage of the heuristic. The greedy-adding with substitution also performs optimally, but only for the first half of the solution. Interestingly, the greedy-adding technique, which is sub-optimal to start with, overtakes the substitution method after the 11th facility and remains optimal from then on. This indicates the existence of many alternate-optimums. Generally however, the substitution method is close to optimal for the whole process. The number of substitutions defined (1-4) make little difference, with one substitution appearing sufficient. On the real-world Florida network however, the performance of the genetic algorithm drops in comparison to the greedy approaches. To begin with (i.e. for solution up to p=20), the genetic algorithm underperforms in comparison to the greedy solutions. When more facilities are placed in the network, the genetic algorithm provides a slightly improved solution but at the cost of time. For instance, when p=25 the genetic algorithm captures 0.53% more flow in comparison to the greedy-adding approach, but the time needed to solve is 100 times greater. The greedy substitution methods provide an occasional improvement compared to the greedy only technique – but again the improvement is minor and the time to process is longer (up to 18 times greater).

Thus, in conclusion, it is found that most location models of this type require an efficient heuristic to be able to handle large scale and complex networks. This is likely due to the problem of having to solve a model given multiple combinatorial options – referred to as being NP-hard – meaning that it is often impossible to solve optimally, and a solution can only be approximated with a heuristic (Garey and Johnson, 1979). While several alternative methods provide improvements to the standard greedy-adding technique, it is generally reported that solution time increases exponentially in proportion to the gain in optimality. Furthermore, although the reviewed models have been solved heuristically, and in some cases optimised mathematically, their results have not been validated against real-world usage patterns.

2.7 Development of Modelling Objectives

Based on the findings from previously published work certain shortcomings need to be overcome to help meet the aim. These are discussed in the following section, with proposed modelling objectives derived from the requirement.

2.7.1 Network choice/design

If the model were just to be tested theoretically, it may be adequate to demonstrate its use on a simple simulated network. However, given the need to quantify the results in a realistic setting, and compare them to real-world usage data, it is necessary that the model can be built, computed, and solved on a realistic network. As described in section 2.1 several authors have built, or adopted, a realistic network on which to demonstrate their model. Usually, because of the size of the network they are analysing, the time/data they have available, and the complexity of modelling many routes for the same OD pair (for problems encountered, see section 2.6), modellers in this field have chosen a simple traffic assignment technique which assumes all-or-nothing route choice, and can be computed at a large scale. These options are discussed further in section 3.2.2.

An additional facet of network choice and design is the problem of aggregation. As described by McNally (2008), to be able to represent a geographic area as nodes and arcs in a network, it is necessary to aggregate zones into sources for the origins and destinations. This implies that certain regions or areas are simplified and represented by a single point (usually the centroid). This process can help provide more generalised meanings to the outputs, i.e. rather than saying 1 person travels from house A to office B, an aggregated network could describe 1000 people travelling from town A to town B. However, the scale of this aggregation is linked to the feasibility and efficiency of the resulting model. Since individual routes must be computed for every OD pair, the number of OD locations exponentially affects the amount of computing that is required. Thus, if the aggregation scale is very small, the number of OD pairs that must be generated is very large. Conversely, if the scale is too big, spatial errors are introduced and enhanced (Francis et al., 2009).

In many cases these errors may not be significant to the problem in hand, or may be negligible in the context of the greater distances involved in the network. For a location model concerning limited range vehicles however, aggregation error could cause a problem. Consider Figure 2-6

which shows a 90km route from O to D. Both point O and D represent zones with a radius of 15km, such that a potential journey could commence or finish up to 15km away from O or D. Assuming a BEV has a full range of 100km and if aggregation errors are not considered (as with previous work in this field), then a journey from O to D would be possible without the need for an intermediate charge. In reality however, someone who lives 15km from O would feasibly have to drive 15km first before undertaking the 90km route. In this case, the journey may not be possible without an en-route charge. Thus, if aggregation errors are considered fully, the length of this route could range from 60km – 120km (assuming someone on the edge of area O nearest D travels directly towards D).
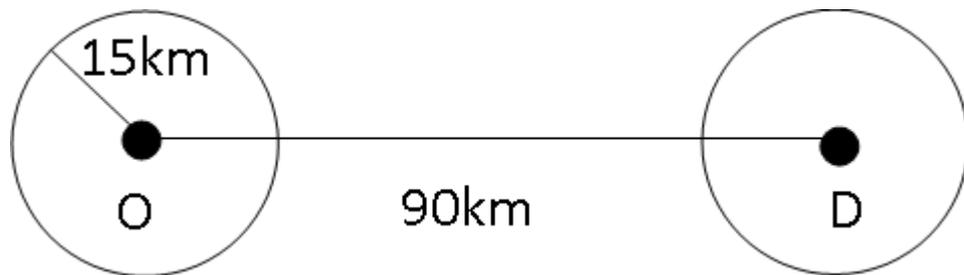
Figure 2-6 - Aggregation error in an OD network

Kuby and Lim (2005) in part account for this by setting the starting range of the vehicle to 50% of its full capability. In practice this means aggregation error will not be a problem unless it is greater than half a vehicle's range – however, applying this concession means that range is represented conservatively meaning for zones with smaller aggregation distances, vehicles will arrive at their origin with an excess of range – which in practice may mean modelling recommendations are overprovisioned. In many other cases (Fang and Torres, 2011; Hodgson, 1990; Wang and Lin, 2009) aggregation scale and error is not accounted for. Given this, the following modelling objective is proposed to account for aggregation error, without overly compromising the feasible range of the vehicle.

Modelling Objective a: Develop a method to represent source/destination areas in the model, such that OD aggregation scale is considered and accounted for in the modelling procedure.

2.7.2 Modelling choice - Representing demand

In previous work, demand is only quantified at fixed points in a network. This means, in a modelling sense, that for every other location in the network (such as arcs and areas) demand is not quantified. As an alternative the use of areas was discussed. Typically, areas are used to represent continuous features, such as land cover, where the same attribute is assumed at every internal point.

For routing options, however, this would not be the case. Instead, the area could be used as a holding feature which contains underlying demand, observable as lines (any contained road), or points (any network node). Representing a series of individual data points as a single areal unit, is well established in the literature (Church, 2002; Murray, 2003) – notably as a means of storing and representing Census data. With a continuous approach to demand evaluation, quantification can be assessed at every point on the network, allowing for enhanced flexibility when comparison across a network is made. This approach thus extends flow-based modelling, which allows demand to be represented along lines (albeit only quantifiable at nodes). As such, based on these needs, the following modelling objective is proposed:

Modelling Objective b: Represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated.

The development of this objective is also relevant in relation to the proposal in the next section.

2.7.3   Candidate site selection

Based on the reported findings in sections 1.4, 1.6.3, and 1.7.3.3 it is likely that a BEV will be able to carry out most of its journeys needs if there is access to a home-based charger. For those who cannot charge at their home location, public charge points may be needed nearby. To assist the process, point-based location models could be used. However, because BEV recharging can take a long time – potentially too long for someone to wait (see section 1.7.1) – it will be necessary to model journey impedance as walking distance, or some other form of transport, similar to Chen et al. (2013). This may allow a BEV owner to park nearby to their home, charge overnight and return to their fully replenished vehicle the next morning. In all other cases, a BEV is restricted by at least its half-range (where no charging opportunity exists at the destination), and at most by its full-range. Given this, a provision of rapid charging sites to enable journeys beyond these ranges is required. As discussed in section 1.7 the locations for these chargers can be constrained by many factors, however, alongside the road network there is still likely to be considerable scope for new locations. Therefore, and based on the fact that detailed land/electricity data is not available, the following objective is proposed to allow the model to be implemented without this prior knowledge.

Modelling Objective c: Create a modelling procedure which relaxes the need for an input candidate set, instead choosing from the continuous plane.

2.7.4 Solving models

Based on the reported findings from section 2.6, it is unlikely that a model which needs to be expandable (need b in section 1.9) and realistic (need d) will have a solution that can be found optimally. Given this, it may be necessary to employ solving heuristics which can approximate the optimum solution. Additionally, given the need to maximise service provision, it may also be desirable to improve the initial solution. Based on this, and the needs in section 1.9, the following objective is proposed:

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale.

For the purposes of this thesis, suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed (which is defined as the fitness function).

2.8   Summary

In this section, a summary of chapter 2 will be given in relation to objective 1 below.

Objective 1: Understand how location modelling has previously been applied for similar purposes, and identify the assumptions and short comings inherent in these methods.

Based on the objective, the field of location modelling – which can provide an efficient means to *'site facilities in some given space'* (ReVelle and Eiselt, 2005) – was identified as an appropriate infrastructure planning tool, and reviewed throughout chapter 2. Of the various types of location model available, flow-based modelling was recognised as a suitable means to represent non-stationary demand (such as vehicles) – since, unlike fixed demand models, flow modelling can quantify and represent demand at several locations throughout a network (which is key to understanding range and habitual journey patterns of BEVs). Application of these models is reliant on Origin Destination networks as these provide an awareness of full route distance, which is important in the context of range limited vehicles. These ideas have been used for several applications, most notably by Kuby and Lim (2005), and Kim and Kuby (2012) who developed ideas from Hodgson (1990) and Berman et al. (1995) to create location models which can recommend sites for alternative fuel infrastructure (applied to a hydrogen refuelling context).

However, models of this type have not previously been validated with empirical usage data or real world behaviours. In addition, based on the identified shortcomings in these published works additional novel requirements for the modelling process are defined in section 2.7. In the next chapter, these objectives are explored given a number of options with possible solutions proposed to meet these requirements.

3 MODEL DESIGN

3.1 Modelling Considerations

In section 1.9, the research aims and objectives were established. The first objective to: 'Understand how location modelling has previously been applied for similar purposes, and identify the assumptions and short comings inherent in these methods' was undertaken and discussed in chapter 2. A summary of this literature was then used to highlight advantages and disadvantages of certain approaches, and formulate specific modelling objectives. In the previous chapter, the modelling objectives were developed as a means to help achieve the aims. In this chapter the designs of the location model are considered and proposed to meet the following objectives:

Modelling Objective a: Develop a method to represent source/destination areas in the model, such that OD aggregation scale is considered and accounted for in the modelling procedure.

Modelling Objective b: Represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated.

Modelling Objective c: Create a modelling procedure which relaxes the need for an input candidate set, instead choosing from the continuous plane.

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

Specifically, these objectives relate to objective 2 in section 1.9, which is:

Objective 2: Develop a model and appropriate methodology to recommend sites for a charging network, and overcome issues with previous work in this area.

Given these objectives, and the considerations discussed in chapters 1 and 2, a framework for the modelling process, with inputs, formulations (which are needed to meet the objectives), and outputs (which can be used to meet the objectives 3 and 4 and are discussed further in chapters 4 and 5) is shown in Figure 3-1. In the next two sections, the inputs into the model are studied with a consideration of available options discussed. The formulation of the model is then proposed in sections 3.4-3.8.
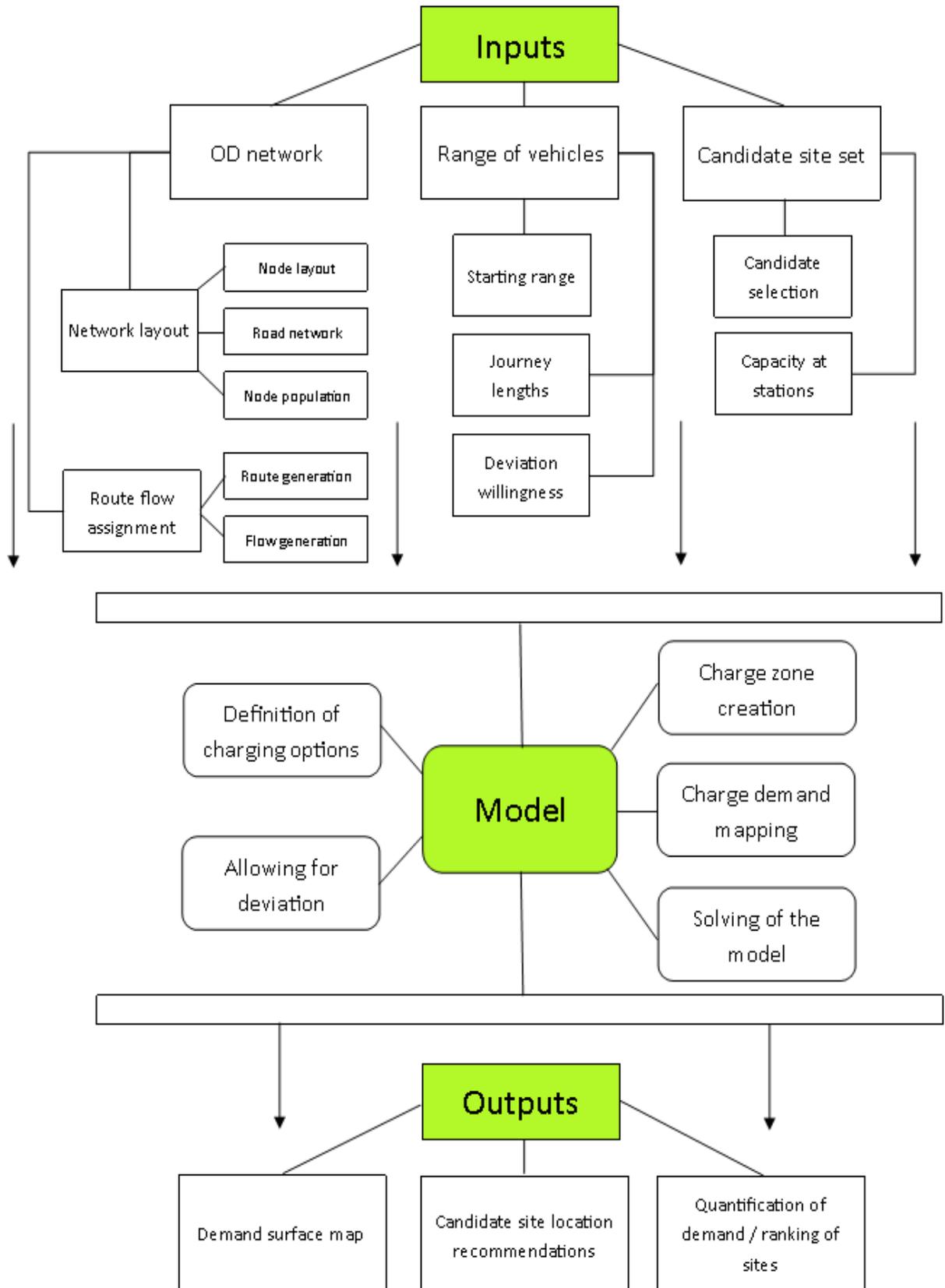
Figure 3-1 - Modelling inputs and design

3.2   Creating an OD network

As shown in Figure 3-1 an OD network is a key input for a location model, providing a platform for formulation and demonstration. As discussed in section 2.1 the use of an Origin-Destination (OD) matrix provides knowledge about how many people are expected to travel throughout a network. For the development of a charging network, it details how many people are travelling from one specific location to another. As such, it provides the means to calculate likely distances for each journey, and in turn infer whether charging facilities are needed for that route or not. Given the purpose of an OD network – to represent travel patterns across a geographic region (Magnanti and Mirchandani, 1993) – there are two main considerations in its design; 1) the representation of the geography in a network form, and 2) the definition of traffic flow throughout the network. These are denoted respectively as 'Network layout' and 'Route flow assignment' in Figure 3-1. The following section therefore describes the options available in the use and design of an OD network, and the consequences these decisions may have on the model performance.

3.2.1   Network layout

Given the options around network layout choice (reviewed in section 2.2), and the proposal given in section 2.7.1, this section explores the development of a network such that zone to node aggregation distances can be considered in an OD network and tailored for use in an electric vehicle infrastructure model. In particular, a method which can meet the following objective is required:

Modelling Objective a: Develop a method to represent source/destination areas in the model, such that OD aggregation scale is considered and accounted for in the modelling procedure.

To demonstrate the following methods the British mainland is used as a case study. The development of this network also allows a comparison with real data – which was collected in the UK (and is presented in chapter 4) – however, it should be noted that the following techniques can be applicable to any region or network design where sufficient data exists.

The British mainland has an area of ~225,000 km^2 and a north to south length of ~1,000km. In the UK, road network data is available from the Ordnance Survey, and is digitised into the Meridian 2 GIS layer (Ordnance Survey, 2012). This network represents the entire physical road network in the area – although dual-carriageway lanes and one-way systems are not modelled. As with Lines

et al. (2007), most of the road network is maintained, except for minor roads below B-road categorisation. This ensures the network maintains overall integrity from the real world and can be used to represent longer journeys which tend toward major routes. The network was loaded into the ArcGIS 10.1 software (ESRI, 2012a) with simplification of the remaining road network carried out to reduce the size of the GIS layers. This involved the straightening of all road segments between two nodes, with the original distance transposed to the new road section. In addition to this, speeds were assigned to each road type (which affects the route flow assignment described in section 3.2.2). This information is presented in Table 3-1.

Table 3-1 - UK road network composition

Road type	Frequency	Total length (kms)	Avg Length (kms)	Speed (kmph)	Speed (mph)
Motorway	1200	3,508	2.92	96	60
A-road (major)	23996	45,370	1.89	60	38
B-road (minor)	10543	28,968	2.75	41	26
Total	35739	77,845	2.18		
Road junctions	22435				

Table 3-1 shows the composition of the road network used in the analysis. The frequency represents the number of edges between junction nodes for each road type. The speed shown represents a typical average speed for each road type (UK Government, 2015). This network is displayed graphically in Figure 3-2.

UK Road Network
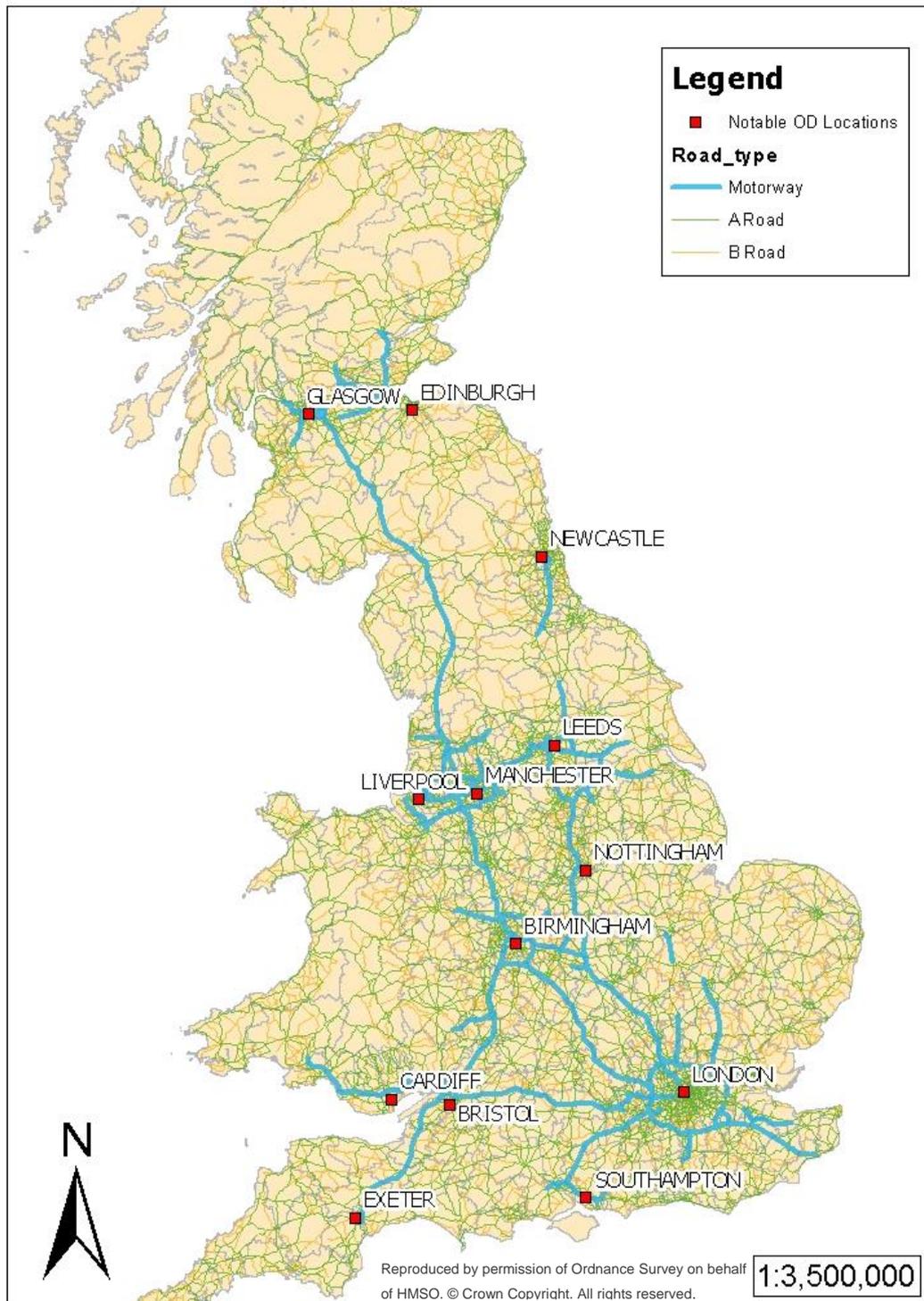
Figure 3-2 - UK road network (Study Area)

Population and boundary data for the region is available from the 2001 UK Census and is published online by the UK Data Service (UK Data Service, 2012). This data is separated into several available aggregation zones – from Output Areas, the smallest representation of population of which there were 218,038 – which are aggregated into districts, of which there were 403, through

to aggregated regions, of which there were 13. As described in section 2.2, the number of OD locations used in the network is exponentially proportional to the number of OD pairs which must be generated between them. Given this, the Census Output Areas (COAs) layer is deemed to too large to form an OD network. On the other hand, the number of regions is too small to be considered since the aggregation distance to the centroid would be excessive. As such, the districts layer is initially used to form the basis of an OD network. These areas represent administrative zones and are generally formed based on population, such that many districts exist in densely populated areas and only a few exist in sparsely populated regions (Martin, 2000). For each zone in the layer, a centroid point is generated in ArcGIS which represents the geographic centre of each area. The same process is also carried out for the COA layer, with both presented in Figure 3-3.

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Figure 3-3 - UK Census data - Districts layer & Output Areas
Data Source: Census data from (UK Data Service, 2012)

The 403 district points shown in Figure 3-3 could represent OD locations from which to build the network. However, the effect of the aggregation from area to point implies that, in a modelling sense, every vehicle assigned to the location is actually resident there too. In fact as is shown in the layout of the COA points, people are spread around the aggregation point and thus, must travel to their designated OD location to implicitly take part in the model. In cases where this distance is large, a proportion of the population will not be accounted for in the model. If the resulting model is constructed based on these populations, then there is likely to be an overestimation of those who

will use the network. To negate this effect, it may be sufficient to place the centroids in the population weighed mean of the area (ESRI, 2015a). This could be achieved using the lower level COA points which more accurately represent where people live, and would improve the solution for the majority – since the centroid would be placed closer to more people. However, many on the region's periphery would still be excluded. In the extreme case, households in large districts, furthest from the centroid, would effectively be locked out of the model because they would be unable to reach their assigned centroid. This phenomenon is exampled in Figure 3-4.

Figure 3-4 - Census district aggregation

Data Source: Census data from (UK Data Service, 2012)

Figure 3-4 shows an area of the study region where differences in aggregation distance could have a large impact. Population in the south of the region is relatively dense and, as a result, is divided into several small district areas. Further to the north however, population is disparate and is thus aggregated into larger districts. For instance, the central district area shown in Figure 3-4 is

~120km in length from north to south (as the crow flies). In the Census aggregation, all COA level data is accumulated and assigned to the district it falls in. As such, COA points are assigned to their designated district even though a closer point may be available. The example above illustrates this. The blue line represents the shortest path route (in journey time and coincidentally, distance) from a COA point on the outskirts of a district to its centroid. The journey distance is 88km, which if undertaken in a BEV with a range of 100km, would leave the vehicle's battery virtually depleted. If the model does not consider aggregation, the assumption is that a journey starts from the Origin point (district centroid) with a full battery. Thus, if the intended destination, or an interim charge point, were more than 12km from the Origin (in the opposite direction) the outlying COA population could, by consequence, be unable to take part in the model. In reality therefore, it makes more sense for the COA point to be assigned to the much closer district point to the south. However, in some situations even this may not be sufficient. For instance, vehicles leaving some COA points in the very north of Scotland (and the north of the study area) would need to travel over 200km to reach their nearest district point – which would inhibit their ability to participate in the model.

One option, to meet the objective, is to calculate the current spread of population (COA points) around the district centroid to determine how far people must travel to reach this point. As described by Martin (1989), this aggregation distance could then be applied by adding a decay function, or a fixed value, to the centroid so that all (or a proportion) of the population can be incorporated into the model. In the context of an infrastructure location model, this could mean calculating the distance which would incorporate 95% of population and adding it to any journeys leaving that point. This possibility is examined for the British mainland, with standard distances calculated for each district and its assigned set of COA points. The results are shown geographically in Figure 3-5 and statistically in Figure 3-6.

Figure 3-5 - Population spread around UK district centroids

Data Source: Census data from (UK Data Service, 2012)

Figure 3-5 shows how distances from a district centroid to the population in that zone vary. For each district the standard distance was calculated in ArcGIS to determine how far a proportion of the population was from the centroid (as the crow flies). The standard distance describes the distance limit for each standard deviation away from the centroid and assumes the population is Normally distributed (ESRI, 2015b). In Figure 3-5, the purple circles represent the area around the

centroid which encapsulate approximately 68% (or 1 standard distance) of the population. The green circles represent 2 standard distances from the mean, and thus represent the distance which covers approximately 95% of the population. Thus, for the Highlands district (the largest circles in the north of the study area), if representing 68% of the population was sufficient, a distance of 65km would have to be added into the model. Similarly, if 95% population representation was required, then an aggregation distance of 130km would need to be added. The spread of these distance limits are also shown in Figure 3-6 (where each column represents the number of districts whose standard distance falls in the distance categories shown). This confirms what is shown in Figure 3-5, that the spread of population around most districts is small. In some cases though, these distances are large – to the extent that added aggregation distances may undermine the feasibility of the model. Despite this, the aggregation distances calculated could, in most cases be added into the OD network formulation so that a proportion of the population is considered. However, since these distances are calculated as the crow flies, it is likely that the actual road distances involved would be more substantial. As such, an alternative method which incorporates the road network and a greater proportion of the population may be more suitable.
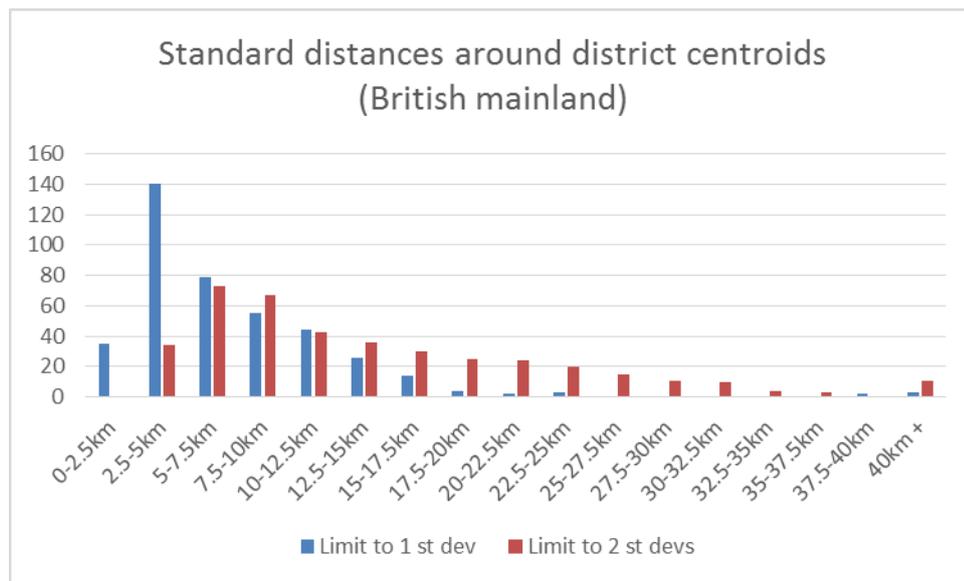
Figure 3-6 - Standard distances around district centroids

Given this problem, an alternative method of reassignment of COA points to more appropriate OD locations is proposed. The premise for reassigning is to choose aggregated OD locations which are geographically weighted, instead of population weighted. This will ensure a greater coverage, increasing the number of points in sparsely populated areas and reducing the number in heavily populated areas. Additionally, the maximum aggregation distance from a COA point to its nearest Origin location can be limited so that all modelled journeys are feasible. For a geographical reassignment, a coverage model like those described in section 2.1.2 is deemed most suitable. This ensures that the distance between COA points and OD locations does not exceed a given maximum

limit, and that sparsely populated areas are realistically represented, whilst dense areas will likely be assigned to fewer OD points – thus reducing the number of locations in the network.

Most conventional coverage models require a set of candidate sites to which the demand points will be assigned; in this case the COA points. Since a general coverage is desired across the UK, a satisfactory solution may be to place a uniform, or random (as in (Brimberg and Drezner, 2013)), grid of points across the country. The spacing of these could correspond to the desired aggregation distance so that no COA point is out of reach. However, because the OD network must be traversable by road, every candidate site must also be accessible by road. As such, a uniform placement of points across a region is unlikely to place points directly onto the network. Even if the candidate locations are subsequently snapped to the network, the preservation of distance integrity may be lost. Preferably therefore, the candidate locations should correspond to points on the network and have context within the road network. The COA locations themselves could be used, but computing a model which assigns a set of 200,000+ points to a corresponding set of 200,000+ would prove too intensive. For these reasons an alternative, ready-made set is chosen which contains a computationally manageable number of points which are already spread across the network in relevant locations. Along with a digitised road network of the UK, the Ordnance Survey also publishes a GIS layer termed 'settlement points' within the Meridian 2 dataset (Ordnance Survey, 2012). There are 1,285 of these points on the British mainland meaning a detailed coverage is provided. As their name suggests, they represent points of settlement and were created for mapping purposes, rather than from an aggregation of Census data collection areas. Thus, they tend to lie at confluences in the road network and be in areas of known population. Figure 3-7 shows a subset of these candidate sites consistent with the area shown in Figure 3-4.

Figure 3-7 - Set of potential candidate sites for OD allocation
Data Source: Census data from (UK Data Service, 2012)

The suggested locations shown in Figure 3-7 represent areas of known population and as such, already provide a good fit for the COA locations. As with the district aggregation shown in Figure 3-4, the number of potential sites is greater in heavily populated areas. However, this set also provides a greater choice of points in the less populated, rural areas. This should enable the majority of COA points to be assigned to a location that is close, both as-the-crow-flies and in network terms.

For the coverage model, as well as the choice of candidate set, a maximal covering distance must be specified (Church and ReVelle, 1974). This distance represents the maximum aggregation distance that is desired in the network. Although, any suitable distance could be chosen based on the range limitations of the vehicles being studied, and the size of the desired network, it may be pertinent to choose an aggregation that is not greater than one quarter of the vehicle range. This is demonstrated in Figure 3-8 which shows a diagram of an aggregation zone. In an origin-destination network, an OD route cannot be generated between the same point (the distance would be 0). Therefore, since journeys within a single OD zone cannot be modelled, it is necessary that they do not require any infrastructure provision. Thus, all return journeys within a zone must be possible without the need for en-route charging. Figure 3-8 shows an OD zone and a feasible return journey from one side to the other. In this case the aggregation distance must be covered four times, twice on the way out and twice on the way back. Therefore, if a vehicle undertakes this journey with a full battery (this assumption is explored further in section 3.3), it can be completed without the need to charge en-route if the aggregation distance equals ¼ the vehicle range. The incorporation of a maximum threshold also minimises the inconvenience encountered by someone whose actual destination is located en-route before the model destination. In such situations, a BEV may need to go beyond its destination so that it can charge and come back again – but in all circumstances, this is accounted for and the inconvenience is limited to a quarter of the vehicle's range.
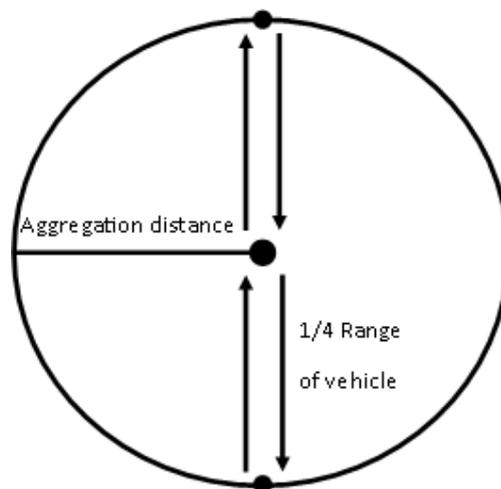
Figure 3-8 - Choosing an aggregation distance to match vehicle range

To demonstrate the use of a coverage model to re-aggregate population data, the British mainland data is used as an example. Firstly, so that actual driving distances can be considered, the road network is loaded into the ArcGIS Network Analyst (ESRI, 2015c). This allows travel distance and time (based on the speeds described in Table 3-1) to be calculated based on the configuration of the road network. Using the Ordnance survey settlement points as a candidate set, a coverage model is

run such that the maximum distance from any COA point to its assigned OD location does not exceed 25km. Based on the explanation above this assumes a vehicle range of 100km or more – however, in general this parameter can be varied by the model implementer depending on their needs. An example of this output is shown in Figure 3-9.

Figure 3-9 - Assignment of COA points to candidate sites
Data Source: Census data from (UK Data Service, 2012)

Figure 3-9 shows a set of results from the reassigning coverage model. COA points have been assigned to the candidate locations which can capture the greatest number of people within a 25km limit. The blue squares represent the chosen OD locations, whilst the red squares represent the points which were rejected. Each green line symbolises the route from a COA to its chosen OD point. Straight lines are used here for visual clarity, although the actual, non-straight, network routes were calculated in the model.

Reconfiguring the layout of an OD network in this way means a greater proportion of the population can reach their OD point within an achievable distance. As a result, 99.75% of the total population is able to participate in the model with at least ¾ of their range available when they reach their nearest OD point (based on a range of 100km). The remaining 0.25% is not assigned to the network because a few COAs are out of reach of the road network used. This is because the minor roads were removed from the network leaving a small percentage of the COAs isolated. In the completed OD network, the population at each OD node is attributed the sum of the populations from each assigned COA location. Additionally, the aggregation distance is set as the distance to the furthest COA point. Figure 3-10 shows the complete set of newly assigned OD locations throughout the study area. A comparison to the original district aggregation is also provided. In both cases, the OD points are symbolically represented in relation to their assigned population.

Figure 3-10 - OD aggregation comparison
Data Source: Census data from (UK Data Service, 2012)

The output from the coverage model produces a more even dispersion of OD locations, compared to the original district layout. Thus, COAs in rural/remote areas are not neglected and are represented by a similar number of OD points as in urban areas. Consequently, urban OD points in this new aggregation have a much greater population weight than remote ones. This transformation

means that the OD network is more geographically weighted, instead of population weighted as with the districts set. Information from the three methods to consider aggregation distance is shown in Table 3-2.

Table 3-2 - Comparison of OD network aggregation methods

OD Location comparison	Number of locations	Max distance to population	Proportion of population included	Advantages	Disadvantages
Census – 1 standard distance	403	65km to reach limit (as the crow flies)	<68%	Aggregation distance small for most OD locations	Large portion of population excluded
Census – 2 standard distances	403	130km to reach limit (as the crow flies)	<95%	Higher proportion of population considered than 1 St dist	High aggregation distances in some cases means further population may be excluded
Re-aggregation using coverage model	300	25km (by road)	99.75%	High proportion of population considered, aggregation distance minimal, smaller set of OD points required	Aggregation distance increased slightly for majority

So that the objective – to develop a method to represent source/destination areas in the model, such that OD aggregation error is considered and accounted for in the modelling procedure – can be met, three methods are proposed in this section. In all cases, it is necessary to have a more disaggregated layer of population so that information about how far people reside from the centroid can be calculated. The first two methods proposed involved maintaining the input data layout, in this case the districts layer used in the UK Census (UK Data Service, 2012). As described by Martin (2000) the layout of this dataset was generated for administrative purposes and population division. As a result, areas with sparse population tend to be assigned to a large district area, and areas where population is dense are assigned small districts. This means, if a single centroid is used to represent the population, the aggregation distance varies considerably throughout the dataset (as shown in Figure 3-6). Attempting to account for this – by adding the distance on to the OD routes – would mean in some cases that a BEV in practice could not reach their OD point, or continue on to the nearest charging point. Thus, it may be possible to add a smaller aggregation distance at the known expense of a portion of the population. The two methods described show how this could be done so that ~ 68% or 95% of the population could be integrated into the model. These techniques mean that the input layer can be preserved; however, the use of standard distances assumes that population is Normally distributed around the centroid – which is not necessarily the case, and that

a trade-off must be made between aggregation distance and the proportion of population that is maintained. An alternative to this involves re-aggregating the input layer such that the aggregation distance can be minimised and the majority of the population is incorporated into the model. Although this involves further work for any model implementer: to find a suitable candidate set, and implement the coverage model; it ensures that the network will be more inclusive and the outputs are likely to be more representative of the input data. Based on these advantages and given the specific layout of the UK Census data, this final option is deemed most appropriate for the case study area. However, the actual choice between these options does not affect the model formulation, and so, in the following sections it is just assumed that an OD network is available.

3.2.2 Route flow assignment

Although a specific objective/novel contribution is not defined for route flow assignment, as described in Figure 3-1 a central input into an OD network is the assignment of 'flow', or demand across a region. Section 3.2.1 described how an OD network can be generated and amended to meet the requirements of the model with this layout representing the geographical study area in network form. The next step involves the generation and distribution of traffic flow across the network to represent the movements and travel patterns of vehicles. Depending on the availability of data, time, and the outputs desired, this could be achieved in several ways (as described in section 2.2). Given this, a variety of options are considered that have been used by previous authors to populate flow across a network.

1) Use an existing OD network with flows already assigned (such as the network available for Scotland produced by (National Records of Scotland Web, 2013))
   a. Advantages: Assignment and population of network has already been carried out – more data/resource may have been used to construct network which might not be available to model implementer.
   b. Disadvantages: The model is restricted to the use of a pre-assigned OD network, meaning that aggregation error may not have been considered and the network cannot be changed. The particulars of traffic assignment technique, relevant for BEVs may not have been considered in a pre-made network.
2) Simulate traffic flows by random (such as the 25-node network produced by Simchi-Levi and Berman (1988)).

   a. Advantages: This is likely to be a fast method which allows for a quick demonstration of modelling procedure. Random flows can be regenerated and the model can be run many times to test for sensitivities.

   b. Disadvantages: The model is not based on realism and so no real decisions/conclusions can be made from the results.

3) Implement a simple traffic assignment model – such as an 'all-or-nothing' gravity model (such as in the Florida network constructed by Lines et al. (2007)).

   a. Advantages: Realism can be added to the demonstration of the model by using population and/or other widely available data. The assignment is likely to be reasonably fast to implement and replicate. Traffic between each OD pair is only assigned to 1 route, so computational intensity can be minimised, especially important if the model will be run at macro level.

   b. Disadvantages: Dynamic/stochastic movement of flow, and traffic levels are not considered. Flow may be over-assigned to certain types of routes based on 'all-or-nothing' implementation, meaning traffic is assumed to travel down similar roads.

4) Implement a complex traffic assignment model – such as dynamic flow models, equilibrium models, route assignment based on alternative method, such as 'most efficient route' like that suggested by Neaimeh et al. (2013), or traffic count conversion models.

   a. Advantages: Assignment can consider variation in flow at times of day/week etc. Equilibrium models assume traffic is aware of network conditions and splits directions of routes to minimise travel time based on traffic levels. Traffic count models consider real historic traffic flow patterns. High level of detail and realism in these types of models provides increased realism in results.

   b. Disadvantages: Splitting of traffic between several routes may increase computing and storage demands. Complications may be introduced regarding the capture of flow – i.e. if flow from one OD pair is split between 3 routes and a charging facility is placed on 1 route, would the other drivers ignore the 'equilibrium' rules and choose the serviced route? Approach suited to more micro level applications such as city wide scenarios where high level of detail is required. Computational intensity could become exhaustive at macro level. From traffic count data – it is not always apparent where vehicles have come from and are going to. Some routes might observe a high traffic count where many people are driving short routes (and hence wouldn't require charges). Other routes may be more likely to observe long-range journeys (but this difference wouldn't be obvious from data).

The choices for route flow assignment within a network suggest that advantages and disadvantages exist for each one. Thus, depending on the needs of the study, and the data that is available, a

certain approach may be deemed more appropriate than another. However, for the purposes of general model design, route flow assignment choice can be considered exogenous to the process. As such, any of the methods discussed could be used to populate a network. For methods not using an 'all-or-nothing' assignment the following processes discussed in this chapter would be more computationally difficult to implement. Additionally, as suggested above, rules about how flow might be split before and after charge placement would have to be defined. Thus, for this reason, the following sections assume an 'all-or-nothing' assignment approach is used (meaning everyone travelling between the same Origin and Destination is assigned to the same route). Alternatives to this approach are discussed in chapter 6.

3.3   Parameter Choice and Assumptions

Section 3.2 described the creation and population of an OD network onto which a location model can be built. The following sections details the methodological design of the model based on the requirements presented in section 1.9, and how this can help achieve the aim. Before this, the input parameters which the model requires, and the assumptions on which it is built, are discussed in this section. Similar to previous location models in this field, each version of the model is discrete (based on the discussions about computational times in 3.2.2), meaning inputs parameters are fixed for each simulation. However, in a general sense, the methodology is developed to be applicable on any OD network, meaning these parameters can be varied depending on the situation and needs of the study. As well as parameters, the model is constructed with several assumptions about BEV use – and so the distinction between variable parameter and fixed assumption will be made clear.

3.3.1   Journey lengths (Vehicle range) – Parameter

As shown in Figure 3-1, one of the main inputs into the model regards the distance range of BEVs and how this is interpreted in the model. In this sense range relates to the assumed journey capabilities of the vehicles modelled in the network. Given this, a single range value must be used to represent these vehicles and to describe which routes can be carried out without charging, and which require provision. As with the FRLM (Kuby and Lim, 2005), and since the value of range must be discrete, it follows that range is a function of distance.

As described in section 1.6, the total range of a vehicle describes how far it can travel with a full battery. However, this value can vary depending on, among other things, vehicle make, ambient temperature, road topology, and driving style. Such that a suitable value can be chosen, an awareness of this variation is needed. Figure 3-11 shows a mix of BEV makes which were sold in the UK in 2014. Statistics from the Department of Transport (2015), who collect vehicle registration details for every vehicle in the UK, are combined with vehicle range calculations from the US Department of Energy (2014) (where data is available from both). The range calculations shown are calculated using the EPA with figures for city, combined, and highway driving (explained in section 1.5). Thus, in effect, these figures already partially account for topological and driving style variations (as dictated by the general type of roads travelled). As demonstrated by Walsh et al. (2010), Neaimeh et al. (2013), and Strickland et al. (2014) greater variations may be observed in some cases (such as aggressive driving style, heavy traffic, or low temperatures), but at a network wide scale such variation may be difficult to model, and may compromise the requirements of the majority. Additionally, based on current sales figures, it is clear the Nissan Leaf (with ranges varying from 74-92 miles) is the most popular BEV in the market. Given this, a choice could be made between covering every range and vehicle type possibility, and representing the majority. Although precise variation in range is unclear in all cases (due to the number of parameters), it could be that this variation follows a Normal distribution (a description of which is given in Steel (1960)), and can also be observed in Figure 1-22. If this is the case, then it is prevalent to choose a value that is slightly conservative (to cover most of the variation), but perhaps not one that covers 100% of variation. This will ensure that the majority of vehicles can arrive at charging points and destinations as modelled, with some, but not most, of their excess capacity remaining. Thus, a range value which incorporates the majority of the market, under the majority of driving conditions should ensure that practical implementation of the modelling results represents expected utilisation.
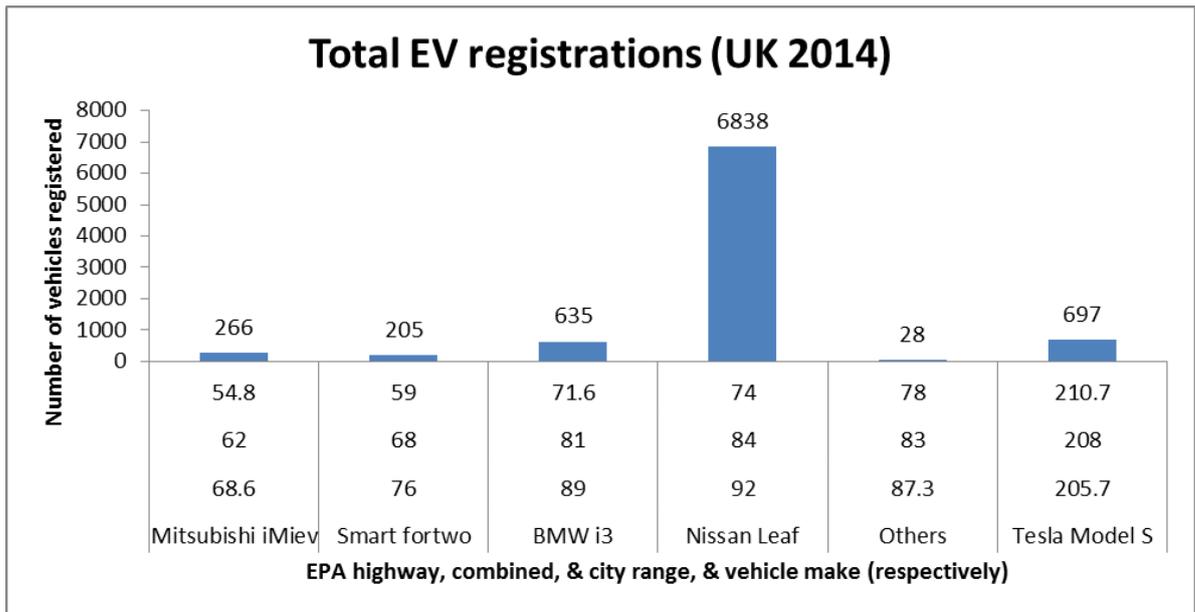
Figure 3-11 - EV registrations in UK with stated ranges

Data Source: Vehicle ranges based on EPA tests from (US Department of Energy, 2014)

Data Source: UK BEV registrations (2015)

Vehicles shown include those available in both data sources. 'Others' vehicles include Chevrolet Spark EV, Fiat 500e, Ford Focus Electric, and Toyota Rav4 EV

Because the value of range can be varied depending on conditions, in the general formulation described in this chapter, this parameter will be referred to as R. In chapters 4 and 5 a demonstration of the model is carried out with a suitable value for R chosen. Discussion on alternative values and the implication on the results is presented in chapter 6.

3.3.2 Starting range – Assumption

The total range describes how far a vehicle can travel starting with a full battery. However, depending on charging availability it may not always be possible to start long journeys with a full range. In the FRLM, Kuby and Lim (2005) set the starting range of hydrogen vehicles to 50% of their full capacity. Implicitly, this ensures that most vehicles can reach their nearest OD point and continue on to refuel from there. However, given that aggregation distance can be considered in this model, it may not be necessary to constrain the starting range to 50%. To determine what figure may be applicable, journeys from the CABLED dataset are studied. Although rapid charging was not available for this cohort, some long journeys were undertaken (which required enough available charge). Figure 3-12 shows all journeys >10 miles from the CABLED BEVs, where state of charge (SoC) data was available. The starting SoC for each journey is shown along the x axis with the number, and distance, for each subsequent journey shown on the y axis. The main observation is that most journeys – regardless of their distance – were started with a >90 SoC %.

This suggests that most people plugged in their BEV whenever slow charging was available, even if they didn't specifically need to charge for following journey requirements. On occasions when people didn't start their journeys with a full, or near full, battery the subsequent journeys weren't that long (and it is likely the drivers anticipated this in advance, given there were no reports of people being stranded mid-journey during the trial). For long journeys, such as those greater than 40 miles, people started with 90% SoC+, 92% of the time (as opposed to 52% for all journey lengths). This suggests that people deliberately plan their charging based on knowledge of their subsequent journeys – a sentiment which is reflected by other BEV users, reported in section 1.4. Given this, an assumption that BEV drivers will start long-range journeys (which require en route charging) with a full, or near full, battery is deemed appropriate for the modelling in this research.
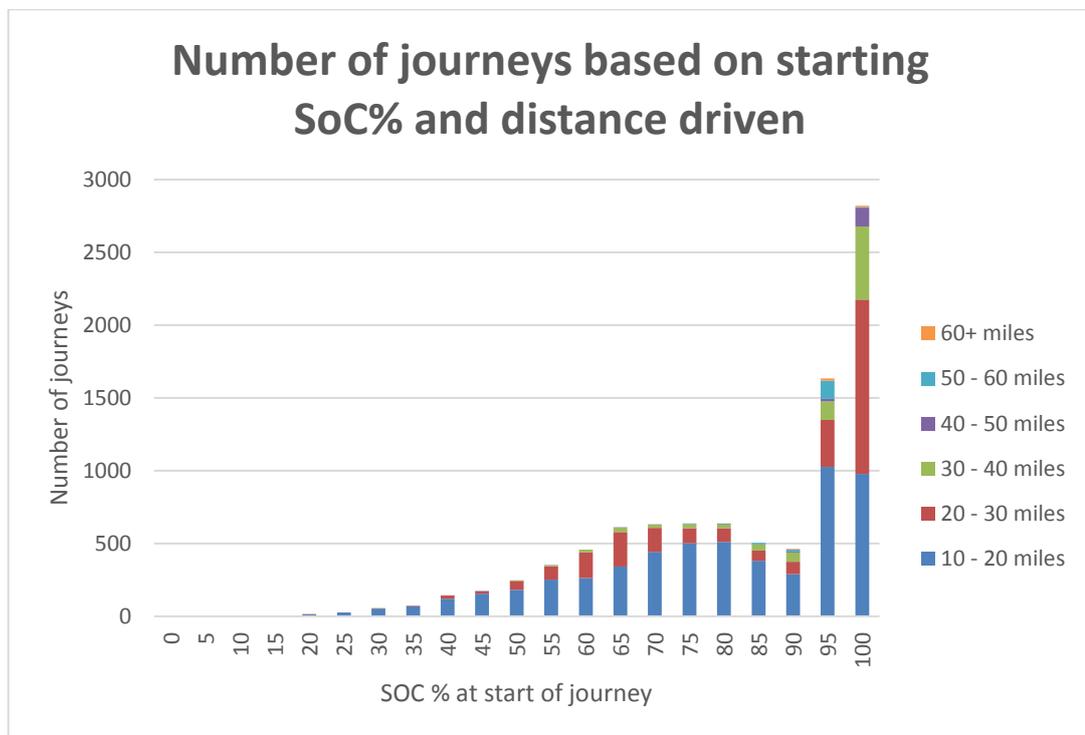
Figure 3-12 - Starting SoC% based on following journey distances

Data Source: CABLED trial – see section 1.4

3.3.3 Charges per trip – Assumption/Parameter

Explored in many transport routing systems is the idea of minimisation, such as in the vehicle routing problem (Toth and Vigo, 2001) where it can be desirable to minimise the number of stops (or time, or distance etc) a fleet of delivery vehicles must make to deliver a number of parcels; or in a transit route network (Zhao and Ubaka, 2004) where the number of transits, or the directness of the route, may be minimised. In reference to charging along a route, similar to delivery vans, a BEV driver may wish to minimise the number of times they need to stop and recharge. For

alternatively fuelled vehicles, this idea is developed by Kuby and Lim (2005) who develop the minimum refuelling route – which removes the possibility of stopping at facilities that are redundant to achieve the route. In a practical sense, if refuelling stations were placed every 5km along a road, a driver could stop at each one and top up with a small amount of fuel. However, from a journey completion point of view, many of these stops could be considered redundant. The opposite of this would be to assume that drivers stop a minimum number of times to refuel. In these cases, redundant stops are not considered, and only those which are core to the completion of the route are utilised. Based on this assumption, the location model can be used to enable as many routes as possible and avoid recommending sites that could be redundant or end up receiving a fraction of anticipated demand.

Additionally, if it is assumed that drivers wish to minimise the number of charges they carry out, it follows that they may avoid journeys where many charges are necessary. For instance, based on the charging time needed to use a rapid charger, a BEV driver may find it inconvenient to carry out long multi-charge journeys (charging 4 times on a route could add at least 2 hours to the journey time). As such, if a BEV owner wishes to undertake such a journey, they may employ another mode of transport. Consider Figure 3-13 below which shows results from the National Travel Survey regarding long-distance trips by mode of transport (Department for Transport UK, 2013f).

Figure 3-13 – Long distance trips based on the National Travel Survey

Data Source: (Department for Transport UK, 2013f)

Results from the National Travel Survey suggest that for very long journeys (150 mile+), people switch from their car to other modes of transport, such as bus, train, or plane. Additionally, the frequency of trips decreases as distance increases. For instance, out of all 50 mile+ trips, only 2.8% are greater than 250 miles, and carried out in a car. When combined with all trips, of which 2.37% of car journeys are greater than 50 miles (Department for Transport UK, 2013f), journeys greater than 250 miles represent ~0.07% of all car trips. As suggested above, for BEV drivers this percentage may be even lower given the added inconvenience of recharging time.

3.3.4 Deviation willingness – Parameter

Explored in Berman et al. (1995) and Kim and Kuby (2012) is the notion of someone's willingness to deviate away from a shortest path in order to reach a service. In both cases, deviation is considered an inconvenience. As such, it follows that a BEV driver would wish to minimise the deviation they must make to reach a charge point. In previous work, this has been applied experimentally; however, following the CABLED trial Berkley (2012) asked the opinions of all BEV drivers in the trial (whose profiles are discussed in section 1.4) regarding their willingness to deviate.

When asked the question '*If you were planning a long journey (beyond your EV's range) and a rapid charge point is not on the direct route, how far would you be willing to deviate off the direct path?*' 14.5% said they would be willing to deviate up to 5 minutes, 32% would be willing to deviate up to 10 minutes and 32% would be willing to deviate up to 15 minutes. The remaining 21.5% said they would not use their BEV for a journey requiring a rapid charge and would instead seek alternative transportation. Because each threshold is inclusive of the previous one, it is assumed that of all the people prepared to deviate; they are all willing to deviate up to at least 5 minutes. It is also assumed that a 5 minute deviation represents the total maximum time spent travelling off the shortest path (not including the charge itself) for each charge needed. Thus, a 5 minute deviation equates to a 2.5 minute one-way detour. In addition, it is assumed that 40% are willing to deviate up to 10 minutes for each charge, and a further 40% are willing to deviate for 15 minutes. As with other parameters, the future application of the method can take into account alternative values or thresholds, based on the data and information available. As such, in section 3.5, deviation is described in the general case, where the limiting factors are the driver's tolerance to deviate, and also the remaining charge needed to complete the route. As a case study example, the above deviation limits are applied in chapters 4 and 5 (with simulations assuming both minimum and maximum deviation tolerance). Furthermore, since route measurements are calculated in kilometres, the limits are also converted to this unit – assuming an average deviating speed of 60 kmph (which is equivalent to the modelled speed for A-roads). Thus, in the case study examples, a 5 minute deviation equates to a one-way deviation distance of 2.5km.

3.3.5 Candidate site selection – Parameter

Described in section 2.7.3 is the requirement to allow siting of charging stations throughout the plane. The formulation of this idea is detailed in section 3.7 with charging demand being

quantifiable and serviceable across an area. As such, it is feasible to quantify demand at any location in the study area. However, as is later discussed in section 3.7, it is prevalent to represent these areas with a grid to make the computations more manageable. Because this process is similar to rasterisation, the main condition dictates that demand is constant across each individual cell. As such, when choosing the size of the grid squares it is important that demand and distance variations within each cell can be considered negligible. On the other hand, if the grid squares are very small, the amount of processing required to quantify demand at each one is intensified (the number of cells in a grid assuming a size of 500*500m is four times greater than those with a size of 1km*1km). Thus, this decision must be taken depending on the vehicle range (i.e. is the grid size negligible compared to the vehicle range?), and the processing power available.

Because a grid can be applied across a continuous area, the grid squares do not necessarily have to represent specific candidate sites. However, in some applications it may be desirable to reduce the size of the grid based on a set of criteria. In chapter 4, the model is compared directly to a set of existing locations. As such, it is only necessary to evaluate the model at these locations, so in such situations the demand grid can be reduced to reflect just these points. In chapter 5 however, the model is run assuming only one candidate criteria: that the locations are on, or just off, the road network. This is likely to always be a criteria as the sites must be reachable by car, meaning demand cannot exist away from roads. There is freedom therefore to run the model with a fully continuous candidate grid (the road network) or with a specific set of sites, or any combination in-between.

3.3.6 Capacity at charging stations – Parameter

Capacity, in an infrastructure sense, refers to a set of constraints which may limit a facility's ability to provide service (Daskin, 2011) – in this case, the number of BEVs that could charge in a locale. In previous infrastructure modelling, capacity has been defined as a function of the available amount of fuel on site. Upchurch et al. (2009) therefore set a constraining element into their model which limited the number of vehicles that could be served at one site, based on the amount of fuel contained within a hydrogen tank. For electric vehicles, the analogous is the amount of available electrical capacity and the impact this might have on the wider network. As discussed in section 1.7.2, the use of charging is unlikely to affect overall electricity Network capacity until BEVs reach a higher level of penetration (and this assumes that all charging is carried out in an uncontrolled manner). However, localised constraints may have to be applied.

As a general means of handling this in this location model – as highlighted above, it is unlikely that overall Network constraints and/or reinforcement will be needed. Capacity therefore, could be set based on specific spare transformer capacity at each location. Coupled to this is an appreciation of the variation in travel peaks which will have consequences on service provision. As a way of handling this practically, several charging sites within a locale may be able to handle capacity based on Network constraints and temporal variation. For the location model, this can be handled by inputting a fixed service capability to each site. The solving of the location model is described methodologically in section 3.8 and empirically in 5.3. Thus, based on the site recommendation given, the amount of flow removed from the model could be set to the capacity limit. However, given that in-depth localised Network information is not available – in the empirical example in section 5.3, capacity constraints are not implemented into the model, but could form future work as discussed in chapter 6.

3.4   Defining a Charging Zone

Modelling Objective c: Create a modelling procedure which relaxes the need for an input candidate set, instead choosing from the continuous plane.

As described in sections 2.5 and 2.7.3, previous location models in this field have assumed that a candidate set is already available and can be inputted into the model. Based on this, demand is quantified at each specific candidate site rather than across the network. If a candidate set is not provided, then it is necessary to define everywhere in the network where demand could arise. Given this, as well as an understanding of where traffic is flowing (generated by the assignment of flow – as in section 3.2.2), it is important to understand how many charging facilities may be needed along each route, and where these could be placed to enable the journey. This idea is explored in Figure 3-14 which gives an example journey between two points O and D:

O   D

0   120
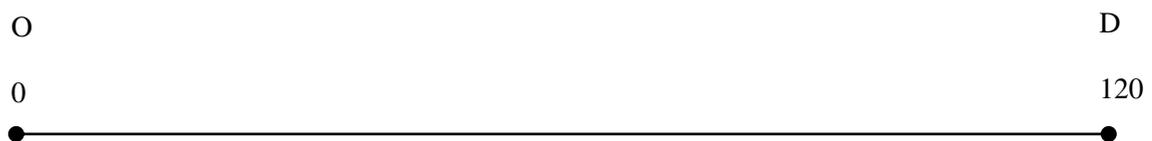
Figure 3-14 - An OD route requiring 1 rapid charge

Assume a vehicle with Range (R=100) sets off from O with 100% charge towards a point D 120 away. Clearly, without a charge facility (CF) en-route the vehicle will not be able to reach the

destination, D. It is therefore important to firstly define how many CFs are needed to satisfy the route and then to find the range of possible locations for each CF. As illustrated in Kuby and Lim (2005) it is sometimes important to consider the round trip as well – since, if a CF at the destination does not exist, the requirements of the return trip may not be symmetrical to those on the way out. For instance, if a charge facility A was placed at 30 distance units along the route, a BEV would be able to leave O, charge en-route and arrive at D successfully. However, it would not be possible to return to O because its battery would be near empty at D and the remaining range would not be sufficient for a return to A. Conversely, if a CF were placed at 80 distance units, the vehicle could charge at this point and arrive at D (40 units from the CF) with 60% capacity remaining. This would be sufficient to allow for a return to the CF and then back to O. Because of this phenomenon, routes where a destination charger does not exist must be treated slightly differently to those where one does exist.

Number of CFs needed for routes with a destination charger

If a destination charger exists (slow or otherwise), it means that a vehicle can arrive at D with a near empty battery and recharge there. It is then assumed that a full charge will be carried out and they can set off again with 100% capacity. In effect, if a destination charger exists, the need to consider the round trip is made redundant. This therefore, provides greater possibility when placing a rapid charge point along the route, since it can be placed anywhere within a full range from the destination. Additionally, since candidate sites are not required, complete locating freedom is possible within a set of limits along the route. In Figure 3-15 an upper bound limit, for a CF which can satisfy the entire route, exists at 100 (since the vehicle can reach this point from O but go no further without a charge). Similarly, the lower bound limit can be defined as being one full range backward from D. A CF therefore, could be placed anywhere along the route between 20 and 100, allowing a vehicle to rapidly charge once for each leg of the journey.
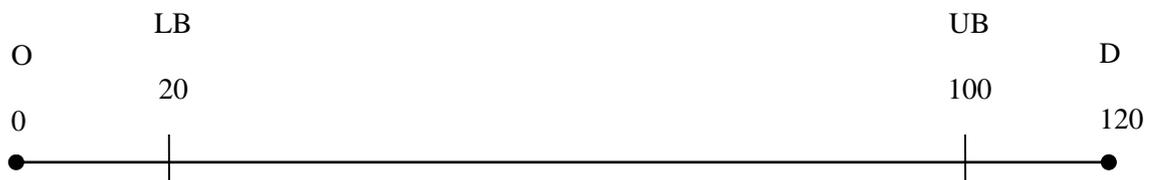
Figure 3-15 - The Charge Zone limits for a route with a destination charger

To calculate the number of CFs needed for any route, the following formula can be derived:

Number of CFs = ceiling ((d – R) / R)

where:

d   =   distance of route

R   =   range of vehicle

ceiling =   rounds up to the nearest integer

$d - R$ effectively calculates the position of the lower bound from point D, i.e. it is possible to travel from the lower bound to D and then fully recharge there. If this position is within one range of the vehicle, then no additional charges are needed before the lower bound is reached. On longer journeys it may be necessary to charge before reaching the destination's lower bound. The number of CFs needed to get to the lower bound is a function of the range, since it is assumed that the battery is fully replenished at each CF. Thus, the number of CFs needed for a route is calculated by defining the need for a CF at the lower bound, plus the number of CFs needed to get to the lower bound. For short journeys where $d < R$, $d - R$ is < 0 and thus no charge points are needed.

Number of CPs needed for routes without a destination charger

To be able to complete the return trip, it is necessary for the vehicle to have at least 50% charge when arriving at D (Kuby and Lim, 2005). This ensures that the vehicle can return to the previous CF from D within one range and hence return to O. Because of this necessity, the position of the lower bound is defined as $d - (R/2)$ meaning it must be placed within a ½ range of the destination. Thus from the example shown in Figure 3-15 the lower bound limit is set at 70 (50 away from D) and the upper bound limit remains at 100.

The formula for finding the number of CFs can therefore be amended to allow for situations with no destination charger:

Number of CFs = ceiling (((d – (R/2)) / R)

where:

d   =   distance of route

R   =   range of vehicle

ceiling =   rounds up to the nearest integer

Defining the Lower and Upper Bounds of a Charging Zone

If one CF is needed for a route, the upper bound constitutes the distance furthest from the Origin where a CF can be placed to enable the route. If it is assumed that a BEV leaves the origin with full capacity, R, then the position of the upper bound can be defined as:

Upper Bound (UB) = R

where

R is the range of the vehicle

Similarly, if a charger exists at the Destination (D), then the lower bound equates to the furthest position away from D along the shortest path which can be reached within the range of the vehicle. Thus:

Lower Bound (LB) = d – R

where

d is the distance from O to D and

R is the range of the vehicle

For journeys which require more than one charge a UB and LB can be defined for each charging zone.

Since the Upper Bound defines the furthest point reachable from the Origin on the way out, subsequent UBs can be defined as an additional iteration of R from the last UB.

Hence:

$UB_i = (R * i)$

where

R is the range of the vehicle and

i is the CZ number in the sequence (i.e. for the 2nd CZ, i would be set to 2)

Similarly, subsequent LBs can be defined as an iteration of R from a previous LB in the sequence, such that:

$LB_i = d – (R * ((CF\# + 1) – i))$

where

d is the distance from O to D,

R is the range of the vehicle,

i is the CZ number in the sequence and

CF# is the total number of CFs needed for that route
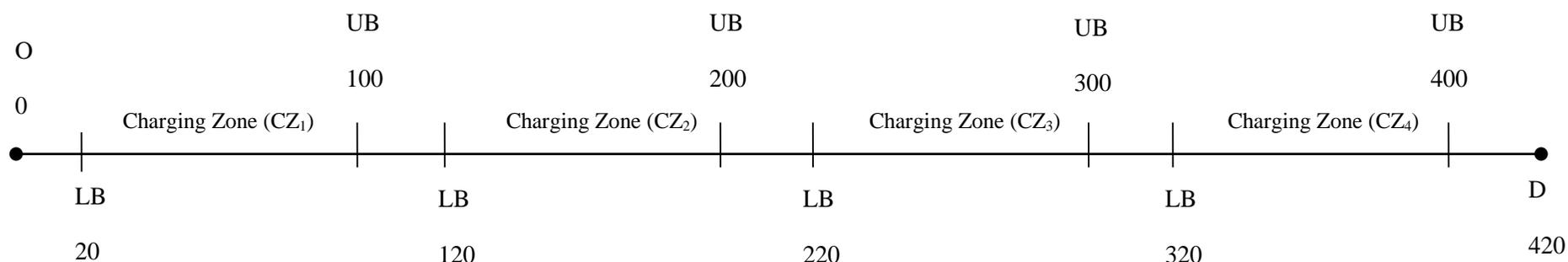
Figure 3-16 - Example of a route requiring multiple charge facilities

Figure 3-16 displays the extent of charging zones on a long route which requires multiple charges. The Destination (D) is 420 away from O and the vehicle range is assumed to be 100. This solution requires 1 CF to be placed in each CZ so the journey from O to D can be completed. There are many different ways CPs can be placed to allow this journey to take place; however there is not complete freedom when it comes to locating the CFs within each CZ. For instance if a CF is placed at the LB of CZ$_1$ (i.e. 20), then every other CF also needs to be placed at the LB of each CZ, since the range of the vehicle would not allow travel from 20 to the next UB (i.e. 200). Thus, it is necessary to dynamically adapt the size of each CZ after each CF has been placed. Effectively, once a CF has been placed, its location represents a lower and upper bound such that subsequent LBs and UBs must be within R of the this point. Alternatively, the CZs could be narrowed so that infinite locating freedom is possible within each individual CZ. However, this process would narrow the width of the charging zones by a factor of CF# (total number of CFs required) and would deny the model a lot of its initial locating freedom.

<u>Defining Lower and Upper Bounds for Routes with no Destination Charger</u>

If no destination charger is present then it is necessary to restrict the position of the lower bounds such that the LB of the last CZ is positioned ½ R from D. Since it is assumed that full charges are carried out at every CF, the position of subsequent LBs can be placed in multiples of R away from the last LB.

Thus, if there is no destination charger the position of each LB is defined by:

$$\textbf{LB}_\textbf{i} \ = \textbf{d} - (\textbf{R} * (\ (\textbf{CF\#} + \textbf{½}) - \textbf{i}) \ )$$

where

d is the distance from O to D,

R is the range of the vehicle,

i is the CZ number in the sequence and

CF# is the total number of CFs needed for that route

It should be noted that this method constructs CZs such that the total number of CFs needed for each route is minimised. However, the positioning of the CFs may enable the round trip to be completed with one less instance of charging. For instance, if ½ R < d < R (where d is the route distance and R is the vehicle range) then feasibly the round trip could be driven with a CF visited just once (rather than once on the way out and once on the way back at the same location). In this instance, if the CF were placed just before D, then it would be possible to drive beyond the CF and reach D without needing to charge. Since d > ½ R, it would not be possible to return to O without a charge, and so, one must be carried out before the battery is depleted. Whilst this phenomenon might slightly aid the driver, being able to charge an odd amount of times on a round trip is not considered in the model, since doing so would restrict the locating possibilities for CFs. However, if ½ R < d < R then the positioning of the UB is restricted to the location of D. For instance, if the distance from O to D is 70 and the vehicle has 100 range, then the UB is set to 70 rather than 100. This avoids the situation of a CF being placed beyond the destination.

Therefore, the positioning of UBs for routes without a destination charger can be defined as:

If $(R * i) - ½ < d < (R * i)$

and if $i = CF\#$

then $\textbf{UB}_\textbf{i} = \textbf{d}$

otherwise   **UB$_i$ = (R * i)**

where

d is the distance from O to D,

R is the range of the vehicle,

i is the CZ number in the sequence and

CF# is the total number of CFs needed for that route

This section defined how charging demand along routes can be constructed into segments. These segments represent potential sections of a route, where if charging provision was located, could enable a long-range journey in a BEV. Given this, a specific set of candidate sites (see modelling objective b) may not be needed – as potential *segments* where facilities could be placed are now known. The formulae provided allow the creation of demand segments for any OD network based on an input vehicle range. Currently however, this formulation assumes charging demand can only be satisfied on the shortest path. As such, an extension of these formulae is provided in the next section to allow for the possibility of deviation from the shortest path.

3.5   Adding Allowable Deviations to a Route

Considering deviation increases the realism of the model and more closely simulates the possibility of drivers leaving the shortest path in order to charge (Kim and Kuby, 2012). Thus, a method which allows for this and extends the formulations of the last section is sought. This objective is described in section 2.7 as:

Modelling Objective b: Represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated.

In the previous section a definition for charging segments along routes was established. These define where, on the shortest path, charging demand may exist so that journeys can be completed with a minimum number of charges. To be able to expand this so that vehicles can deviate away from the shortest path, it is necessary to understand their remaining range at each point along a route. With this considered, if a BEV departs from the shortest path to access a CF it must be able to do so without running out of charge. Similarly, having reached the CF and replenished its range there, the BEV must be able to return to the shortest path and drive to the next facility (or

destination) within a full range. Thus, if deviations are to be implemented, range limits must be extended in two dimensions across the plane. Consider the diagram in Figure 3-17.
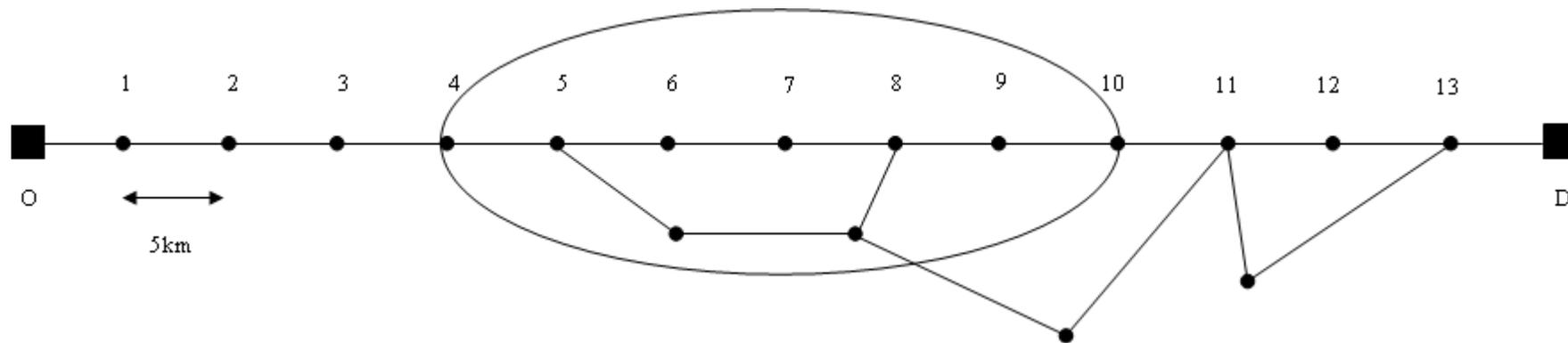
Figure 3-17 - Defining deviation possibilities for a route

Figure 3-17 represents a route from O to D. The BEV range is 100 and the journey distance is 140. A slow charger is present at point D. As proposed in section 3.4, one CF is sufficient if it is placed within the limits between 40 and 100. After setting off from point O, a BEV's range diminishes until it reaches 0 – coincident with the upper bound limit (at point 10). Similarly, on the return journey, the BEV departs D with a full battery and its remaining range diminishes until it reaches the lower bound (at point 4). Thus, if a deviation is to be taken, sufficient remaining capacity must be available at the point the vehicle leaves the shortest path. At point 7, on both legs of the journey, the BEV's remaining range is 30. Thus, the BEV could potentially leave the route at this point and deviate up to 30 away from the shortest path. If it is to do so, a CF must be reached within this limit with a full charge carried out. This would allow the BEV to return back to the shortest path (if needs be) and carry on to its destination with enough range remaining.

A route where a destination charger exists is considered symmetrical; since the range constraints on the way out are mirrored on the way back. Thus, departing from point 7 which is the midpoint of the route, allows for the greatest deviation in both directions. Consequently, any other deviation from the shortest path can be measured as a deviation from the midpoint, minus the distance between these points. For instance, point 8 is 10 away from point 7 and so, the allowable deviation from point 8 is 20 (30 – 10). Because of this effect, the limit of deviation around the shortest path can be constructed as a circle with radius R – (d/2) around the midpoint. Thus, the circle (not to scale) shown in Figure 3-17 contains the set of location possibilities where a CF could be placed. Additionally, the construction of the circle, or charging zone, can be forced to adhere to network topology such that it contains all areas within an allowable driving distance from the midpoint. If this is done then every node and road edge within the charging zone can be considered a candidate site.
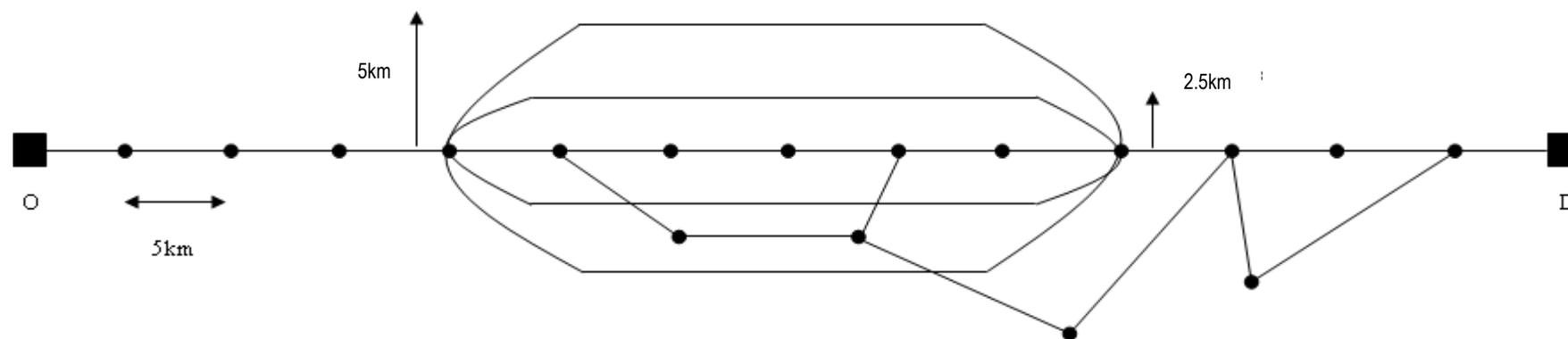
Figure 3-18 - A route with deviation limits applied

If a deviation threshold is set, it is necessary to limit the charging zone such that it does not exceed this distance (or time) from the shortest path. Consider Figure 3-18, which shows how a deviation threshold would limit the construction of a charging zone. Similar to Figure 3-17 the zone intersects the lower and upper bounds – a constraint determined by the vehicle range. Around the midpoint, a BEV can deviate in any direction up to their deviation willingness limit. Indeed, this limit acts as the main constraint until the time to the upper or lower bound is less than the limit. For instance, if it is assumed that a driving is willing to deviate 5km in one direction (see section 3.3 for a further discussion on such assumptions), then the range of the vehicle will only affect its ability to deviate

when the upper or lower bound is within this distance along the shortest path. Therefore, to construct the charging zone it is necessary to extend a buffer around the central portion of the shortest path by a radius of the deviation limit. For example, in Figure 3-18 the shortest path zone extends from the lower bound at 40 to the upper bound at 100. If a deviation limit of 5km is set (i.e. total deviation of 10km), a buffer of radius 5km should be extended around the portion of the route from 45 to 95. This would result in a charging zone which intersects the shortest path at the lower and upper bounds and does not allow deviation beyond a distance of 5km.

3.6   Charge Zone Creation

In the previous section, general formulae were presented to allow demand to be represented across an area such that a demand surface can be generated. In this section, information on how these processes can be applied in a modelling sense is given, with a series of demonstration examples shown. To apply demand across the network, as described in sections 3.4 and 3.5 it is necessary to define the demand limits for each route in the network. Using the input of all feasible OD pairs it is therefore necessary to create the charging zone(s) for each route which contains the set of all potential facility locations. An example of how these limits are applied practically, assuming a value of R of 100km, is shown in Table 3-3.

Table 3-3 - Charging Zone measures applied to OD routes

Route ID	Route Length (metres)	Destination CF?	#CFs Needed	Origin Aggregation	Destination Aggregation	Lower Bound 1	Upper Bound 1	Deviation Limit	Lower Measure 1	Upper Measure 1
1	55,000	No	1	22,000	23,500	28,500	55,000	5,000	33,500	50,000
2	102,514	No	1	16,000	21,954	74,468	84,000	4,766	79,234	79,234
3	108,735	No	2	20,500	24,374	0	79,500	5,000	5,000	74,500
4	112,562	No	2	23,450	24,261	0	76,550	5,000	5,000	71,550
5	162,671	No	2	22,376	23,054	35,724	77,624	5,000	40,724	72,624
6	223,217	Yes	2	24,200	24,704	47,921	75,800	5,000	52,921	70,800
7	251,291	No	3	21,843	24,673	25,963	78,157	5,000	30,963	73,157
8	199,301	Yes	2	22,013	21,639	20,940	77,987	5,000	25,940	72,987
9	249,372	No	3	19,000	23,647	23,019	81,000	5,000	28,019	76,000
10	188,528	Yes	2	20,000	20,701	9,228	80,000	5,000	14,228	75,000

Using the output from the list of OD routes, which contains an identification attribute and the route length, the limits for each CZ can be calculated in a spreadsheet (or similar). Using the formulae presented in section 3.5, the number of CFs needed for each route is calculated. As an addition to this formula, the aggregation distances from both the Origin and Destination are taken into account and effectively added to the journey length. As described in section 3.2.1 this ensures that the majority of the population are considered in the model. To ascertain the location of the charging zones, the lower and upper bound is found for each route. Due to the aggregation effect, the feasible bounds could exceed the actual journey length. For example, a vehicle departing on route ID 1 would arrive at the Origin with at least 78km of range left. It could then reach the model destination with at least 23km of range intact. Thus, it would be possible to drive a further 23km distance before a charge is necessary. However, since the actual destination locations are variable, the extent of the charging zone beyond the *modelled* destination would need to be circular to reflect the fact onward drivers might travel in any direction. To avoid the likely inconvenience this could cause, charging zones are restricted to fall within the shortest path limits. For routes requiring more than one CF, subsequent bounds are also calculated (although not shown in this table). Finally, the limits needed to create the charging zone in the GIS are calculated by adding (to the LB) and subtracting (from the UB) the deviation limit. Thus, for route ID 1, the charge zone can be created by setting a buffer of 5km around the portion of the shortest path from 33.5km to 50km. For routes where UB – LB < 2 * Deviation Distance, the remaining vehicle range becomes the overriding constraint. As such, a buffer is taken from the midpoint of this segment such that it intersects the LB and UB, as in route ID2.

A separate instance of this table can be produced for each deviation limit and be imported into ArcGIS. Based on the set of OD shortest paths, portions of each route can be cut out to represent charging segments using linear referencing (ESRI, 2012b), which can be used to identify a single point of reference on a non-spatially orientated 1-D route (Scarponcini, 2002). The application of linear referencing in a GIS can convert the non-spatial attributes presented in Table 3-3 and define where, geographically; the charging bounds exist for each OD route. These bound limits (taken from the Measures column in Table 3-3) define the segment of the route to which the deviation buffer can be applied. Thus, a charging segment can be created by extending a buffer of the 'Deviation Limit' distance around the segment. Importantly, the buffer is created such that it represents the impedance distance around the route, instead of the 'as the crow flies' distance. This process was achieved using the ArcGIS Service Area creation in the Network Analyst toolkit (ESRI, 2014a), which can create buffers based on network impedance.

An example of this process is shown in Figure 3-19 where the set of charging zones for a particular route are shown. The left-hand side shows the entire OD route with two CZs positioned along it. The right-hand side shows the extent each deviation threshold can capture. Because the buffer complies with network impedance, certain sections are only apparent around junctions; but it should be noted that each zone also includes the contained portion of the shortest path. Additionally, since each zone includes all areas *up to* the threshold, the higher deviation limits also include the smaller zones. Thus, a CF placed anywhere within the inner deviation limit could capture all flow from the route.
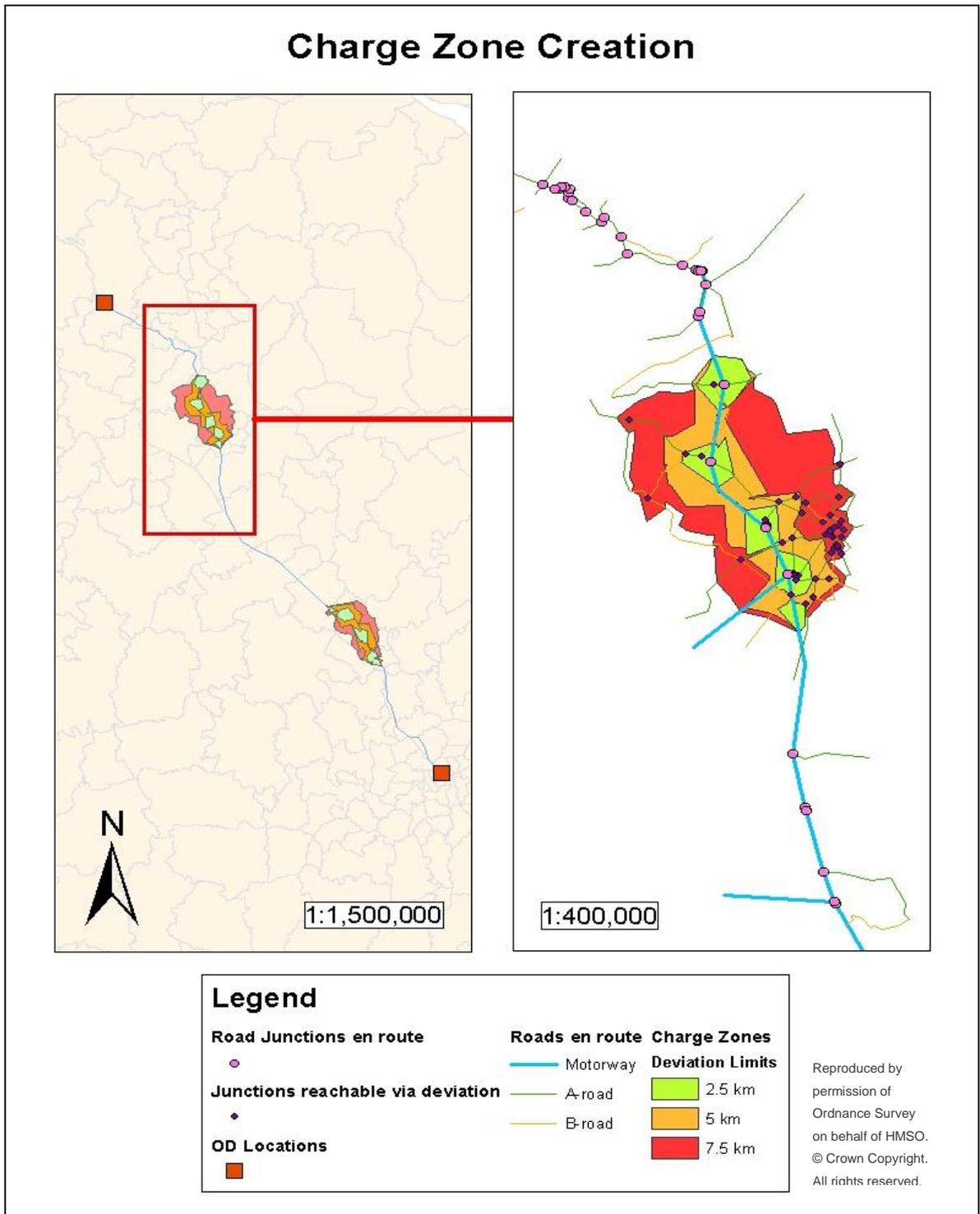
Figure 3-19 - Charge Zone creation in GIS

Since CZs are represented as areas, the entire set of potential sites for each route can be contained within a maximum of 9 zones (3 for each deviation threshold and up to 3 for each CF needed). The route displayed in Figure 3-19 requires 6 CZs, since two CFs are needed to enable the route. Based on the upper deviation charging zone, the first CZ (shown on the right-hand side of Figure 3-19) contains 63 road junctions which can be reached from the shortest path; the second CZ contains 19

junctions. If the set of all node based combinations is sought, as in the DFRLM, this example would produce 692 distinct and feasible combinations. Thus, rather than storing and processing hundreds of CF combinations for each route, the use of polygonal charging areas means all combinations are contained in 9 or less zones.

In this section, an example of how charging zones can be created was given using the methodologies developed in sections 3.4 and 3.5. The creation of charging zones, as in Figure 3-19, can be replicated for each OD route which requires service. The resultant set of polygon zones can then be used to define the charging demand for the whole network.

3.7   Charge Demand Mapping

Given the production of charging zones for each route, detailed in section 3.6, this section demonstrates how a demand surface can be generated across the network. This can be achieved by overlaying all of the individual demand routes/charging zones. An example of this type of overlaying is shown in the diagram in Figure 3-20, and is part of meeting modelling objective b (to represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated).
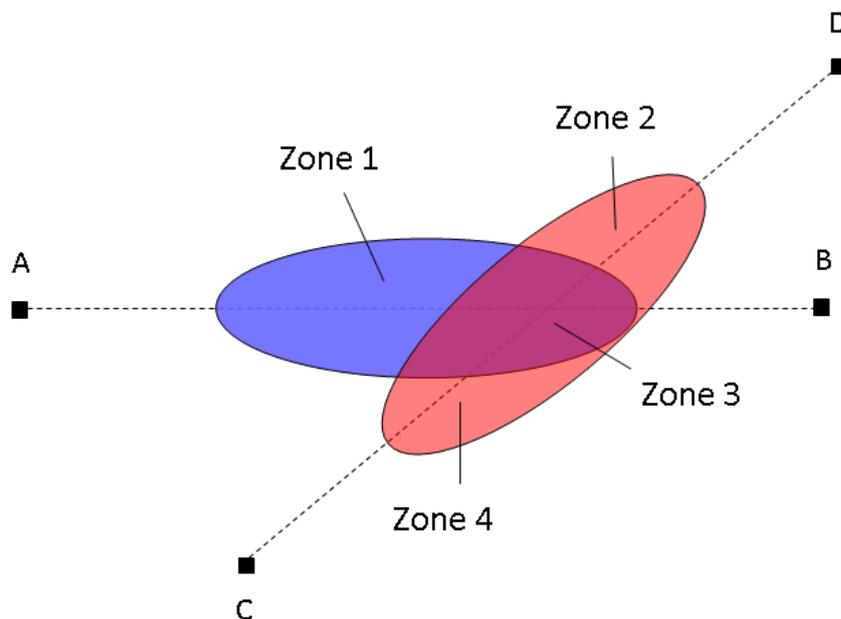
Figure 3-20 - The intersection between two routes

Two OD routes, AB and CD, require one CF to enable the route. Following the methodology described in section 3.6, Figure 3-20 shows the positioning of a charging zone around each route. If

these zones are overlaid within a GIS, four distinct zones can be defined. Clearly, if a charging facility were placed in either Zone 1, 2, or 4, it would only service one of the routes. However, a CF placed in Zone 3, which forms the intersection between the two charging zones, enables both routes to be serviced.

In a small scale network, it is possible to perform intersections in the GIS, which create separate distinct zones – such as in Figure 3-20. The flow attributes from each underlying route can be summed to define the available demand in that location. For instance, if the BEV flow along each route is assumed to be 10, then the demand in Zones 1, 2, and 4 would be 10. Zones 3 on the other hand, would produce a demand of 20. However, as the size of the network increases, the computational power needed to segment each individual zone becomes onerous. This issue becomes particularly marked along sections of major highways, which are used by which many routes. If the positioning of multiple charging zones do not exactly overlay (which is unlikely, given that each route has a different start and end point, and that route measures are not rounded), then it was found that the creation of distinct zones becomes difficult. Typically, the problem manifests in the creation of many fragmented polygons which become repeatedly sub-divided. This effect is illustrated in Figure 3-21, which shows a section of road where many routes, and charging zones, meet. Although a problem of this size would be manageable, it is apparent that several 'slithers' are created. In a large and complex network, this effect is exacerbated to the point where the tiny polygons created do not physically constitute realistic charging sites.
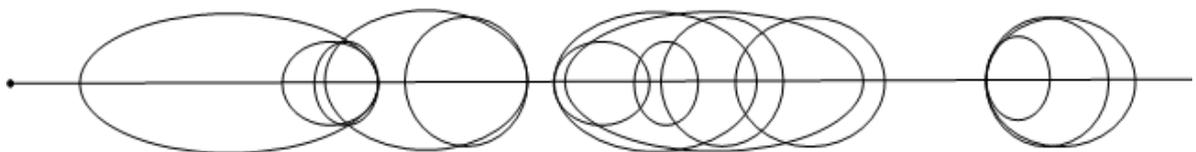
Figure 3-21 - Multiple overlapping charging zones

To overcome this issue, the application of a grid across the network – similar to Mennis (2003), allows the assignment of zone flow to demand map to be tractable. Demand quantification can be maintained by summing all underlying zone attributes and assigning them to each grid square. Although a grid can be maintained in vector format, so it can hold multiple attributes, the process of creating a continuous demand surface is synonymous with rasterization (Maguire, 1991). As described in section 3.3.5, each grid square could be equivalent to a candidate site (although this is not necessary as a feasible site could be made up of more than one grid square). However, since attribute information from all underlying zones is assigned to the grid square, it is implied that a facility placed within the square must be reachable. Consequently, the size of each square should not create an additional range constraint. For these reasons, the resolution size chosen is 500m x

500m. Thus, if a CF is placed in the middle of the grid square, the additional distance which may need to be travelled can be considered negligible. Feasibly, larger squares would also be permissible, but following tests (which involved summing attributes to a grid with these size cells over the British mainland network) the computational power required to process the model with 500m^2 squares was not deemed excessive.
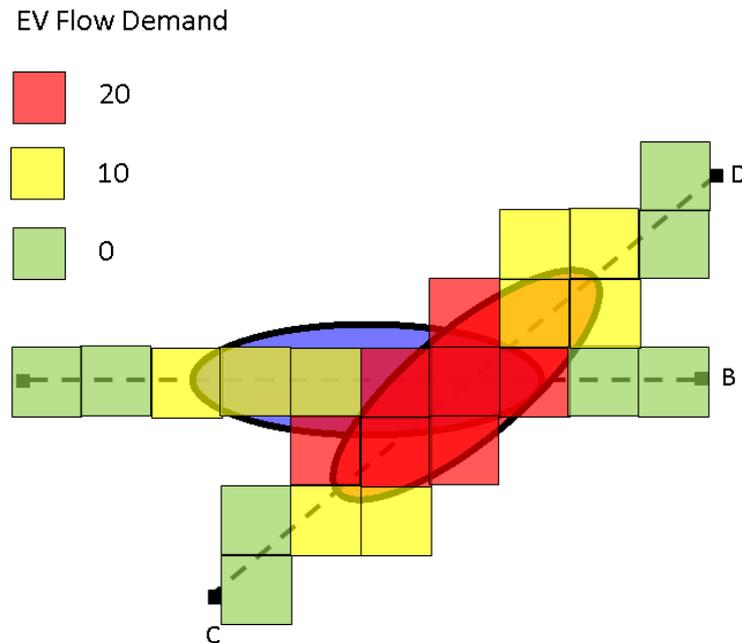
Figure 3-22 - Application of a grid to quantify route flow demand

Figure 3-22 shows how an example of how a grid can be applied to the route diagram presented in Figure 3-20. The grid has been overlaid onto the network and trimmed to exclude squares which are not intersected by road. The underlying route attributes are then joined to the intersecting grid, such that each square contains the route flow demand at that point. Assuming each route has a flow of 10, the diagram shows the resultant demand at each point. Thus, for flow capture to be maximised with a single facility, one of the 7 red grid squares could be chosen. The fact that 7 sites are available shows the benefits of the candidate-free approach. Rather than just being restricted to choose the road junction at the intersection, a quantified choice of any other point on the network is possible. Hence, if it is more practical to place a facility away from the junction, the precise cost (in terms of demand lost) can be estimated, without the need to re-run the model to consider an alternative site. Figure 3-23, in section 5.8, also provides a demonstration of this.

Additional considerations of this methodology could include the application of filters or constraints to limit the number of sites in the grid. For instance, a filter could be applied such that only sites within a particular region are considered (as in section 5.8). Alternatively, a GIS layer containing

land registry information could be overlaid onto the map. Certain filters could then be executed which would either exclude a category of site, or adjust the likelihood of them being chosen, by assigning a weight. This would be particularly relevant if the cost of land at various sites were known. Weights could be assigned to each site proportional to its cost of purchase/rent. Thus, expensive sites would only be chosen if the expected demand would make the facility viable. Finally, if a strict set of specific candidate sites are known, then these can be used as the 'grid'. In this case, the model would only choose from the limited set defined. An example of this process is given in section 4.4.

In this section two possible options to meet the objective (*represent demand for charging across two-dimensions, such that a potential demand surface can be generated*) were considered. The first considered a direct intersection of every charging zone in the network. In this situation, precise quantification throughout the network can be calculated, and in turn a demand surface – in vector form – could be generated. However, as discussed, in a large network an intersection of many overlapping polygons was found to be computationally intractable. As a means to overcome this, an alternative method, which borrows properties from rasterisation was proposed. This process involves overlaying a grid onto the network and summing the attributes from every intersecting charging zone. However, this method introduces some loss of spatial accuracy – both geographically and in a network topology sense. As a result, it is important that the size of these grid squares is not too excessive (this is discussed in section 3.3.5). Using this transformation, from vector polygons to raster style grid, still maintains the possibility for a demand surface to be generated – like that shown in Figure 3-22 (thus meeting the objective). A full scale demonstration of this process is given in section 5.2.

3.8   Solving the Model

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

In a single-facility problem, such as the network presented in Figure 3-22, the location which best satisfies the objective (to maximise the number of extendable BEV journeys) corresponds to the area with the highest demand in the network. In this case, the highest demand area covers 7

individual sites. Thus, choosing either one of these sites will result in the optimal solution. However, as demonstrated by Kuby and Lim (2005), Lim and Kuby (2010), Lam et al. (2013) and Snyder (2007), once problems of this type are expanded, they become NP-hard, to the point where the optimality cannot be found. If more than one facility is required in the network, to solve the location model with a MILP it would be necessary to assess every zone in the network in combination with every other zone. Clearly, since this model can be utilised as candidate-free, this would prove an impossible task. Thus, in the context of solving, models such as the FRLM can be considered more relaxed versions of this one – since they include many of the same constraints, but do not choose from as large a set. As such, it is necessary to develop an efficient heuristic which can be used to solve the problem.

As described in section 2.6, the application of various algorithms and heuristics has been used to successfully solve locations models. The performance of these methods is largely dependent on the network analysed and size of problem involved. More advanced techniques, such as the use of a genetic algorithm, can provide optimal solutions at a small scale. However, as shown by Lim and Kuby (2010), as the size of the problem increases, the time needed to run complex algorithms increases exponentially. In addition, as well as a compromise in solving time, the performance gap of such techniques also decreases in comparison to a greedy-adding approach. As a result, the use of a greedy-adding approach is deemed appropriate to solve a large-scale version of this location model. Further heuristics are also developed and evaluated in sections 5.4 - 5.7 in an attempt to improve the fitness function as described in the modelling objective d.

As shown in section 3.7, when solving a model using a greedy-adding approach, the location with the highest demand is chosen based on the underlying charging demand grid. Within the GIS, the maximum flow grid square is selected, and can at this point be inspected to assess whether it constitutes a feasible site. If, due to practical constraints, a facility is unable to be placed at a recommended site a set of near-optimal sites could be considered instead. This scenario is presented in Figure 3-23. At each step of the solving process, the top percentage of high demand sites could be found. Ideally to capture the greatest amount of flow in this example, it is necessary to place a facility in one of the sites with 2.01% of network demand (the darkest red areas). However, if this is not possible, then the next best site in the network could be chosen, given any practical constraints. The chosen facility can then be fixed into the model and the process can be continued.

Charge Facility Placement Options

Placement options for 1st CF
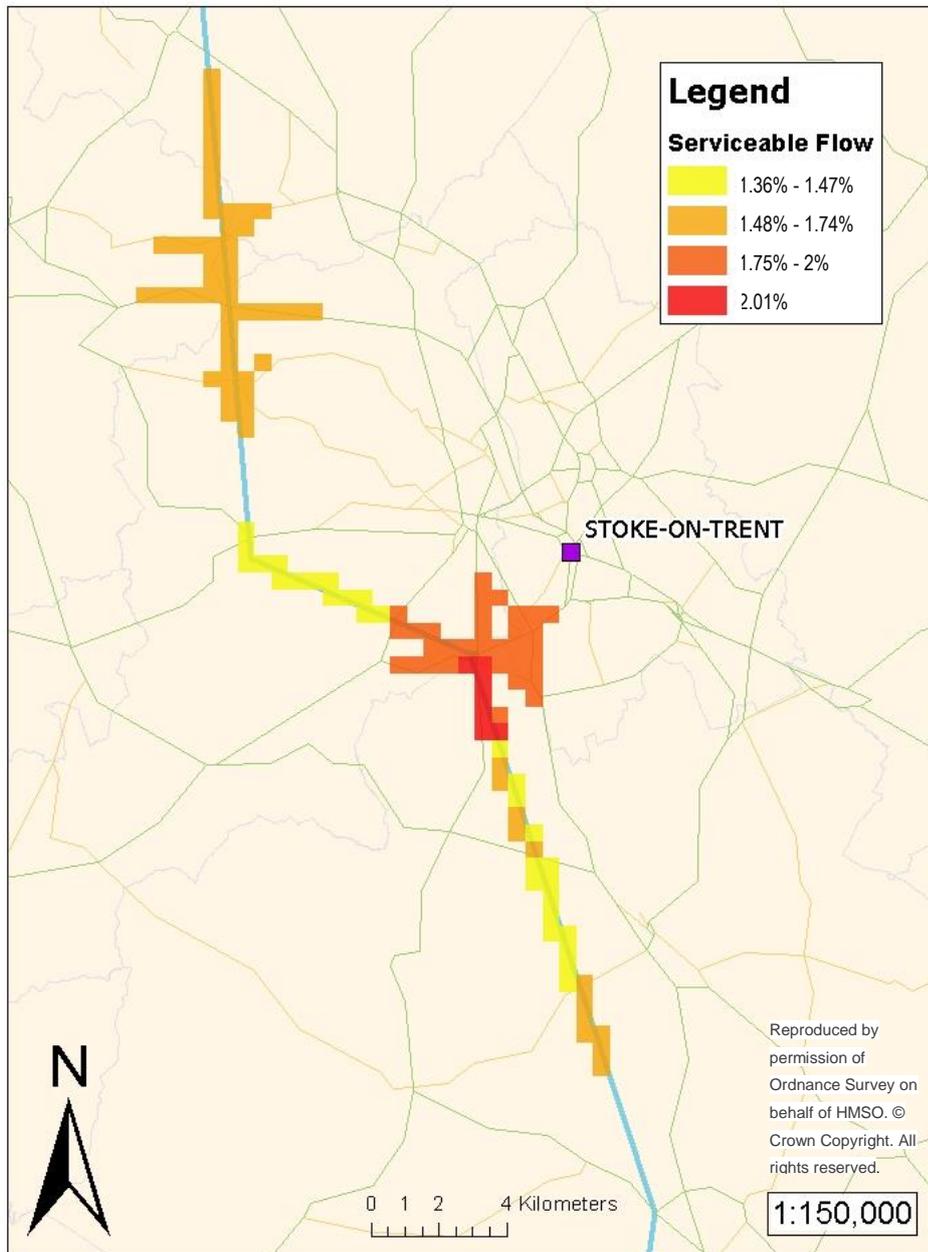
Figure 3-23 - Charge Facility Location Options

Once a site is deemed suitable (and all unsuitable sites are removed), the heuristic is then developed to assign a facility to the chosen grid square and select all underlying flow (using a spatial join (ESRI, 2013a)). Similar to Hodgson (1990) these captured routes are removed to avoid cannibalisation. At this point, if all routes in the network were single-charge, then it would be sufficient to remove the captured flow and update the demand map to reflect this. The next facility

could then be chosen in a greedy fashion and the process would continue until a certain number of points have been placed, or the model captures a designated amount of flow.

However, as with the FRLM (Kuby and Lim, 2005), it is recognised that some routes may require multiple charges to be completed. In these cases, the placement of a single facility is not sufficient. Thus, to handle longer routes, flow is designated as either 'potential' or 'serviceable'. Serviceable flow is so called because it is immediately serviceable; that is, one facility placed in a route's charging zone is sufficient to service the whole route at that moment. Multi-charge routes on the other hand, are designated potential flow because the placement of a facility in one of its charging zones only has the potential to service the route. Not until the final facility is placed (the second point for two-charge routes, or the third for three-charge routes) can the route be considered properly captured. Thus for two-charge routes, flow is initially handled as 'potential'. If a facility is placed in one of the charge zones along its route, it is considered partially satisfied. At this point, because only one more facility is needed, the designation of flow switches from potential to serviceable.

In the greedy-adding algorithm, a demand search only seeks areas with maximum serviceable flow. Initially therefore, provision is only granted to single-charge routes. For longer routes to become captured, there is a reliance on an initial facility being placed to partially satisfy the route. However, because the greedy approach does not recognise potential flow, multi-charge routes are dependent on the placement of single-charge routes to help enable them. A more detailed explanation about this relationship is given in section 5.4.

The charging zone configuration for multi-charge routes is presented in section 3.4 and shown graphically in Figure 3-16. This layout was chosen to maintain as much locating freedom as possible, given the need to minimise the number of facilities required for each route. However, as shown in the description accompanying Figure 3-16 – arranging charging zones like this enables many distinct combinations to be placed. Because every lower, and upper, bound is separated by R (one full vehicle range), the configuration of subsequent facilities is dependent on the first one placed. For instance, if a facility is placed exactly on the lower bound, then the remaining facilities must also be placed on the lower bound of every other charging zone. This implies, that if a route is partially satisfied, its charging zones must be dynamically updated such that no portion of the next charging zone is >R. An example for how this can be managed is shown in Figure 3-24.

Cutting a Charge Zone
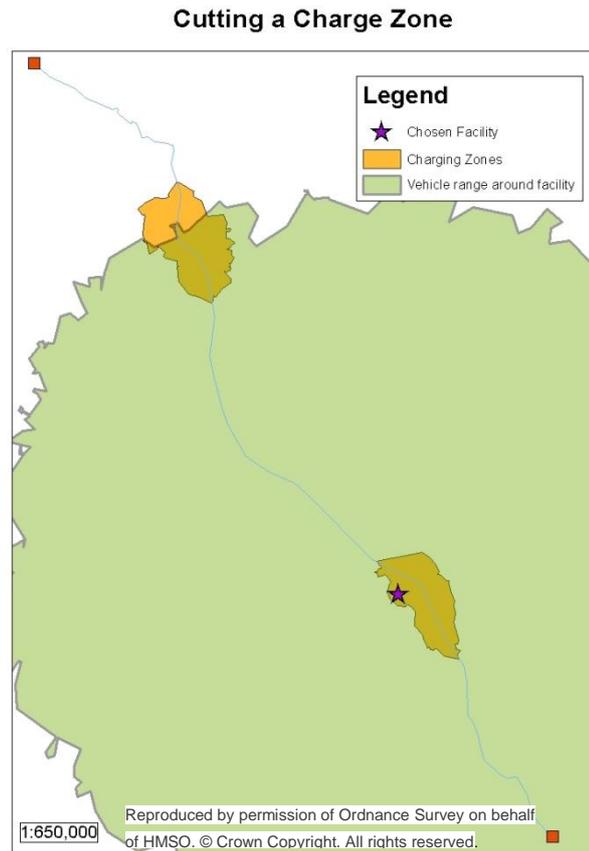
Figure 3-24 - Cutting a charge zone

Figure 3-24 shows an example of how multi-charge routes are managed in the location model. After the placement of a facility, a spatial join (ESRI, 2013a) is run to identify all 'captured' zones. In the case above, the route shown requires two charge points to enable it. Once the first facility has been placed, the underlying charging zone can be removed. To ensure that the next facility in the route can be adequately reached, the remaining charge zone needs to be cut. To do this a buffer of radius R is extended around the facility placed. This buffer represents the driveable distance of R from the facility – and so guarantees that any point within it can be reached by the BEV that has just charged. For every route which is partially serviced, the remaining zones are selected, and a 'clip' function is performed (ESRI, 2013b). The clip is used to effectively cut the remaining zone, such that one portion of it can be reached from the facility and the other portion cannot. Having identified the inaccessible portion of the charging zone, this piece can be discarded from the model. The remaining portion is kept and represents the updated possibility of locating options. In this example, because only two charges are needed, the flow in the remaining 'cut' zone is redefined as being serviceable. Thus, this charge zone can be recognised by the greedy-adding algorithm and provisioned accordingly. For routes which require three facilities, a second buffer of 2*R is also extended around the facility. If a mid-sequence zone is serviced (i.e. if a facility is placed in the second zone on a route), only the 1*R buffer is needed and a cut is performed in both directions.

To conclude, once a facility is placed, the following processes are enacted to ensure that all zones and flow in the network are up-to-date:

- Identify all zones captured by the facility.
- Remove all zones with 'serviceable' flow – these routes can be considered fully serviced.
- For all zones with 'potential' flow identify their sister charging zones. Having done this, remove the captured zone.
- Extend a buffer of 1*R and 2*R around the facility. Perform a 'clip' to cut all sister zones identified in step 3. Discard portions of these zones outside of the buffers.
- Re-evaluate the charging demand grid such that it represents the newly updated set of charging zones.
- Select maximum demand zone in the grid and place new facility. Repeat through steps 1 – 5 until number of desired facilities is reached.

3.9   Summary

This chapter developed a model suitable for determining rapid charging locations for BEV journey needs. Key to this was the requirement to meet new objectives, as described in chapter 2, to overcome shortcomings in existing methods. The following section provides a summary of how these objectives were approached and met.

Modelling Objective a: Develop a method to represent source/destination areas in the model, such that OD aggregation scale is considered and accounted for in the modelling procedure.

For objective a, three approaches were proposed which could allow for a consideration of aggregation scale within the network and be applicable into the modelling procedure (see section 3.2.1). Based on the test case studied (the Census district points within the British mainland), a re-aggregation of the network was deemed appropriate to maximise the potential population that could realistically be considered in the model. In the modelling procedure (see section 3.6), the aggregation error can be added to route lengths to ensure that all assigned population can modelled. Given that the aggregation scale was set to ¼ vehicle range – which ensures that all internal 'origin' journeys can be completed with a full charge and without rapid charging – it is deemed that the approach developed sufficiently achieves the objective.

Modelling Objective b: Represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated.

For objective b, the methodology described in section 3.6 – which defined demand along linear segments – was extended to allow demand to be stored as an area (and represented by multiple nodes/junction and arcs/roads). Given this, a methodology was proposed which can be used to create these areas, or 'charging zones', in a GIS by defining the limits which may constitute the furthest someone can travel or deviate before they need to recharge. As such, all areas within these limits can be defined as demand zones. The next step involved merging demand from each route across the network. One option to do this could involve running a GIS intersection (ESRI, 2013c) across all zones to split demand based on the underlying flow attributes. However, after conducting small scale tests this operation proved computationally excessive resulting in process error (and termination). This is because the created charging zones did not overlap in a homogenous fashion, resulting in multiple 'slivers' where attribute information was subtly different to nearby areas. As a result, another process was tested which incorporates features from rasterization. For this approach, a grid was overlaid onto the network with underlying charge zone attributes assigned to separate grid squares. Tests on this process were found to be manageable, since complex splitting of spatial features was not required. The resulting output is shown in Figure 3-22 (and demonstrated at a full scale in section 5.2). Based on this, the above objective is deemed to be met, and a representation of a demand surface can be generated.

Modelling Objective c: Create a modelling procedure which relaxes the need for an input candidate set, instead choosing from the continuous plane.

The meeting of this objective is tied to the outputs from objective b. In previous location models in this field, demand was only quantified at single points in the network. As a result, only these locations could be recommended for facility placement (since demand is not known elsewhere in the network). For candidate options to be considered across the plane it is therefore necessary to have a quantification of demand across a continuous area. Based on this, every location in the network can feasibly be considered as a candidate site. The only constraint that is employed in this process is the idea that all sites must be on, or just off from, the road network (as it is necessary that sites are reachable by vehicle). If this is considered, then the objective is met where sites are 'chosen from the continuous plane' and are coincident to the road network.

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale

where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.

In section 3.8 the definition of this objective was considered such that a potential site can be chosen where the number of extendable BEV journeys is maximised. In a greedy process, this involves selecting the next site which satisfies this objective. Other heuristic types were considered, such as genetic algorithms, or greedy-adding with substitution. However, previously published literature showed that other techniques offered little additional optimisation benefit and were computationally detrimental in solving models as complex as the one developed in this research. A further exploration of this objective, where attempts to improve the heuristic solutions are made, is presented in sections 5.5 – 5.7.

Based on the development of the novel methodologies in this chapter, the solutions presented for the four modelling objectives are deemed to meet the following objective from section 1.9:

Objective 2: Develop a model and appropriate methodology to recommend sites for a charging network, and overcome issues with previous work in this area.

To test the efficacy of the developed model, one of the most important aspects of the work is the ability to validate the model and method behind its use. Previously published literature in this field has not been validated with real world data. Given this, a novel method of validating the model is discussed in chapter 4.

4 MODEL CREATION AND VALIDATION

In the previous chapter, formulation of the model was developed to meet overall objective 2, and the subsequent modelling objectives a, b, c, and d. In this chapter a demonstration of the model is applied to a real-world network, with expected outputs compared to observed usage at current charging locations. As such, the following objective will be addressed:

Objective 3: Apply this model to a real world network and analyse its outputs against current charging usage.

Initially, in sections 4.1 and 4.2, an introduction and analysis of observed charging data across a network is given. Given the need to compare this observed usage with the modelling outputs, a demonstration of the modelling technique is carried out in section 4.3 such that it can be applied at a macro level (need b in section 1.9). Further examples of this process are also provided in chapter 5. In section 4.4 the model is used to evaluate the network of existing sites, with a comparison between the two datasets provided in section 4.5. Further discussion of the comparison results is provided in chapter 6.

4.1 Real World Charging Data

The data used to validate the modelling outputs was collected as part of the Midlands Plugged-in-Places project (Plugged-In Midlands, 2015), a government backed scheme to roll-out and support electric vehicle charging infrastructure in the Midlands area in the UK (which covers the geographical regions of the East and West Midlands). Since 2010, a network of over 700 charging points has been deployed throughout the region to help encourage electric vehicle take-up and use. Of these, 47 chargers are rapid, all of which were installed after the CABLED project finished in March 2012. Most of the points have been installed at motorway services in partnership with Ecotricity (Ecotricity, 2015), or at Nissan car dealerships (Nissan, 2015b). The points can be used by anyone who is a member of the Plugged-In Midlands scheme, which allows unlimited and free at use application of the points for a £25 annual fee. Membership ID cards (which operate and allow access to the charging points) are available to anyone via a website. Parking fees at sites can apply, although in the case of most rapid charge points, parking is free for the first 2 hours – a time sufficient to complete a full charge (Ecotricity, 2015). Recent roaming agreements are also in place, which allow customers on similar schemes to use the points using their own ID card from a different region. Agreements are currently in place with Source London (covering the Greater

London area), Source East (covering East Anglia), and individual Ecotricity members (nationwide, for use at Ecotricity service points). This means that someone from London could travel into the Midlands region, recharge there, and then head back. However, since specifics about individual drivers is anonymised (for data protection reasons), it is not known to what extent inter-region travel takes place. Additionally, information regarding members' home and work addresses is unavailable – meaning a clear idea of origin-destination patterns cannot be established.

The charging usage data across the network is compiled by Cenex (Cenex, 2015) – who run and manage the Plugged-In Midlands scheme. Each charging event is recorded by the local charge point and relayed to a main database. For each event a record is taken indicating the charge point location, the time and date, the charge duration, the amount of energy transferred (in kWh), and an anonymous ID for each vehicle card holder. An example of the data storage is shown in Table 4-1.

Table 4-1 – Example of layout of Plugged-In Midlands charging data

Charging Event ID	Unique User ID	Charge Point ID	Charger type	Location	Start time/date	Duration	Total kWh transferred
2876	CA4536	12	Rapid	Welcome Break Warwick M40 South	08:35 12/01/14	00:26	20.3

4.2   Charging Data Preparation

To achieve a comparison between the charging data and the model outputs, it is necessary to represent each dataset across the same geographical region and format. As described above, charging data is available for the Midlands region, thus to compare the results to the location model it is necessary to evaluate its outputs at these locations. This process is explained schematically in Figure 4-1.
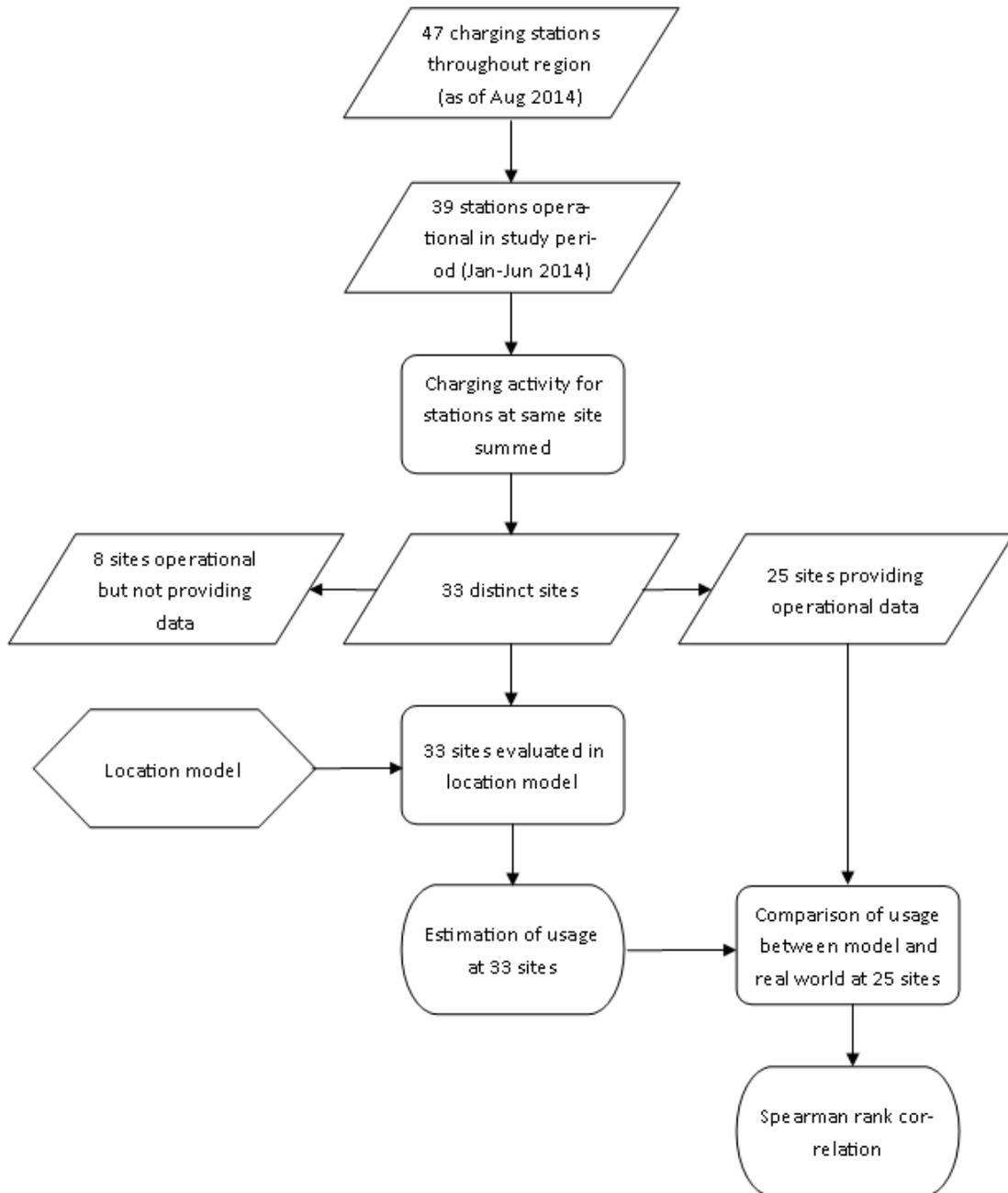
Figure 4-1 - Charging usage data comparison flow process

Figure 4-1 provides a diagrammatic explanation of the processes undertaken to validate the location model. The input charging data, like that exampled in table 4.1, details the number of recorded charging events that took place in the Midlands region up to the end of June 2014. 8 posts were installed near to, or after this date (3 in May, 4 in June, and 1 in August) – and so are excluded from the analysis due to a lack of sufficient data. Similarly, many posts were installed throughout 2013 – meaning the charging data for this period is uneven. Thus, the period considered covers the first 6 months of 2014 – when most of the charging posts were installed, operational, and recording reliable data. The second step described in Figure 4-1 involved aggregating the data from each post into similar locations. In this context, charging stations located on opposite sides of

a motorway carriageway are considered as the same site (this allows comparison to the modelled data which doesn't include individual carriageways). Thus, from the 39 rapid chargers in the dataset, 33 were identified as distinct sites. For posts sharing a site, the charging data was summed to generate the total usage at each site. Given that charging posts were operational at 33 sites, these locations are fed into the model to determine the amount of demand that is expected at each site. This process, including generation of the location model, is explained in detail in section 4.3.

Even though charging was possible at 33 sites, data pertaining to their usage throughout the study period was only available at 25 sites (it is understood that this was due to back office/communications faults in several of the posts). Hence, as explained in Figure 4-1 although 33 sites are loaded into the location model, as this reflected the actual useable network at the time, only the 25 sites with data are taken forward into the comparison. A geographical representation for the 25 sites is provided in Figure 4-2.
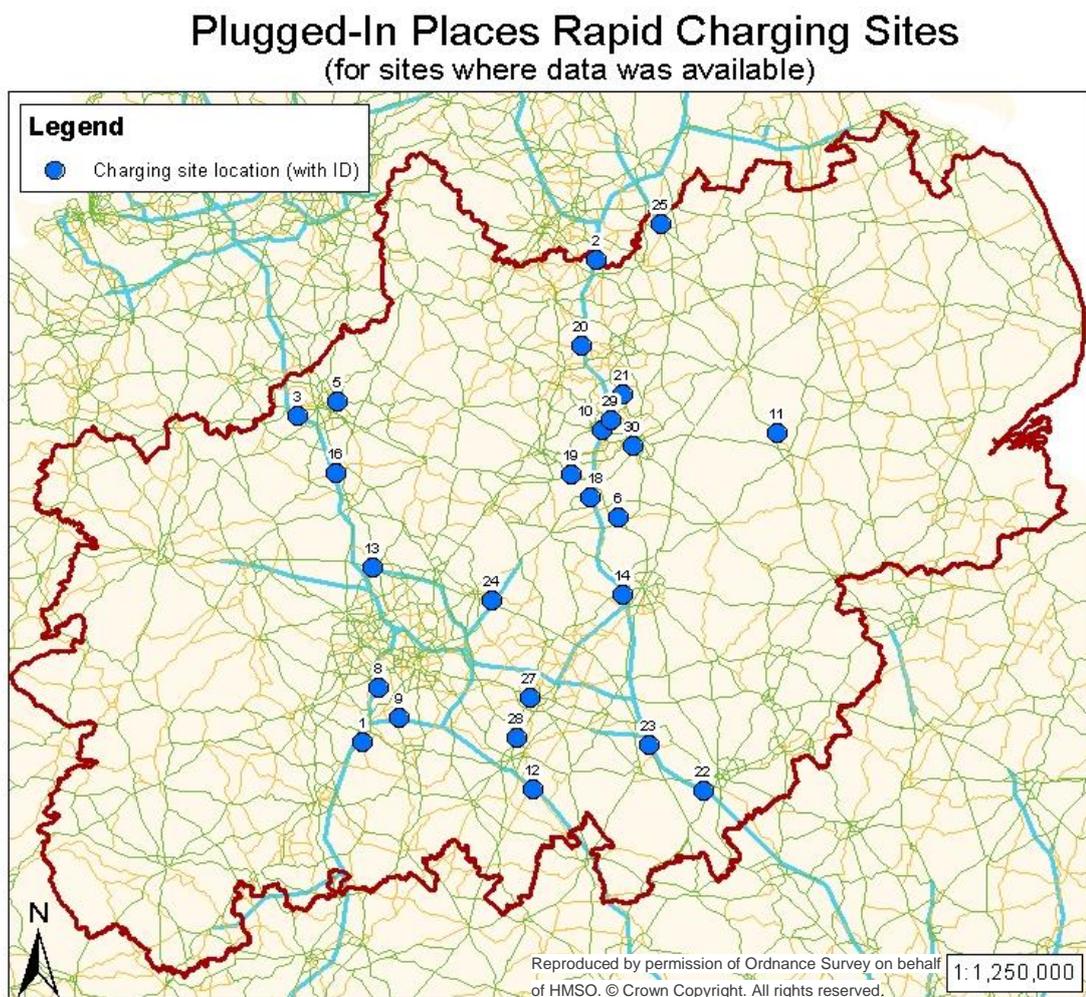
Figure 4-2 - Plugged-In Places charging points with recorded data

Based on data from these 25 sites, a total of 3922 rapid charges were recorded by Cenex in the study period. On average, this equates to 157 charges per site, or just less than 1 charge per site per day. Individual details of users were not known, but unique IDs show that 577 drivers charged at least once in the period. Most of these users were not frequent chargers however, with 83% not charging more than 10 times in the 6 months. This supports the assertion that rapid charging could be an infrequent component of BEV ownership.

The data presented in Table 4-2 shows that the total number of charges varied considerably across the region from ID14, which recorded 474 events (approximately 2½ each day), to ID13, which only received 31 visits. This is further highlighted by an observed deviation of 119 between all the sites. On closer inspection of the data it was also observed that the total number of different users who visited each site varied considerably (by a standard deviation of 40). Although the identities and origins of each user were not known, a unique record for each was available. Thus for certain sites a low diversity of users was noticed. For instance, charging site 5 was visited 69 times by the same user (which accounted for all its usage). Similarly, charging site 1's 77 charges were carried out by just 4 repeat users. On the other hand, site 2 was visited by 93 different users, indicating the location has a more broad appeal and is useful for a lot of different people – as opposed to convenient for a few. Clearly therefore, and given that this dataset represents an early stage of infrastructure use, the behaviours of one or two drivers can heavily skew the outlook. To determine if this skew has an effect, the number of visits from each user is separately limited to a maximum of 10 and 20 visits (i.e. the 69 visits to site 5 by one user are restricted to 10 and 20 respectively). The justification for this is presented in Figure 4-3 which shows that the number of visits per user per site is generally small – except for a few heavy users at the far end of the distribution. This method of partial filtering still maintains 71% and 80% of all charges respectively, but discounts the heavy skewing affects from one or two individuals. The results of this process are denoted by the 'Limitation of heavy users to 10 (and 20) charges' in Table 4-2. Further to this partial limiting of the effects of heavy users, their data is also completely excluded from the analysis (i.e. all users who charged 10/20 or more times are excluded) – this is shown in the last two columns in Table 4-2 for comparison.
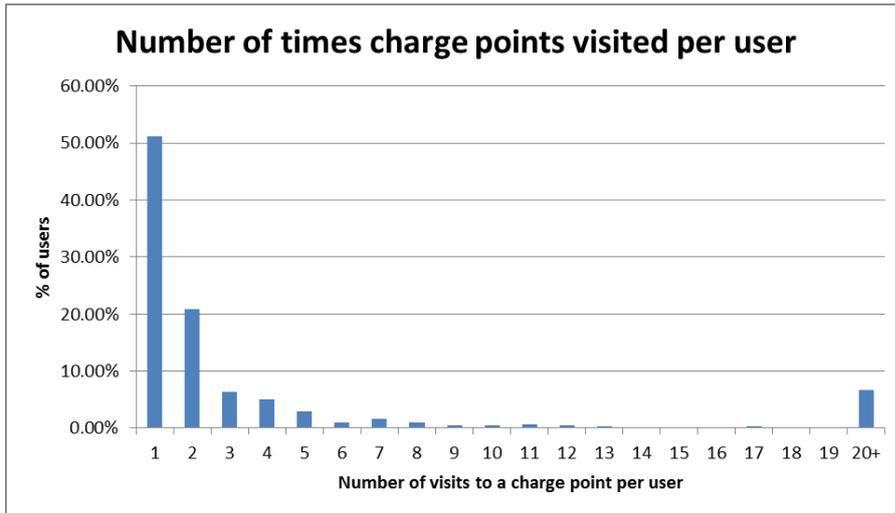
Figure 4-3 - Number of times each user visited each charge point

Table 4-2 - Recorded Charging Events in the Plugged-In Midlands region

Charging Site ID	Total charging events	Number of different users who visited site	Limitation of heavy users to 10 charges	Exclusion of heavy users (10+ visits to the same site)	Limitation of heavy users to 20 charges	Exclusion of heavy users (20+ visits to the same site)
1	77	4	40	0	68	28
2	240	93	195	175	206	186
3	108	41	95	75	106	86
5	69	1	10	0	20	0
6	100	7	17	7	27	7
8	259	81	227	177	246	226
9	70	35	70	70	70	70
10	363	85	182	132	222	142
11	136	39	105	95	115	95
12	311	95	198	168	210	190
13	31	5	24	14	31	31
14	474	151	352	322	377	337
16	51	30	50	50	50	50
18	177	86	155	135	173	153
19	205	53	172	112	191	171
20	174	74	158	128	174	174
21	106	6	44	4	64	24
22	376	113	243	213	266	226
23	154	75	151	131	153	153
25	35	16	35	25	35	35
27	153	36	108	58	141	101
28	150	37	78	58	98	58
29	70	12	43	13	57	37
30	5	3	5	5	5	5
31	28	9	28	28	28	28
Standard deviation	**119**	**40**	**87**	**80**	**93**	**86**

Further to the charging events listed in Table 4-2, data at 8 sites appears ambiguous since no charging events were recorded during some months. It is not clear if this is an accurate representation of events, or a function of communication and/or data storage issues. For this erroneous data, the analysis will be conducted both with and without these sites present to understand the potential impact they have on the correlation. The data pertaining to the ambiguous sites is listed in Table 4-3. The removal of such data is commonly referred to as 'case deletion', and is often employed in similar statistical applications (Donders et al., 2006; Rubin, 1976; Scheffer, 2002). The correlations for all of these sets of data compared against the expected model outcomes are presented in section 4.5.

Table 4-3 - Potential missing data at sites

Charging Site ID	Total number of charges (2014)					
	Jan	Feb	Mar	Apr	May	Jun
ID3a	12	1	0	0	0	0
ID3b	19	26	20	7	10	13
ID5	0	0	0	9	3	57
ID9	39	23	0	0	0	8
ID16	1	0	0	1	21	28
ID25	23	12	0	0	0	0
ID29	11	37	22	0	0	0
ID30	0	3	2	0	0	0
ID31	11	6	11	0	0	0

4.3   Model Preparation

4.3.1 Network choice

Chapter 3 describes how the location model proposed in this thesis is formulated and can be applied, in general, to any network. This section provides demonstration of this process on a specific real world network and validates its outputs by comparing to data recorded from current rapid charging locations. The modelled network considered for this analysis covers the British mainland (i.e. all areas directly accessible from London via road). This is because the Plugged-in Midlands scheme had roaming agreements in place, meaning people travelling from outside this region could feasibly use one of the Midlands posts (the only criteria required to apply for a usage card was to be UK resident). Thus, for comparative purpose, it is necessary to construct the model to allow for this, such that journeys starting outside the region would be recognised. Given this, the

network and method of re-aggregation as described and discussed in section 3.2.1, is deemed appropriate to allow for comparison with the real world network.

4.3.2 Route flow assignment

Based on the discussion of options regarding route flow assignment in sections 2.2 and 3.2.2, and the needs of the study (i.e. to be realistic, and expandable), the objective in this chapter, and the availability of data (access to an existing populated OD network was not available), the implementation of a traffic assignment method as described by point 3 in section 3.2.2 is deemed appropriate. However, to provide validation of the method used, a comparison with traffic count data recorded by the Department of Transport (2014) will also be implemented. Most route assignment methods follow the four-step method as described by McNally (2008). This involves assigning a trip generation rate for each origin location (1), assigning a trip attraction for each destination location (2), defining the modal split of traffic (3), and generating travel flows for each route based on a traffic assignment method (4).

Based on this approach, the production and attraction rates are defined for each OD point using the underlying Census data (UK Data Service, 2012) in the current network. This process, discussed by Purvis (1997) can utilise a range of Census statistics to define these rates, such as population, household income (although this is not specifically attributed in the UK Census), number of cars etc. However, given that precise geographic data on BEV ownership/residence is unknown – and the demographics for future BEV drivers is uncertain, the production rate is assumed proportional to the resident population. As described in section 3.2.1, a population count for every COA point is known based on the 2001 UK Census (UK Data Service, 2012). Following the re-aggregation of these points to new OD locations, the corresponding populations are also assigned and summed such that an overall population for each OD location is known. Potentially, measures which indicate a future geographic spread of BEV take-up could be used as a weight, such as those defined by Campbell et al (2012). However, this work was theoretical and only applied to the Birmingham region, so it is unclear whether these trends would be observed in reality/across the rest of the country. If empirical data did become available, more accurate representation could be incorporated by updating this production rate.

For the attraction rate, a combination of statistics was deemed appropriate, since the population figure alone may not wholly define which locations received the most visitation (Purvis, 1997). Thus, to achieve a more appropriate attraction figure travel-to-work statistics are used in combination with destination population levels – a technique that has also been applied by Theriault et al. (1999). For the UK Census, the travel-to-work statistic is available in an assimilated matrix containing a count of people who travel from one COA to another to visit their place of work (UK Data Service, 2012). Statistics relating to long journey origins and destinations may be more appropriate, but this data is not available in the UK Census, and so travel-to-work statistics are used a proxy for general destination attraction. However, a mode of transport statistic is available for this dataset such that the matrix can be filtered to provide this. Based on this, the total number of visiting 'car drivers' can be summed for each COA point and assigned to their local OD point. This process is equivalent to the third step in the four-step model: mode choice. As well as the travel-to-work count, the destination population is also used as a weight, and combined in the ratio 2:1. Applying this technique therefore, produces a total weight for each OD location that can be used to represent its relative attraction (compared to other points in the network). Additionally, the attraction rate is normalised with the production rate such that the total outgoing demand is equal to the total incoming weight. This ensures that, across the network, the total production rate is equal to the total attraction rate (i.e. for every location that produces a journey, a destination somewhere in the network receives one).

For the fourth step of the route assignment, as described in section 2.2, the least-time routes are calculated for every OD pair and an all-or-nothing assignment is chosen to avoid the complications described in section 3.2.2. In this network, because there are 300 OD points, an initial set of 89,700 routes is created (300 x 299 – since a route is not created between the same OD point). Further, a gravity model is applied as described in Erlander and Stewart (1990) to estimate the possible weight of traffic between each location. This process is exampled below, where a small network of three nodes is used to show how production and attraction weights are combined with the route distance to create the flow weights. Consider Table 4-4 which shows the production and attraction rates for this set of (example) OD nodes.

Table 4-4 - OD production and attraction assignment

OD node	Production Rate	Attraction Rate
A	10000	11000
B	13500	10000
C	9000	10000

As described in Erlander and Stewart (1990), the gravity model estimates the flow weight between two pairs using the following formula:

Route weight (Index) = <u>Origin Production Weight * Destination Attraction Weight</u>

Route Length (kms) ^ 2

To example this, data from Table 4-4 is combined with the set of OD pairs and the gravity formula is applied. This results in the production of a route weight index, as in Table 4-5. The weightings themselves do not signify actual traffic flow (i.e. a number of vehicles travelling between each OD pair). However, it can be used as a comparison between routes; for instance, RouteID 1 is assumed to have 4 times the flow of RouteID 2 since their respective route weights are 10,000 and 2,500. Also note that the weight between an OD pair is not necessarily the same in both directions. This is because each route is based on a round trip being available. Hence, A-B-A constitutes a different route to B-A-B (with potentially different drivers using the route). As such, using the gravity model, route A-B-A produces a route weight of: 10,000 (production rate at A)*10,000 (attraction rate at B) / 100 (route distance) ^2 = 10,000.

Table 4-5 - OD pair route list

RouteID	Origin node	Destination node	Route Distance (kms)	Route Weight	Index Weight
1	A	B	100	10000	25.11%
2	A	C	200	2500	6.28%
3	B	A	100	14850	37.29%
4	B	C	150	6000	15.07%
5	C	A	200	2475	6.21%
6	C	B	150	4000	10.04%
			Total	**39825**	**~100%**

To carry out this process in practice, each OD point, and the road network described in section 3.2.1 is loaded into ArcGIS Network Analyst (ESRI, 2015c), such that the set of 300 OD locations (shown in the right hand side of Figure 3-10) is connected via the road network (derived from (Ordnance Survey, 2012) as described in section 3.2.1). This network consists of 35,739 arcs (roads) and 22,435 nodes (junctions). The least time routes are calculated using the 'OD cost matrix analysis' in ArcGIS (ESRI, 2014b), which implements Dijkstra's algorithm (Dijkstra, 1959) to find the fastest route between a set of OD pairs. The layout of the OD network is shown in Figure 4-4.

UK OD Network
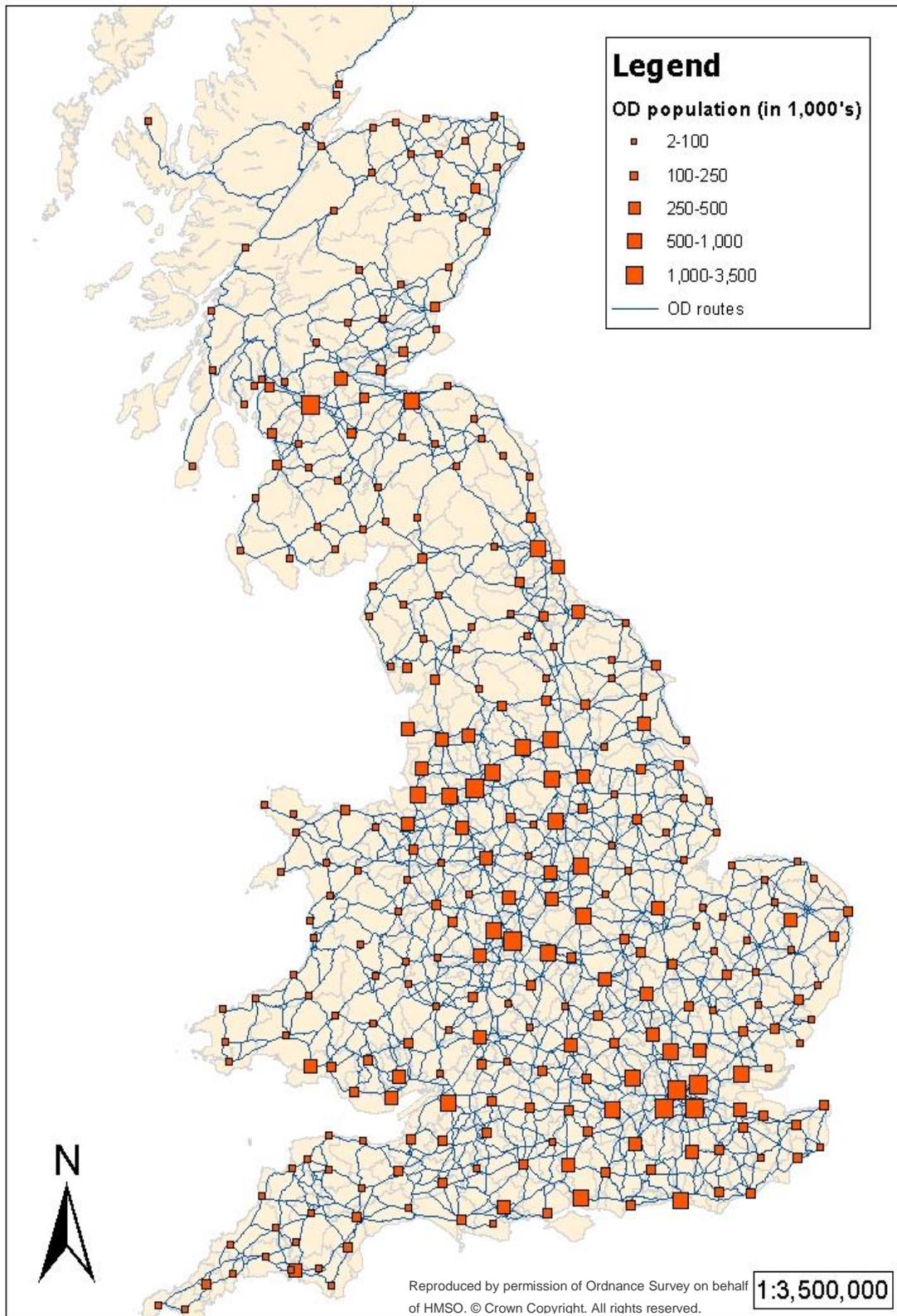
Figure 4-4 - UK OD network

4.3.3 Parameter choice

As described in section 3.3, several parameters can be set (based on available data) and used for each instance of the model. As an example of the modelling process, the following parameters are chosen based on the discussions in section 3.3, and the best available data.

Journey lengths: As discussed in section 3.3.1, the range of a vehicle can vary due to differences in vehicle make, driver behaviour, road topology, and ambient temperature, but for modelling purposes it may be pertinent to choose a range that covers most situations such that the majority of drivers will be able to carry out their journey. Therefore, based on the available data presented in section 3.3.1, the range of a Nissan Leaf is deemed representative (80% of vehicles shown in Figure 3-11 are Nissan Leafs), and a 25% conservatism is applied to cover variations observed by Walsh et al. (2010), Neaimeh et al. (2013), and Strickland et al. (2014) (albeit not over the whole range of a BEV in every case), and the likelihood that a higher proportion of long journeys may take place on highways (which has been shown to decrease overall range). As such, a range of 63 miles (84 mile combined range of Nissan Leaf as in Figure 3-11 - 25% conservatism) is deemed representative.

Starting range: Based on the findings in section 3.3.2, the starting range for long journeys is set to 100% (minus the aggregation error which is described later).

Charges per trip: Because of the increased overall journey time resulting from necessary charging, journeys requiring 4 or more charges (~ equivalent to routes >250 miles) are deemed excessive for BEVs. In practice (based on National Travel Survey Results (Department for Transport UK, 2013f), this may affect up to 0.07% of trips).

Deviation willingness: Based on the sample survey results presented in section 3.3.4, deviation thresholds are set as described in this section.

Candidate site selection: Because the purposes of this implementation of the model are to compare the expected demand at a set of existing locations, a candidate set is not required. Given this, only the current charging layout is evaluated (see Figure 4-6 in section 4.4).

Capacity at charging stations: For the current set of charging sites, electricity Network constraints were not known. In addition, from the data, it is not clear if queues formed at any time, or whether BEV drivers went elsewhere to charge. As such, capacity constraints are not considered in this implementation of the model.

4.3.4 Charge demand creation

Based on the generation of shortest paths and the weighting of flow as described in section 4.3.2 and shown in Figure 4-4, routes not meeting core criteria on journey distance are excluded from the list. As such, routes in excess of 250 miles are excluded (leaving a set of 45,534 routes). In addition, routes with negligible flow – as determined by the gravity model are also excluded. This threshold is set so that only routes with less than 0.002% of the total network flow are excluded. Based on this therefore, these routes could be considered an insignificant source of charging demand until there are 50,000 daily BEV journeys requiring rapid charging taking place in the network (something which is unlikely based on current BEV numbers as shown in Figure 3-11).

Given the remaining set of OD routes, the position of charging zones are defined for each route based on the developed methodology described and exampled in section 3.6 (where aggregation distances are also added). Furthermore, charging zones are created within ArcGIS (also as described in section 3.6) to define the regions where charging demand may exist for each route. Unlike the process described in section 3.7, which applies a grid across the whole surface, grid squares are only generated for the specific locations of existing chargers. For a visualisation of this demand across the whole network (where the assumptions used are the same) see section 5.9. As described in section 2.2, in addition to gravity model assignment (or another assignment technique), traffic count data can be used to partially assess the validity of the generated network. In the UK, traffic count data is compiled by the Department for Transport (Department for Transport UK, 2014) using traffic counting cameras or sensors on every junction-to-junction link on the A-road and motorway network. These sites (17,600) are loaded into the GIS, and are shown in Figure 4-5 below. Using a spatial join (ESRI, 2013a), each traffic counter is assessed in relation to the underlying road (where the roads are buffered by 500m to ensure adjacent traffic counters are captured). Thus, for every traffic counter (where part of an OD route lies) an equivalent flow weight can be determined. Based on this, a ranked correlation can be calculated to determine the relationship between the expected flow weight and the number of cars recorded by each traffic counter. For the 8,446 traffic counters that lie on, or near, a set of OD routes, the Spearman Rank (Spearman, 1904) correlation coefficient between the two datasets is 0.34 (2 d.p). A further description of the process to generate a Spearman Rank correlation is provided in section 4.5. Overall, this suggests that there is a positive (but weak) correlation between the two datasets. If the data is filtered for motorway only counters, the correlation improves to 0.49 (2 d.p) based on a set of 849 counters. This suggests that the parameters used in the network design more accurately represent motorways than A-roads. A principal cause for this could be the speed definitions which

are applied across the network. Because road-specific speed or congestion data is not available in the Meridian 2 network (Ordnance Survey, 2012), road speeds are set homogenously across road types (see Table 3-1). For motorways, this is not an unusual assumption, but for A-roads speeds can vary greatly (UK Government, 2015). This problem is discussed further in the discussion (section 6.1.2).

Traffic Count Points in network

Legend

Annual car count by location

· 0 - 10000

· 10001 - 25000

▪ 25001 - 50000

● 50001 - 100000

● 100001 - 250000

OD routes requiring charging provision

1:3,500,000
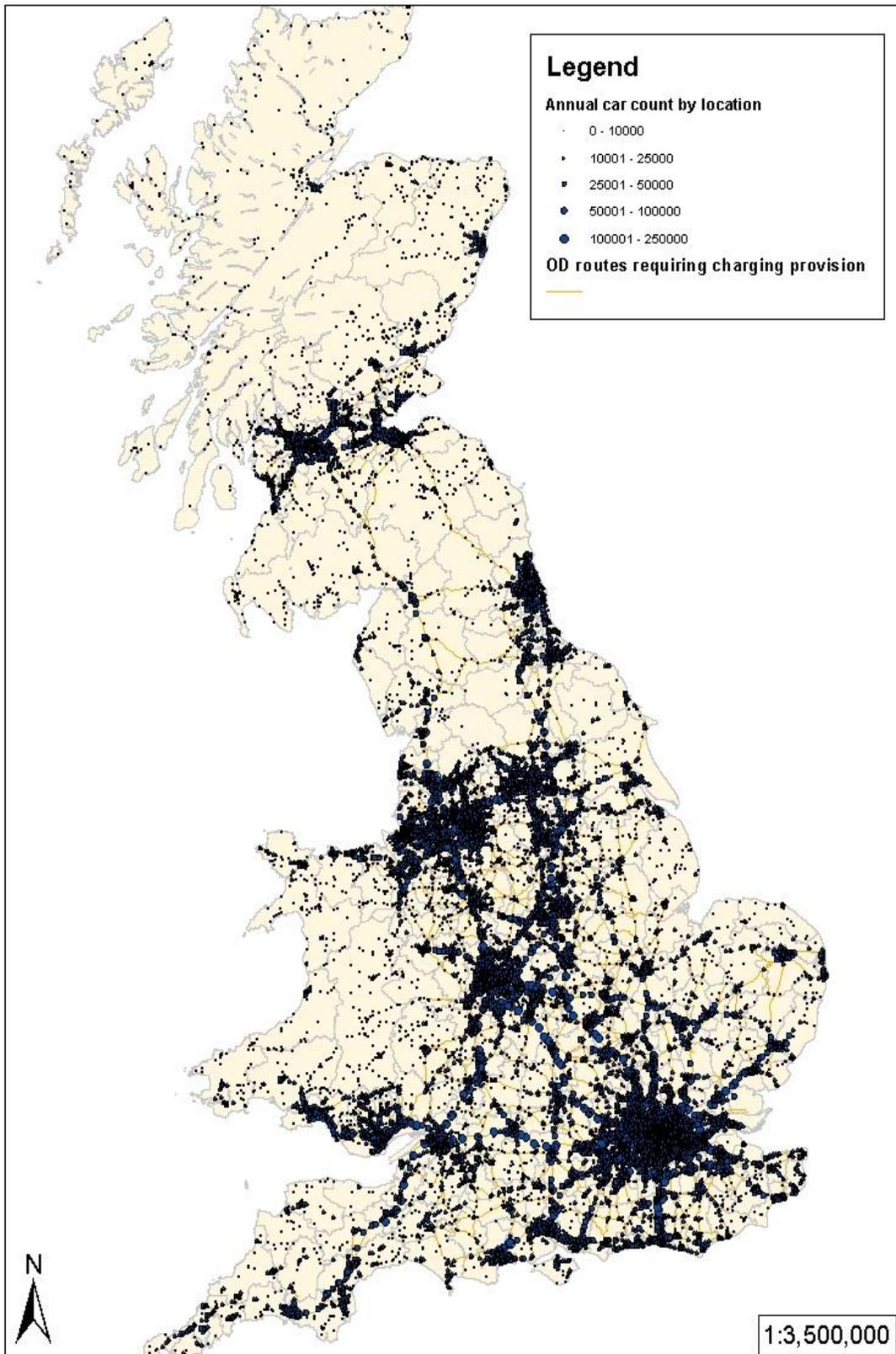
Figure 4-5 - Annual traffic count

Data source: (Department for Transport UK, 2014)

4.4   Real World Charging Sites Evaluated in the Location Model

Based on the generated network described in section 4.3 (and visualised in section 5.9), demand is evaluated for the existing 33 sites in the network to determine the level of expected demand at each location. A geographical representation of this layout is shown in Figure 4-6. In cases of conflict, or cannibalisation – i.e. where two or more sites could service a route, demand is assigned wholly to the site which requires the least deviation from the shortest path. If the deviation distance is the same for two or more sites, typically for facilities located directly on the same shortest path, then demand is divided proportionally between them. From this, the expected demand at each site is calculated – based on the capture of passing demand. Long distance journeys requiring two or more charges are considered, but only if they can be wholly satisfied via a combination of Plugged-In Midlands charging posts. Charging posts outside this region are not loaded into the model, and as such journey-charge combinations which require external facilities are not considered to be satisfied (and hence demand from these routes is not assigned to facilities within the Midlands region).
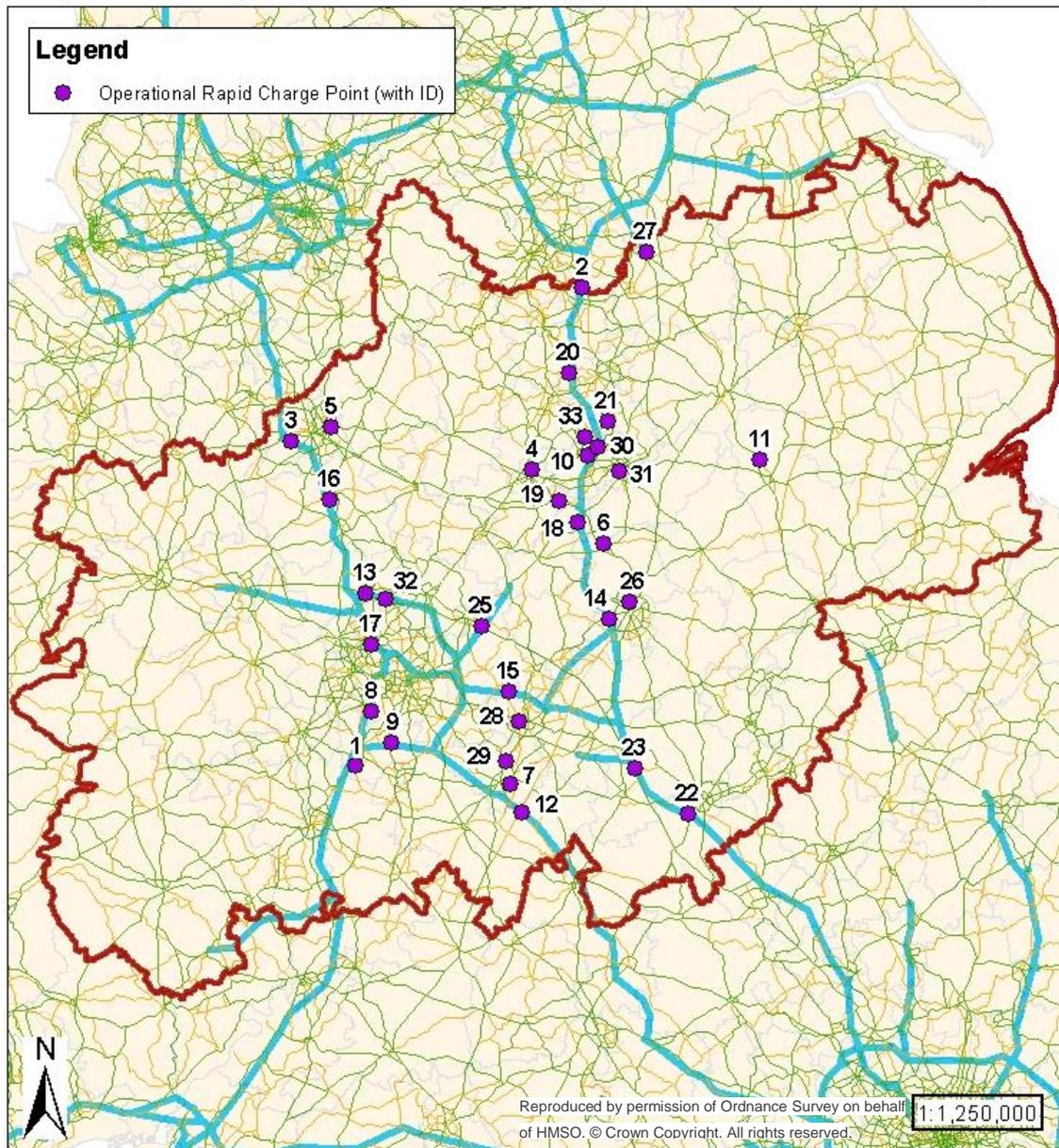
Figure 4-6 - Location of all rapid charging stations in the Midlands

Figure 4-6 shows the 33 rapid charging sites across the Midlands region, loaded into the model. Since all of these points were known to be operational, they are all considered equally in the model. Ancillary services at sites, such as availability of refreshments, toilets, and other amenities are not considered in the model; as such, sites are only distinguished by their location in reference to the road network and passing traffic flow. The points are evaluated based on their capture of passing demand – as described in section 4.3. Deviation is considered, up to 7.5km; but if more than one location is available, it is assumed a driver chooses the site which is nearer to their shortest path. The evaluation of demand across the network reveals the proportion of service expected at each location. The split of demand expected by the model is shown in Table 4-6 (where percentages are

given as a portion of the demand that is expected to be serviced, rather than the total demand that could exist in the Midlands).

Table 4-6 - Expected demand captured at each charging site

Charging Site ID	Percentage of expected demand captured at site	Charging Site ID	Percentage of expected demand captured at site
1	1.32%	18	2.81%
2	9.56%	19	1.61%
3	7.14%	20	6.67%
4	2.12%	21	0.00%
5	1.32%	22	5.15%
6	0.04%	23	5.41%
7	0.49%	24	0.00%
8	7.65%	25	5.78%
9	3.71%	26	1.82%
10	3.96%	27	1.82%
11	1.55%	28	2.42%
12	3.50%	29	0.64%
13	0.35%	30	0.73%
14	8.05%	31	1.05%
15	5.37%	32	2.78%
16	3.26%	33	0.86%
17	1.08%	Total	100%

The site which the model expects to receive the most demand is ID2, located in the north of the region on the M1 motorway. The site is located conveniently to link population centres in the Midlands, such as Leicester, Nottingham, and Derby with those in the North, such as Leeds, Doncaster, and Sheffield, such that only one en route charge is needed. It is relatively isolated in comparison to others, meaning it does not have to 'share' its service with other sites as much; and is located near the confluence of two major routes – the M1, leading to Leeds, and the M18, leading to the A1(M) and the North East. This attribute, being located on a major motorway near prominent junctions, is also observed in the other top ranking sites. Indeed the top 12 sites are all located along motorways, indicating the model's preference for such routes. Conversely, the two lowest ranking sites are not expected to receive any service. Both are located just off the motorway (7.3 and 3.9 kilometres respectively), near other facilities which are located along the motorway. Consequently the model tends to attribute demand to the motorway sites, since this is where most passing traffic is expected to flow without need for deviation.

4.5   Comparison of Model Results and Real World Observations

Objective 3: Apply this model to a real world network and analyse its outputs against current charging usage.

To determine if observed usage is correlated to location, and to validate the formulation of the location model, the two datasets are compared. An appropriate tool that can be used to assess a correlation between observed and modelled data is the Chi-squared test (Pearson, 1956; cited in Plackett, 1983) and the Spearman rank correlation (Spearman, 1904). These tests can be used to determine if the expected dataset sufficiently represents the observed one, and by extension has not been generated by random. As with the Chi-squared test, Spearman's rank correlation determines how well two datasets are correlated, taking into account the ranked order of values instead of the scalar frequencies. This test is particularly useful for comparing datasets measured at different times or in a different manner (Iman and Conover, 1982). For the correlation between the numeric charging data (which was recorded in 2014) and the model results (which are generated from a proportion of origin-destination flows based on 2001 Census data) the specific values are comparable if expressed as ranked percentages. Based on this, the ranking of each charging site within its distribution can be used to determine a correlation. For instance, if a corresponding location is the highest ranked in both datasets, and another is the second highest in both, and so on, then the two datasets have a perfect Spearman's rank correlation.

To generate this correlation it is necessary to order the values within each dataset. Table 4-7 shows the 5 statistical counts derived from the observed usage data. The corresponding expected percentages from the location model (as in Table 4-6) are also shown, with the rankings calculated based just on these 25 points. As described in Figure 4-1, only the sites where observed data is available are compared. Each ID within the datasets is ranked in order from lowest to highest (where a rank of 1 = the lowest value). In cases where frequencies are the same, the rank is split equally between them. To determine the goodness of fit for the expected ranks compared to the observed ones, the correlation can be evaluated as a coefficient between -1 and 1, where -1 represents a perfect negative correlation, 1 a perfect positive correlation, and 0 uncorrelated/random data relationship (Zar, 1998). The Spearman's rank correlation coefficient can be calculated using Equation 1 (Zar, 1998):

$$p = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \qquad\qquad \textbf{\textit{1}}$$

where $\quad d_i^2 \quad = \quad$ the squared difference between matching pair's ranks

$\qquad\quad\; n \quad = \quad$ the number of pairs in the correlation

Table 4-7 - Ranked comparison of charging data

Charging Site ID	Total # charges	Rank	Limit to 10	Rank	Exclude 10+	Rank	Limit to 20	Rank	Exclude 20+	Rank	Expected (%)	Rank
1	77	9	40	7	0	1.5	68	10	28	5.5	1.32%	7.5
2	240	20	195	21	175	22	206	20	186	21	9.56%	25
3	108	12	95	13	75	14	106	13	86	13	7.14%	22
5	69	6	10	2	0	1.5	20	2	0	1	1.32%	7.5
6	100	10	17	3	7	5	27	3	7	3	0.04%	2
8	259	21	227	23	177	23	246	23	226	23.5	7.65%	23
9	70	7.5	70	11	70	13	70	11	70	12	3.71%	16
10	363	23	182	20	132	19	222	22	142	16	3.96%	17
11	136	13	105	14	95	15	115	14	95	14	1.55%	9
12	311	22	198	22	168	21	210	21	190	22	3.50%	15
13	31	3	24	4	14	7	31	5	31	7	0.35%	3
14	474	25	352	25	322	25	377	25	337	25	8.05%	24
16	51	5	50	10	50	10	50	7	50	10	3.26%	14
18	177	18	155	17	135	20	173	17	153	17.5	2.81%	13
19	205	19	172	19	112	16	191	19	171	19	1.61%	10
20	174	17	158	18	128	17	174	18	174	20	6.67%	21
21	106	11	44	9	4	3	64	9	24	4	0.00%	1
22	376	24	243	24	213	24	266	24	226	23.5	5.15%	18
23	154	16	151	16	131	18	153	16	153	17.5	5.41%	19
25	35	4	35	6	25	8	35	6	35	8	5.78%	20
27	153	15	108	15	58	11.5	141	15	101	15	1.82%	11
28	150	14	78	12	58	11.5	98	12	58	11	2.42%	12
29	70	7.5	43	8	13	6	57	8	37	9	0.64%	4
30	5	1	5	1	5	4	5	1	5	2	0.73%	5
31	28	2	28	5	28	9	28	4	28	5.5	1.05%	6
Totals	3922		2785		2195		3133		2613		85.5%	

The Spearman rank correlation coefficient is calculated separately between the location model results and the 5 counts from the charging data. The coefficient between the total number of charges and the model is shown in Equation 2. The ranked scatted plot for this correlation is shown in Figure 4-7.

$$p = 1 - \frac{6 \times 1040}{25(625 - 1)} \; = \; 0.60 \, (2 \, \text{d. p})$$

2
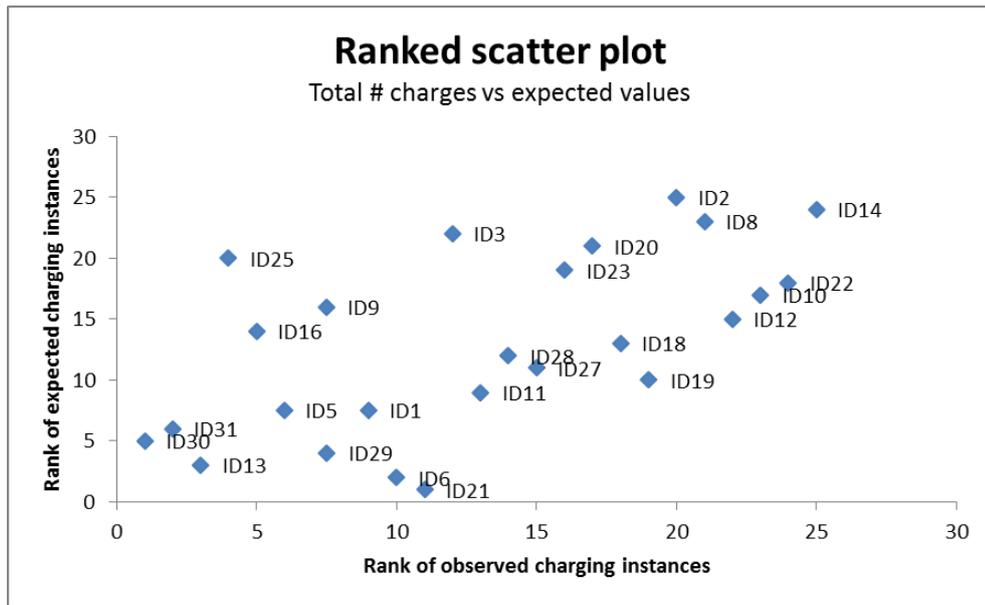
Figure 4-7 – Ranked scatter plot between total number of observed charges and model expectations

The resultant correlation coefficient and scatter plot suggests a positive relationship exists between the total number of observed charging events and the expected model results. This suggests that the location model can forecast whether a charging point will observe a relative low or high usage based on its location. However, as noted by Cohen et al. (2013) a degree of caution must be applied when analysing correlations. They explain that a positive correlation does not imply that one predicts the other; merely that a link between them exists. The degree to whether this link has been generated by a true relationship between the datasets, or by random, can be evaluated by finding the significance of the coefficient (Washington et al., 2010). This process is explained in Zar (1998) who details the method of finding significance levels for independent variables (in this case, the two datasets can be viewed as independent as no implied knowledge from the usage data has been used in the formulation of the model). For the Spearman rank correlation, Zar (1998) recommends the Student's t-test (Haynes, 2013), which with the use of lookup tables can be applied to determine the significance of Spearman's correlation. The formula to calculate the t-test score is given in equation 3 (Zar, 1998).

$$t = \frac{r_s}{\sqrt{(1 - r_s^2)/(n - 2)}}$$

3

where r_s = the Spearman rank correlation coefficient

n = the number of pairs in the correlation

Given the correlation coefficient from equation 2, and n based on 25 paired values, the t-score is 3.60 (2 d.p). Using the significance table lookups from Zar (1998), the correlation between the model and the total number of charges can be deemed significant to >99.92%. Such a value

provides confidence to the existence of a relationship, and the significance is well within acceptable limits in transportation fields, according to Washington et al. (2010), meaning the chance that the relationship exists randomly is small.

Further to the correlation between the total number of charges and the model, coefficients are also found for the remaining counts presented in Table 4-7. This data is presented in Table 4-8 for the full 25 site dataset (*p*), and the 17 site set (*p2*) where ambiguous data from Table 4-3 has been removed. In all cases the confidence levels for these correlations exceed 99.9%.

Table 4-8 - Correlation coefficients between observed data and expected model outcomes

Data comparison (with expected values)	Sample size (*p/p2*)	Correlation coefficient (*p*)	Correlation coefficient with data from Table 4-3 removed (*p2*)
Total # of charges	3922 / 3486	0.60	0.78
Users limited to 10 charges	2785 / 2449	0.73	0.83
10+ charge users excluded	2195 / 1929	0.78	0.87
Users limited to 20 charges	3133 / 2762	0.70	0.83
20+ charge users excluded	2631 / 2302	0.77	0.87

The correlations presented in Table 4-8 show that the effects from heavy repeat users had an impact on the relationship with the model outcomes. If these effects are negated, either by limiting these users to 10 or 20 charges, or excluding them from the analysis completely, then the correlation coefficient improves from 0.60 to 0.70-0.78. Further improvements are also observed if sites with ambiguous data – shown in Table 4-3 – are removed from the analysis (from 0.78-0.87). This effect can be observed by studying the differences between Figure 4-7 and Figure 4-8, where the ambiguous data hasn't, and has, been removed respectively. In Figure 4-7, several outliers are observed in the top-left of the scatter plot. These sites all received a lot less actual usage than was expected by the model – suggesting either that the model overestimated, or that the usage data was underreported. For 4 of these sites, ID3, 9, 16, and 25 it is likely the latter is true as there was a possibility that data was underreported from these sites, as shown in Table 4-3.
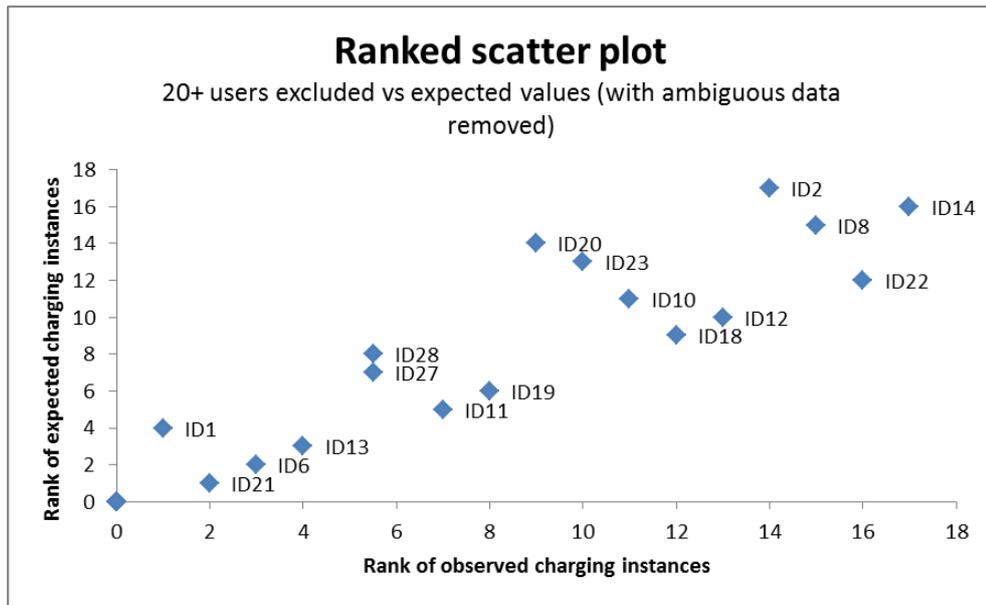
Figure 4-8 – Ranked scatter plot between 20+ charge users excluded and model expectations

With the missing data sites removed from the analysis, the coefficient for each count improves. This further strengthens the results, suggesting that the location model can provide an efficient means to evaluate demand, and thus by extension recommend future locations where high demand could be expected. In addition, the occurrence of missing data is effectively predicted by the modelled results, indicated by a higher expected usage. However, although most sites fit the correlation well (once anomalous data is removed), demand at a few sites is still either slightly under, or overestimated compared to what was observed. For instance, sites ID 20, 2, and 23 received slightly less usage than the model expected, while ID22, 12, and 18 received slightly more usage than was expected (ranked differences of 4, 3, and 3 in both cases). The reasons for these discrepancies cannot directly be evidenced within the data, and as such a discussion on some possible causes is provided in chapter 6.

4.6   Alternative Midlands Network

In the previous section a validation of the modelling outputs was provided by comparing the model expectations with observed real-world data, as reported by Cenex. Based on the correlation observed, the location model appears to be suitable for use as a predicting, and therefore forecasting, tool to suggest expected usage throughout a network (given the various inaccuracies in both datasets, which are discussed in section 6.1). In this section, the location model is used to demonstrate its applicability, and the differences that can be observed, assuming a blank canvas and a continuous plane approach.

Based on this requirement, a layout for an alternative network is produced using the modelling procedures described in chapter 3 and detailed more explicitly in chapter 5. A demand output is generated throughout the network (an equivalent of which is shown in Figure 5-2), and the model is solved using a greedy adding approach (referred to as method W0 in chapter 5). Unlike the output network shown in Figure 5-3, this model is restricted to only consider sites within the Midlands region (contained by the red border). To evaluate the comparison, the model is run until the same level of expected service is provided. The result from this process is presented in Figure 4-9.

Alternative network layour based on possible charging demand
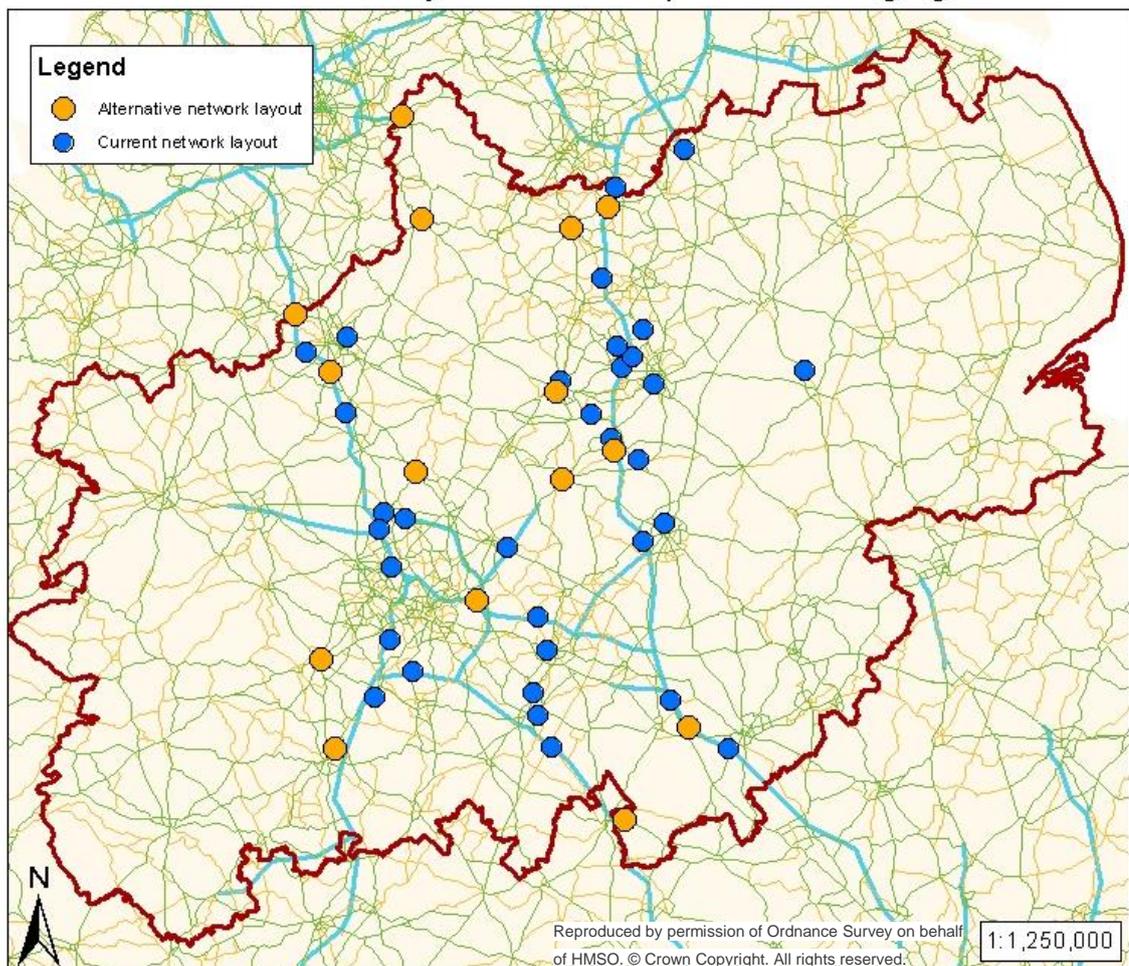
Figure 4-9 - Alternative charging location layout for the Midlands network

Figure 4-9 shows an alternative layout to the Midlands network if a continuous plane approach is assumed. The set of 33 current charging sites is also shown for comparison. Based on the definitions of flow capture described previously, it is found that the alternative layout could potentially have served the same number of vehicles with 15 locations (where location is defined as in section 4.2 – i.e. possibility for several sites within the locale/on opposite sides of a carriageway) compared to the current layout of 33. As expected, the continuous plane method places key

charging locations close to the major motorways in the region (the M1 and the M6). In general, a more coverage based network is recommended compared to the existing layout, with sites suggested at spaced intervals along main routes. It is anticipated that a fixed capacity constraint would affect this layout and require multiple sites close to each other similar to the current layout. These factors suggest that the current network is well designed (based on the assumptions in the model), given that the continuous plane approach is free to recommend sites anywhere (without the restrictions of land, electricity constraints etc. as described in section 6.1). In effect, this model's outputs from a continuous plane approach could potentially be used as a benchmark from which to find feasible sites that are close by to try and maximise demand capture.

4.7   Summary

Previous works on location modelling for BEV charging determination have validated their method through mathematical optimisation and discussion. The work presented in this chapter proposes a novel methodology to validate modelling work with empirical rapid charging usage data. This has been achieved by comparing the ranking of model evaluated locations against used locations as reported by rapid charging operators. It was found that the modelled outputs can provide a good approximation to the observed usage data, and can even identify possible discrepancies in the data itself. In addition, the model was implemented without constraint over the same region to identify differences in the approach. The findings suggest that the proposed model can be representative of empirical usage and approximate similar locations to current sites which received high usage. Based on this, alternative networks could be planned, with levels of demand estimated. The alternative network recommended in this chapter may not be practically implementable, but the demonstrated methodology indicates the sort of coverage that might be suitable and could potentially be used as a benchmark from which a feasible solution could be generated.

The next chapter explores the option for full scale implementation of the model, showing how the methodology could be used to estimate and recommend future sites, or areas, in a network, giving the potential to enable more long range BEV journeys. Examples of this process will be given to demonstrate the plan for wide-scale infrastructure provision starting from scratch, and to highlight potential differences in networks planned at a regional or national level.

5 MODEL DEMONSTRATION AND IMPROVEMENT

In the previous chapter the location model was applied to show how the methodology can be used to evaluate the expected demand at a specific set of existing sites within the Midlands. The comparison with Cenex reported usage data at these locations suggest that the model can be used to represent charging demand throughout a network. In this chapter, the location model is demonstrated to show how it could be used in future, or under alternative scenarios (such as for a region which is not currently provisioned at all). Additionally, a full scale implementation of the location model is undertaken to understand issues around scaling, which may lead to impacts regarding national infrastructure policy. An investigation around the UK network offers the opportunity to look at a large network with the additional complexity of considering internal borders.

Specifically, the following objectives are addressed in this chapter:

Objective 4: Demonstrate differences in modelling outcomes based on comparison between national infrastructure plan and a smaller regional like plan.

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

5.1 Network Preparation

Given the objective to demonstrate the model on a macro level network, the OD network is built using the methodology and parameters described in section 4.3. Following the application of possible route flow assignment onto the network (see section 4.3), 6,668 routes are deemed to contain non-negligible flow. The remaining routes are presented as an OD network in Figure 5-1. Of these routes, 3,066 can be completed with just one charge. 2,574 and 1,028 routes require two and three charges respectively. The amount of possible flow contained within single and multi-charge routes is shown in Table 5-1.

Table 5-1 - Single and multi-charge routes in the UK network

Number of CPs needed	Number of routes	Potential route flow weights	Average flow per route
1	3066	68.7%	0.022%
2	2574	24.1%	0.009%
3	1028	7.2%	0.007%
Total	6668	100%	0.015%

For single charge routes, the flow contained is deemed 'serviceable', since the placing of one charge point will immediately service that whole route. For longer routes, the flow is termed 'potential'. In such cases, placing one charge point only has the potential to enable the whole route; but cannot be fully serviced until the last charge point is placed.

Figure 5-1 - Origin-Destination Network for UK study area

5.2 UK Charging Demand Map

In the modelling procedure, assumptions about a driver's willingness to deviate can be varied, as this quantity is not explicitly known. Because the allowance of deviation has been shown to have an effect on capturing flow (Kim and Kuby, 2012), three deviation bands were chosen. The bands chosen were 2.5, 5 and 7.5 minutes, which represent the maximum time someone is willing to deviate from their shortest path in order to carry out each charge, based on survey results presented in 3.3.4. Although time could be incorporated into charge zone creation and used as impedance, for ease of use all times are converted to distances. This enables the interface between deviation and range limits to be more easily managed. Thus, the bands used in this evaluation (described in section 5.9) are 2.5km, 5km and 7.5km with percentages of flow willing to deviate to these limits of 100%, 80%, and 40% respectively, as discussed in section 3.3.4. In practice, these limits could be varied – especially if more empirical data becomes available.

To be able to benchmark the effect deviation has, it is necessary to firstly evaluate the modelling solution assuming minimum deviation. Strictly a limit of no deviation could be used, but if this were the case then the band would encompass the area 0km from the shortest path, i.e. the linear portion of the route only. Whilst it is possible to model this theoretically, the practical implication would mean a charging facility would have to be built directly on the road itself. Therefore, a small deviation must always be carried out, even if it might not be deemed a 'deviation' in practice. For this reason, the smallest band of 2.5km is taken to mean minor deviations. In practice, this allows someone to temporarily exit the road they are on and charge at a stationary location. If this *nearby* location is signposted off the main road, the implication is that a BEV driver could exit their route without having necessarily planned this deviation before they set off. For longer deviations, it is likely that a degree of pre-trip planning would need to take place so that the driver knows when and where to exit their original path.

The amount of flow at any one point can be quantified by summing the attributes from many overlaying charging zones. Replicated across the whole network, this process produces a 'hotspot' map, identifying locations with high flow. Since longer routes are reliant on a combination of charge points, only the shortest routes are *guaranteed* to contribute to the objective (capturing the most flow) if facilities are placed one at a time. Hence, to ensure the capture of flow without having to rely on a combination 'falling into place' it is necessary to initially target serviceable flow only. Figure 5-2 shows the UK network represented as a hotspot map. Only minimum deviations have

been considered and only serviceable flow is shown. Areas of high flow are shown in red, whereas areas of low flow are shown in green. Attributes for longer routes, including potential flow, are included in the network but are not shown directly in this map.

Figure 5-2 - UK charging demand map (W0min)

The highest demand area in the UK is located in and around central London. Because of its high attraction rate, demand is generated by journeys from the populous outer suburbs and surrounding

regions where a single charge is needed to enable a round trip. High demand can also be observed in the north-west of England where large population centres like Manchester, Liverpool and Leeds are spaced such that one rapid charge sufficiently enables BEV journeys between them. In Scotland demand is generated by journeys between Glasgow and Edinburgh and surrounding towns. However, this area appears somewhat 'cut-off' from England to the south, since it is unlikely that a journey between population centres such as Manchester in England, and Glasgow in Scotland can be completed with a single charge. For such routes to become connected, it is necessary that an initial facility is placed in one of its multiple charging zones. Since the model only considers serviceable flow, such a facility will only be placed if there 'happens' to be sufficient demand from other single charge routes. Unless this happens, longer routes do not have an impact in the model and thus will not become serviced.

As described in section 3.7 the hotspot map can be used as a visual aid, allowing the visualisation of areas where BEV demand for charging is likely to be at its highest. Assessments can be made on the types of areas or roads with high demand and used to shape overall siting strategy. Identification of these zones may lead to an investigation on candidate locations which may otherwise not have been considered. However, if further candidate criteria are known beforehand, they can be used to trim the model at this stage. Individual sites or GIS layers which share a common candidate criterion could be added to the map and used as a filter to limit the model to only select sites within these areas.

5.3   Solving the Model

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

As described in section 3.8, the model can be solved by placing charge facilities additively in a greedy manner. Simply, the first point to be placed corresponds to the location with the highest flow in the network. The model can then be reassessed, with flow completely, or partially, serviced by the first point removed. If the removal of partial flow leaves just one charge zone from a route unsatisfied, the designation of potential flow is changed to serviceable flow such that it becomes an active part of the model. The placement of the second facility therefore corresponds to the highest

demand area in the reassessed network. Using this approach, a number of theoretical BEV journeys could be extended if the recommended sites were placed. However, at this point, it is unclear to what degree this number (i.e. the flow capture) is approaching the maximum feasible solution.

Figure 5-3 shows the placement of the first 10 charging facilities (CFs) across the UK network based on the charging demand map shown in Figure 5-2. Sites are placed in the optimal locations at each stage – i.e. no constraint is placed on site location. The order in which the CFs are placed is noted by numeric labels.

UK Charging Demand Map

Minimum Deviations Only, PFlow weighting = 0 (W0min)
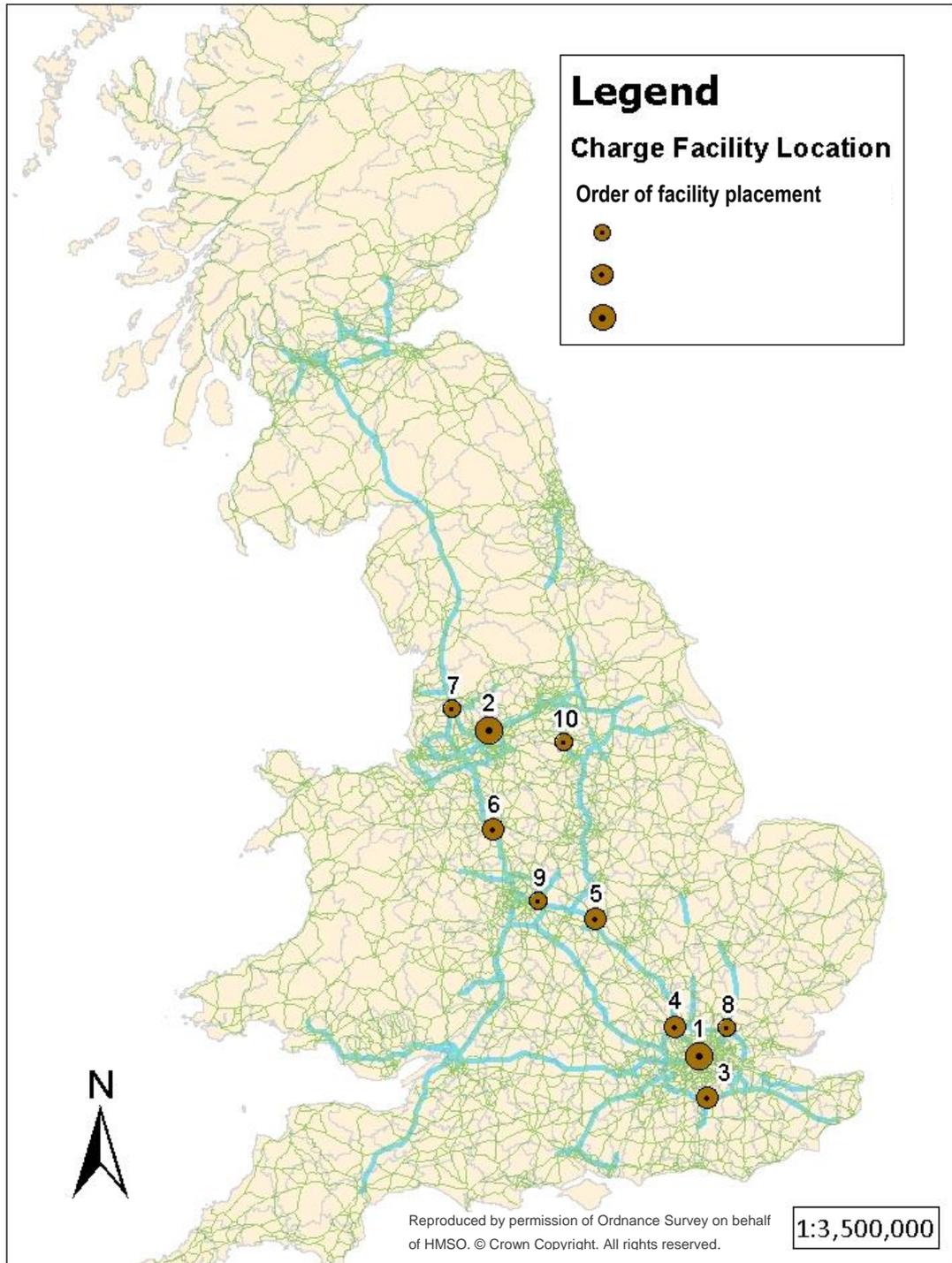
Figure 5-3 - First 10 Charge Facilities (W0min)

As identified in Figure 5-2, the location with the highest demand is in central London, and thus the first CF is placed there (servicing, in the model, a potential 3.75% of network flow). The second point is placed just north of Manchester, in the same location as the first CF in the sub-national

network (Figure 5-13), servicing a potential 3.12%. The fact that this amount of demand was still available for this location shows that the placement of the first CF had no impact in this area (i.e. it didn't enable the service of any multi-charge routes). This is unsurprising considering the second CF is placed more than 300km from the first. Subsequent points are placed on the motorway network around London and other large cities. A more detailed description of this placement accompanies Figure 5-4.

UK Charge Network - First 100 Facilities

Minimum Deviations Only, PFlow weighting = 0 (W0min)
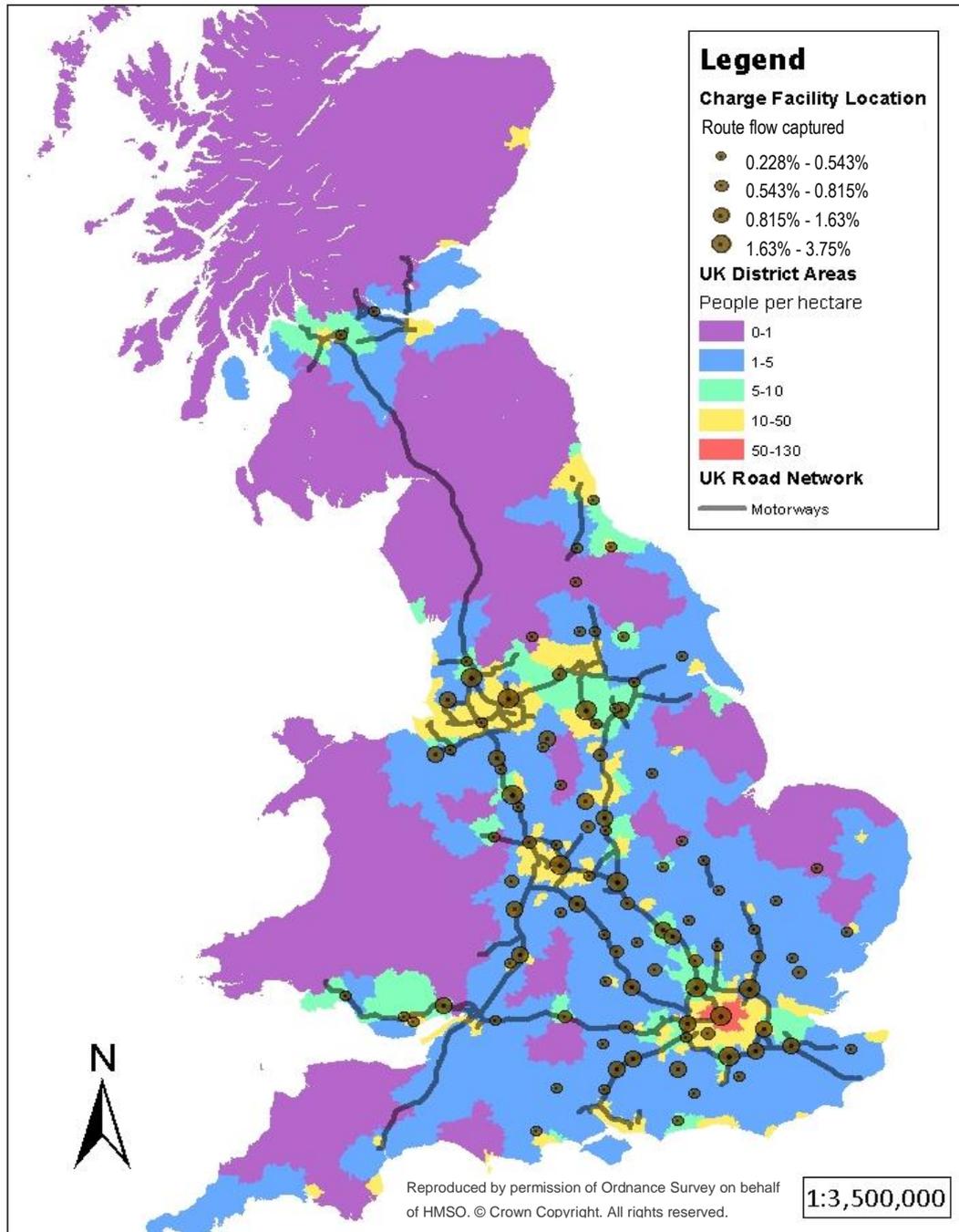
Figure 5-4 - Charge network (W0min) and UK population density

Data source: (UK Data Service, 2012)

Figure 5-4 shows the network output after 100 CFs have been placed. The size of the facility shown on the map indicates the magnitude of flow serviced at that point. Also shown are the UK district areas, colour coded to represent their population density. It can be seen that the large majority of points are placed in, or in-between, the most populous regions in the country. Facilities have

typically been suggested along the major arterial highways. This is partly a result of the use of the shortest path algorithm, which tends to choose motorway dominated routes, and also a reflection of the fact that many routes are likely to converge onto these paths, often in the middle of their journey, which is where charging provision are most effective.

Table 5-2 shows the total amount of flow that is deemed captured by the model depending on the number of CFs placed. The model is solved for 300 CFs, by which point 95% of the total network flow is deemed captured.

Table 5-2 - Flow captured by W0 CF network

# of CFs	% of total	% Increase
10	24%	24%
25	42%	18%
50	60%	18%
100	77%	17%
150	86%	9%
200	90%	4%
250	93%	3%
300	95%	2%
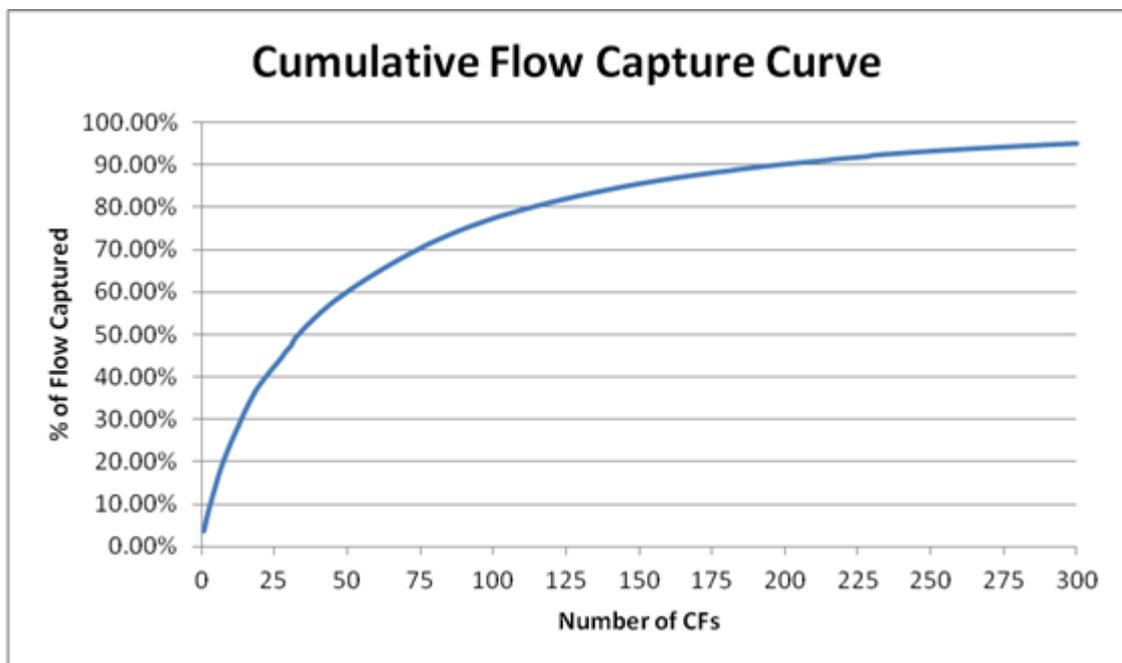
Figure 5-5 - W0 CF network flow capture rate

Figure 5-5 shows the cumulative increase in flow captured as each successive CF is placed in the model. The logarithmic shape of the curve is indicative of most greedy algorithms, where the aim is to select the highest demand point followed by the next highest point and so on. Hence, each

additional point typically contributes less to the total than the previous one. This is highlighted in Table 5-2 which shows that the first 100 CFs capture 77% of the total flow and the placement of a further 200 points only captures an additional 18%. With this approach of solving, successive placement of charging stations results in a lesser increase in the capture of overall flow. While this rule generally holds true for the network above, there are a few instances where a subsequent facility captures more flow than previous ones. For instance, the 14th CF services 1.59%, whereas the 12th and 13th CFs only service 1.53% and 1.51% of the flow respectively. This phenomenon occurs when longer routes become partially satisfied within the network. If a route then only needs one more CF placed to enable it, it can be fully captured and the flow from the entire route is assigned to the last CF placed by the algorithm. Therefore, in the example above, the placement of the 13th CF partially satisfied several routes such that the 14th point could fully enable them.

However, this process took place somewhat by chance. That is, the algorithm was not aware that by placing the 13th CF, it would enable the 14th point to capture more flow. The objective, when placing the 13th point, was to enable as many single-charge routes as possible. Thus, the fact that longer routes were partially satisfied was not intentional. Overall, a flow capturing improvement like this – caused by an inadvertent servicing of PFlow - occurred for 22 out of the 300 CFs placed.

5.4   Considering Potential Flow

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

Section 5.3 demonstrates the solving performance of this research method on a large and complex real-world network. It is clear that the success of each additional CF placement is dependent on the composition of the network and the amount of flow available. For instance, the more expansive the network, the greater the number of facilities required to fully satisfy all of the flow. However, as is evident in this network, if the majority of flow is concentrated in main corridors then it is likely it can be satisfied with a minimal number of points. If the flow in the remaining areas is dispersed, then many points are needed to capture diminishing amounts. Additionally, since long routes are not initially considered, their position in the network is crucial to the likelihood of them becoming serviced. Consider the route in Figure 5-6.
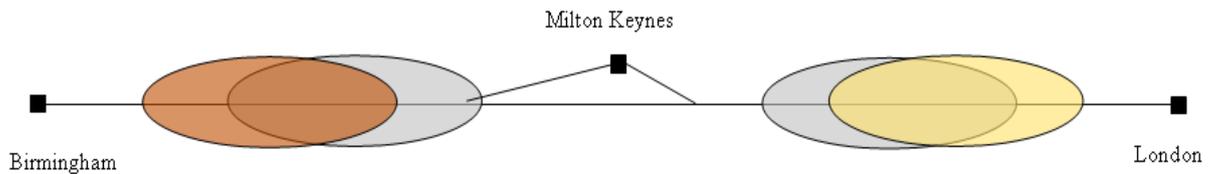
Figure 5-6 - Servicing multi-charge routes

Figure 5-6 shows a major route (Birmingham to London) which requires two charge facilities. As was pointed out in section 5.3, the model can only service a multi-charge route if it happens to become partially serviced first. Consequently, the multi-charge route is reliant on the placement and composition of single-charge routes in the network to help initiate its capture. In this example, it is likely the Birmingham to London route will become serviced thanks to the positioning of Milton Keynes (MK). If there is sufficient demand between either London and MK, or Birmingham and MK then a CF will be placed in one of the coloured charging zones (CZs). Providing this location corresponds to one of the Birmingham to London CZs then the long route will become partially serviced. Then, with only one more charge facility required, the flow from this route would be designated serviceable. At this point, the model would recognise the demand in the remaining CZ and place a CF to fully enable the route.

In its current form, this approach is designed to select the location with the highest SFlow (Serviceable Flow) in the network. As a result, single-charge routes are weighted more than multi-charge ones. However, if a more balanced weighting is applied, the location and significance of longer routes can be considered. Proposed in this section therefore, is an alternative to the original solving method, which attempts to influence the heuristic process by attributing some weight to longer routes, and thus improve the fitness function as stated in modelling objective d. The balance which provides the best results (capturing the most flow) could be variable and may depend on the composition of the network. This idea is explored in the diagram in Figure 5-7.

A—B = 80
C—D = 110
E—F = 50
G—H = 60
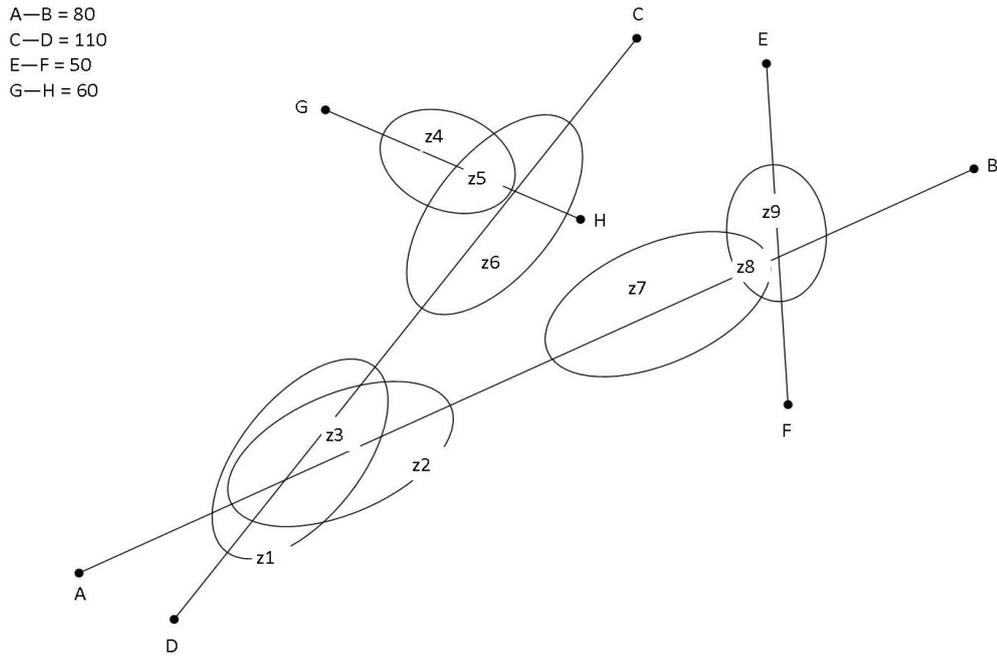
Figure 5-7 - Multi-charge route network

Figure 5-7 shows a figurative network with two single-charge routes and two multi-charge routes. The elliptical shapes on each route represent their charging zones. The overlapping zones represent the unique locations where a CF could be placed and are denoted by z. Route AB has a flow of 80 and requires two CFs; route CD has a flow of 110 and also requires two CFs; routes EF and GH only require one CF and have flows of 50 and 60 respectively. In the initial formulation of the model, only the charge zones from EF and GH would be assigned any SFlow. Thus, the greedy algorithm would select either zone 4 or 5 (randomly), which would contribute 60 to the flow total. The next point would be placed in either zone 8 or 9 and would capture a further 50. Depending on the placement of the first two points, the last point could be placed in z3 and would capture the remaining 190 flow in the network. Table 5-3 proposes four new greedy heuristic methods which assign different weightings to each zone. Method 1 describes the incumbent technique, which considers SFlow only. The second method considers only the PFlow (potential flow). The third, fourth, and fifth methods use a combined weighting of SFlow and PFlow.

Table 5-3 - Weighted flow heuristic proposals

Method	1	2	3	4	5
Zone	Wflow = Sflow	Wflow = Pflow	Wflow = Sflow + Pflow	Wflow = Sflow + (0.5*Pflow)	WFlow = SFlow + (0.2*PFlow)
1	0	110	110	55	22
2	0	80	80	40	16
3	0	190	190	95	38
4	60	0	60	60	60

5	60	110	170	105	82
6	0	110	110	55	22
7	0	80	80	40	16
8	50	80	130	90	66
9	50	0	50	50	50

In Table 5-3 WFlow describes the weighted figure which can be used by the greedy heuristic to choose each location. In this heuristic procedure, once a point is placed, the table can be updated to reflect the removal of some of the flow. The next highest demand zone can then be chosen from the updated list. This example helps to describe a shortcoming in the method described in section 5.3, namely that multi-charge routes are not initially considered in the model. Thus, as the model is scaled up to a larger network where many multi-charge routes exist, it is important to implicitly consider these routes in the solving heuristic.

Table 5-4 - Weighted heuristic results

Greedy Heuristic approach										
CP#	Approach 1		Approach 2		Approach 3		Approach 4		Approach 5	
	ZoneID	Flow captured	ZoneID	Flow captured	ZoneID	Flow captured	ZoneID	Flow captured	ZoneID	Flow captured
1	4 (or 5)	60	3	0	3	0	5	60	5	60
2	9 (or 8)	110			5	170	3	170	3	170
3	0 (or 3)	300			8	300	8	300	8	300

Table 5-4 shows how each approach from Table 5-3 could be solved. Using approach 1 (SFlow only), the entire network flow could be captured by placing points at 5, 8 and then 3. Feasibly however, the first two points could be placed in z4 and then z9 (since the SFlow values at these points are the same as in z5 and 8). If this happened, then the network would be left with no SFlow and as such the heuristic would stop with only 110 flow captured. A similar result would occur with approach 2. Z3 would initially be chosen, capturing 190 PFlow (but crucially no SFlow). The flows in z5-8 would then switch from PFlow to SFlow leaving no further available PFlow in the network. The heuristic would therefore stop, having captured 0 serviceable flow. Approach 3, 4, and 5 however guarantee the capture of flow by combining SFlow and PFlow. Approach 3 weights PFlow the same as SFlow, therefore designating potential flow charge zones just as importantly as serviceable zones. Using this approach, a CF would first be placed in z3 and would capture 0 flow (only potential flow would be captured). Two subsequent points would then be placed, capturing all the flow in the network. Approach 4 uses a weighting which designates SFlow twice as importantly as PFlow. Unlike approach 3, this method places its first point in z5 – capturing 60 flow. Two further points are then needed to capture the remaining flow. Similarly, approach 5 considers

PFlow but only marginally in comparison to the SFlow. Solving with this weighting produces the same outcome as approach 4, with flow captured with each facility placed.

By comparing the results from Table 5-4 it can be seen that methods 4 and 5 outperform (or match) the other heuristics at each CF stage for this example – i.e. they capture the most amount of flow after the placing of each CF. Weighting the SFlow higher than the PFlow implies that the model will favour zones with a greater proportion of single-charge routes over multi-charge routes. However, where the difference in Sflow is marginal, the heuristic chooses the location with greater potential flow. In doing so, an improved chance of capturing greater flow with subsequent CFs is possible; but the immediate objective to capture as much flow as possible isn't neglected. Thus, a weighted heuristic may help ensure facilities are placed to service both short and long routes. Ultimately, this may lead to flow being captured at a faster rate with the same number of facilities, or may provide a method to provision for longer routes (if this was a desirable policy) without hindering the number of BEV journeys that could be serviced.

5.5   Weighted Flow Heuristics

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to: maximise the number of extendable BEV journeys, given a number of facilities to be placed.)

To test the hypothesis presented in section 5.4, as in Table 5-3, and to try and improve the fitness function as defined above, weightings of SFlow + (0.5*PFlow) and SFlow + (0.2*PFlow) are separately applied to a charging demand map (see Figure 5-8). The overall objective for the heuristics remain the same: to fully capture as much flow as possible, given a set number of CFs; but the approach is adjusted so that initial flow gains are slightly sacrificed in favour of longer routes. The rest of the process also remains the same; once a facility is chosen, serviced flow is removed from the model and the network is reassessed such that a new facility can be placed. Weighting this part of the heuristic therefore, only adjusts the location selection process with the amount of flow captured dependent on the number of routes serviced in that instance.

Figure 5-8 shows a heuristic demand map with a weighting of SFlow + 0.5*PFlow (left-hand side) and SFlow + 0.2*PFlow (right-hand side) applied. By definition, both of these maps are fairly

similar to the one shown in Figure 5-2. The weighting given to the SFlow is the same in all maps so the difference shown represents the effect of the PFlow. Noticeably, as the PFlow weight increases, demand along the motorway network becomes heavier, indicating that longer routes tend to these roads. As such, it is likely that CFs will be placed along the motorway network sooner in the 0.5*PFlow heuristic procedure. Unlike in Figure 5-2, Scotland no longer appears cut-off from England with charging routes between the two active in the model from the start. These locations may still not be joined up, but this will more likely be down to the flow weight between them. For instance, the percentage of network flow between Glasgow (the major conurbation in Scotland) and Manchester (a major city in northern England) is only 0.033% – representing the fact that journeys of this magnitude may not be carried out by drivers on a regular basis. A combination of charge facilities placed just south of Glasgow, just north of Manchester and about halfway between the two could service this route, but judging by the demand colouration shown in the map, this is unlikely to happen until late in the heuristic procedure.

As with the unweighted heuristic, both of these methods can be solved in a greedy manner – with the WFlow (Weighted Flow) determining the sequence of points chosen, instead of the SFlow. An output showing the location of the first 10 CFs in each network is shown below with the scale indicating the magnitude of flow captured (i.e. completely serviced routes).

Figure 5-8 - Charging demand maps (W0.5min & W0.2min)

Figure 5-9 shows the output of the weighted heuristics for the first 10 CFs in the network (referred to as W0.5 and W0.2). When compared to Figure 5-3 (referred to as W0), the difference in solving

approach can be seen. In the W0.5 heuristic the first point is placed on a motorway junction on the outskirts of London, as opposed to central London with W0 and W0.2. The second point is also placed differently, this time closer to the first CF, thereby potentially providing a combination of chargers for long routes. The remaining points are then distributed across the network and end up in similar, but not identical, locations as those placed with a 0 PFlow weighting.

Figure 5-9 - First 10 CF network (W0.5min & W0.2min)

The results from the 0.2 PFlow weighting, unsurprisingly, provide an intermediary solution between W0 and W0.5. The first two CFs are placed in the same location as W0 (Figure 5-3) but

the third CF is placed in the same location as CF1 in the W0.5 heuristic. The remaining facilities are placed relatively evenly in the corridor from the South-East to the North-West.

Table 5-5 - Comparison of heuristic results – First 10 CFs

CP#	W0	Wflow = Sflow			W0.5	Wflow = Sflow + (0.5*Pflow)			W0.2	Wflow = Sflow + (0.2*Pflow)		
	Sflow	Pflow	Wflow	Total % Captured	Sflow	Pflow	Wflow	Total % Captured	Sflow	Pflow	Wflow	Total % Captured
1	3.75%	2.18%	3.75%	4%	2.65%	5.57%	5.43%	3%	3.75%	2.18%	4.18%	4%
2	3.12%	1.38%	3.12%	7%	2.91%	3.05%	4.43%	6%	3.12%	1.38%	3.40%	7%
3	2.64%	1.00%	2.64%	10%	3.18%	2.33%	4.36%	9%	2.40%	4.66%	3.34%	9%
4	2.45%	4.37%	2.45%	12%	3.12%	1.38%	3.82%	12%	2.48%	2.80%	3.04%	12%
5	2.40%	4.09%	2.40%	14%	2.36%	2.35%	3.53%	14%	2.72%	0.92%	2.90%	14%
6	2.37%	2.93%	2.37%	17%	2.71%	0.85%	3.13%	17%	2.35%	2.36%	2.83%	17%
7	2.10%	0.71%	2.10%	19%	2.43%	0.73%	2.79%	19%	1.65%	2.00%	2.05%	18%
8	1.86%	1.08%	1.86%	21%	1.65%	2.00%	2.65%	21%	1.85%	0.88%	2.03%	20%
9	1.79%	2.57%	1.79%	22%	1.83%	0.98%	2.30%	23%	1.83%	0.98%	2.01%	22%
10	1.66%	1.07%	1.66%	24%	1.50%	1.32%	2.15%	24%	1.92%	0.29%	1.98%	24%

Table 5-5 compares the flow capturing results for the first 10 CFs using the W0, W0.5 and W0.2 heuristics. For W0, the greedy heuristic selects solely from the SFlow column. Consequently, it is more likely that each subsequent point captures less flow than the previous one. Indeed, this is entirely true for the first 10 points. CF placement with W0.5 however, does not follow this pattern. The first two points effectively sacrifice short-term flow capture in pursuit of greater flow-capturing potential later on. The manifestation of the sacrifice is fairly immediate with higher flows recouped by the third and fourth points. By the time 6 CFs have been placed the W0.5 heuristic compares similarly to the W0 approach.

Table 5-6 - Flow captured by 300 CF networks - W0, W0.5 & W0.2

	W0	W0.2	W0.5
# of CFs	% of total	% of total	% of total
10	24%	24%	24%
25	42%	44%	43%
50	60%	60%	61%
100	77%	77%	78%
150	86%	86%	86%
200	90%	91%	91%
250	93%	93%	94%
300	95%	95%	96%

Table 5-6 shows the performance of W0.5 and W0.2 in comparison to W0 considering the placement of up to 300 CFs in the network. As with the W0 method, the general flow capturing

trend of the W0.5 and W0.2 heuristics is logarithmic in nature, with a point placed at the beginning capturing more flow than one placed at the end. However, thanks to the weighting of potential flow this upward trend is less uniform. For instance, in the W0.5 heuristic there were 112 occasions out of 300 when a CF captured more flow than a previous one in the heuristic sequence, compared to just 22 times for W0. This alternating capture effect occurs when a point is placed in an area with high potential flow but low serviceable flow. Many multi-charge routes become partially serviced and thus the next few points placed can complete some of these routes and capture a greater amount of flow. Generally, the application of the W0.5 heuristic performs similarly or better than the basic W0 capturing one. Likewise, after the placement of the first 10 CFs the W0.2 heuristic captures a similar amount of flow compared to the others. However, after the placement of the 12th CF the W0.2 heuristic begins to slightly outperform W0 and continues to do so until termination. Thus, the *gamble* taken by the heuristic is justified – since the initial flow-capturing sacrifice is recouped and the performance marginally bettered.

The use of a weighted heuristic demonstrates how longer routes can be considered with more importance - but without compromising the solving performance of the model. However, depending on the composition of the network and the number of points to be placed, the relative success of the weighting applied may vary. In general, the scale factor chosen forces the heuristic to consider longer routes with more or less importance. Thus, the greater the weighting the more likely the model is to choose areas with high potential flow in the *gamble* that this partial unlocking of routes will pay back later. However, if the weighting is too strong it is likely that the heuristic will over-sacrifice completing routes, in the pursuit of partially satisfying them. As shown in Table 5-6, these heuristics offer alternative approaches which consider longer, multi-charge routes with greater importance. Although these approaches do not offer a significant demonstrable improvement over the initial greedy approach, they do not appear to hinder the overall performance of the model. Given this, these heuristics offer alternative location methods which could be used to weight longer routes more strongly without compromising the overall efficiency of the solution.

5.6   Decreasing Weight Heuristic

The techniques presented in section 5.5 attempt to address a weakness associated with additive greedy algorithms, namely that facilities are only placed in the 'best' location *one* at a time. The effect therefore that each point has on the future optimisation of the network is not anticipated. Consequently, satisfying longer routes, which require more than one charge, cannot easily be

considered because the greedy technique is only searching for the next best location; not set of locations. However, by applying a weighting to longer routes, the model is forced to consider locations which don't immediately optimise the objective (to service as much flow as possible). Instead, a sacrifice is made in the hope that flow can be recouped later on in the heuristic sequence.

Thus far, the model has been run to additively place charging facilities with no particular limit in mind. That is to say, that the solving procedure does not have an awareness of how many points will eventually be placed. However, it is possible to adapt the performance of the heuristic so that the number of CFs is taken into account. For instance, if only one point is to be placed, then the optimum technique is to choose the one location with the most SFlow. This point may not remain optimum if the heuristic is continued, but it is known to be optimal in this case because it is the *last* point placed. Thus, regardless of the heuristic chosen, the optimum solution for the last point will always be to choose the location with the most SFlow; since there is no point seeking out potential flow given the heuristic is halting immediately afterwards.

As shown in section 5.5, a better result can be achieved if potential flow is considered at the start of the heuristic. However, as the procedure progresses the positive effect of choosing high PFlow areas diminish; since there is less chance that all the routes partially satisfied will be captured before the heuristic stops. As such, a method which considers PFlow at the start of the heuristic but not at the end is desirable. Table 5-6 shows that a PFlow weighting of 0.5 produces marginally better results for the placement of the first 25 CFs. Its peak (i.e. the point at which it performs proportionally better than the other two methods) occurs at the placement of the 30th CF. From this point onwards its performance diminishes with respect to the other heuristics, indicating that a weighting of 0.5 is no longer optimal (within the set suggested). As has been determined, the ideal weighting for the very last point is SFlow + 0*PFlow. Given this, before each iteration within the heuristic, it is possible to recalculate the value for WFlow so that a different criterion is used to select the next CF. A formula, using some sort of diminishing function, is therefore needed which transforms the weighting of 0.5 to 0 as the heuristic progresses. Proposed here is a simple linear function which decreases the weighting applied to the PFlow proportional to the number of CFs to be placed in the procedure.

Thus, WFlow can be expressed as:

$$WFlow = SFlow + (PFlow * (IW - (((CF\#-1) / (((CFs-1) / IW)))))$$

where

IW = Initial Weighting applied to the PFlow

CF# = The iteration value of the next CF to be placed

CFs = The total number of CFs planned

This formula ensures that the weighting applied to the PFlow begins at IW and then, with each iteration of the procedure, decreases in a linear fashion to 0. To test this approach, a value of 0.5 is taken for IW, the CF# sequence starts at 1 and the total number of CFs planned is 300. Thus, the initial numerical application of the weighting is:

SFlow + (PFlow * (0.5 − ((1 − 1) / (598)))) = SFlow + (PFlow * 0.5)   -   W0.5 –> 0

And for the final iteration:

SFlow + (PFlow * (0.5 − ((300 − 1) / (598)))) = SFlow + (PFlow * 0)

Results from this procedure are presented and compared to heuristic W0, W0.5 and W0.2 in Figure 5-10 below.
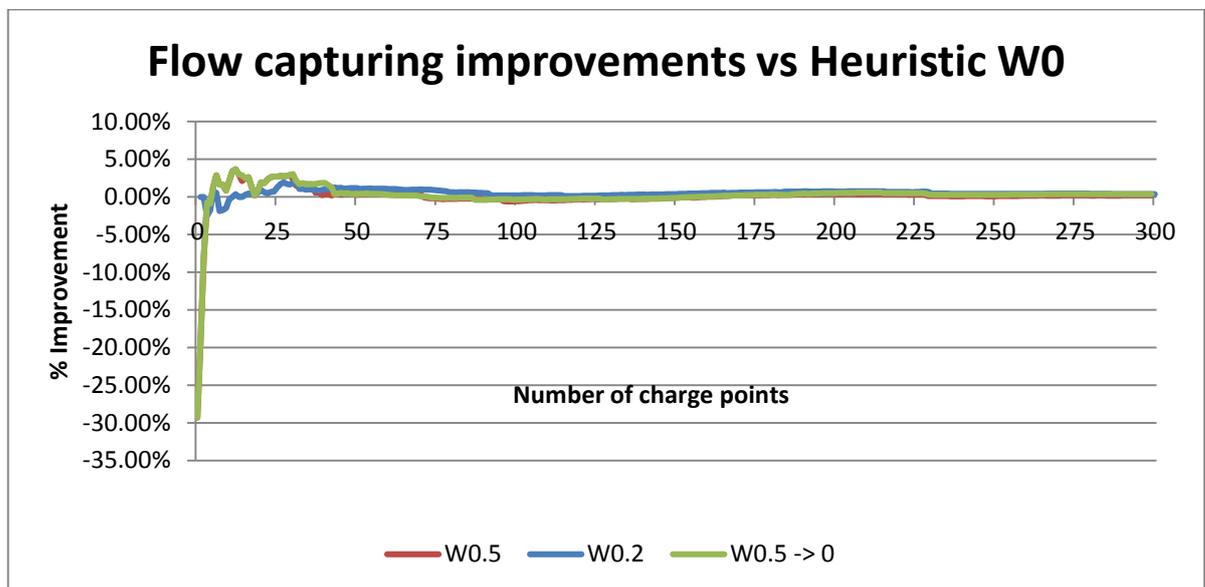
Figure 5-10 - Graphical comparison of flow capturing heuristics

Figure 5-10 shows the results from each method proposed so far (PFlow weighting of 0.5, 0.2 and 0.5->0 respectively) as an improvement compared to the original heuristic (PFlow weighting of 0). The graph shows the cumulative estimated percentage improvement in terms of total flow available in the network. It can be seen that the W0.2 heuristic appears to perform better than W0 over a low number of charge points placed. The W0.5 and W0.5 –> 0 heuristics initially produce similar

results to this since they both start with a PFlow weighting of 0.5. This higher weighting has a more tumultuous impact compared to W0.2. Initially, a greater amount of flow is sacrificed as locations which satisfy longer routes are sought. However, the payback for doing so appears after a low number of locations are placed (12 CFs). By around the 40th point placed, the heuristic approaches appear to converge, and can be considered similar. The rate of the convergence for the W0.5 –> 0 method however is slightly lower than the for W0.5 method only. As the heuristic progresses, the decreasing PFlow weight enables the model to immediately capture as much flow as it can, without sacrificing performance in the hope of future gains. This effect is particularly noticeable towards the end, where the performance gap between W0.5 and W0.5 –> 0 widens in favour of the decreasing weight heuristic, albeit marginally. Overall however, as more facilities are placed, the more the results converge. This is likely due to the fact that even without a weighted search, the W0 method eventually places enough points to satisfy most multi-charge routes, as well as the single-charge routes it was aiming for.

5.7   Placing a Fixed Number of Charging Facilities

The methods presented in section 5.3 and 5.5 all use a fixed PFlow weighting which remains constant throughout the heuristic. As a result, their performance is independent of the desired number of charge facilities set. The advantage of this is that the heuristic can be run beyond the actual number of facilities that are initially desired. Doing so provides a potential insight into the future, allowing the creation of a potential master plan which could be built and implemented in stages if desired. However, as the result from heuristic W0.5 –> 0 shows, applying a constant weighting can be detrimental if the heuristic is ended prior to capturing of the network flow. If an intended number of charge facilities is known, solving the heuristic with this in mind could improve its performance – especially as it reaches termination. To further test this hypothesis, the number of charge facilities is fixed to 50 and the formula presented in section 5.6 is used so that the PFlow weighting decreases to 0 upon termination. An initial weighting of 0.5 is used, producing the formula below:

WFlow = SFlow + (PFlow * (0.5 – (CF# - 1) / 98))   -   W0.5 –> 0

where:

CF# is the iteration value of the next CF to be placed.
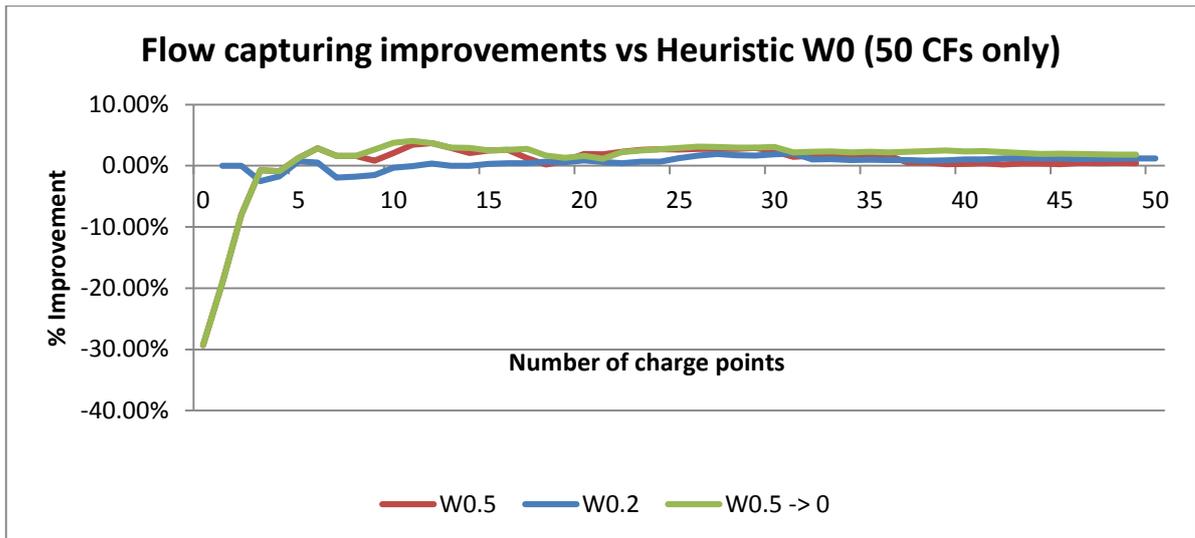
Figure 5-11 - Comparison of flow-capturing methods for first 50 CFs

Figure 5-11 shows the performance of every heuristic in relation to W0 for the first 50 CFs placed. It can be seen that the decreasing weight heuristic slightly outperforms all other techniques and, upon termination, has captured 1% more flow. This could mean – if the decreasing weight heuristic were used – that the same amount of flow could be captured with up to 3 charging facilities less. However, given the number of variable parameters used in the model (notably the flow amounts and the network composition) it is not felt that this is a significant result which would guarantee improved performance. In reference to objective d (improving the fitness function), the application of a decreasing weight heuristic can therefore be described as an alternative approach, which could have the potential to improve the model performance in situations where a fixed number of charging facilities are planned.

5.8   Analysing a Network with Closed and Unclosed Borders

Objective 4: Demonstrate differences in modelling outcomes based on comparison between national infrastructure plan and a smaller regional like plan.

Given the above objective, a comparison is needed between a geographically restricted area (such as the British mainland) and an artificially enclosed area (such as the regions mentioned in section 1.7.3). Based on this, an artificial network is constructed using the same methodology as before. However, only the OD flows within this network are specifically considered – essentially insinuating it has a closed border. This network is shown in Figure 5-12.

Regional Network Design

Network Built at Regional Level
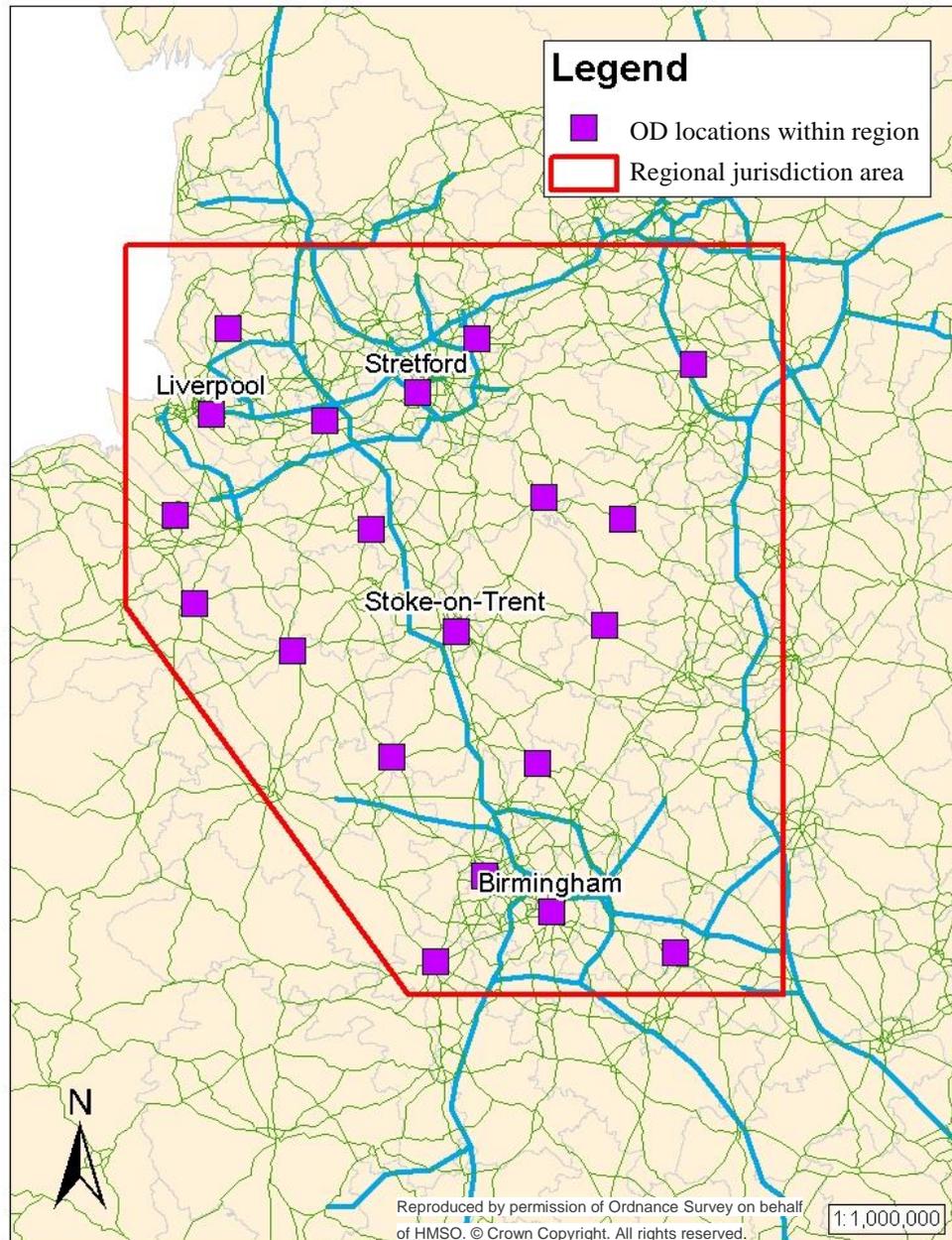
Figure 5-12 – A fictional closed border network

Figure 5-12 shows a fictional area within the UK that could be considered to have a closed border. If this area represented a region where a planner had jurisdiction to place charge facilities, the typical approach would be to create and solve a network for this study area only. However, this policy may result in a sub-optimal network which is isolated in relation to bordering areas. Assuming travel into and out of the area is possible then it is prevalent to consider the effect of external flows. Without this consideration, charge facilities would be placed to serve the internal regional journeys only. Thus, a proportion of the market could be missed. If however, the demand

in this region is 'cut out' from the national network, the effects of external flow can be considered. Cutting and solving a sub-network in this way holds certain advantages over creating a network solely at the regional level. Figure 5-13 shows the difference between the two methods and presents the results if 5 facilities are placed in the region. The upper map shows charging demand built from regional data only. Only journeys which start and end at the OD locations shown in Figure 5-12 are considered. The lower map shows the same area but with charging demand retained from the national model described in section 5.2. Thus, rather than just internal journeys, those which are travelling into, or out of, the region are considered. The difference between this approach and that in section 5.2, is that the model is only solved in the area described, meaning that charging facilities are only placed in this zone, but can service routes which are partially external.

Figure 5-13 - Comparisons of modelling scale – Regional level or Sub-national level

The differences in the two maps presented in Figure 5-13 are particularly marked around the region's periphery. The regional-only network is effectively a 'closed island' with demand tending

to flow through the centre. In the sub-national model, where incoming and outgoing flows are considered, demand is much stronger around the area's edges. The most noticeable effect can be observed in the north of the region where demand is heavily influenced by strong flows to and from large population centres just outside the region to the north-east. With the objective to capture as much serviceable flow in a greedy manner (i.e. the same as that described in section 5.3), the first facility would be placed on the northern edge of this area and could service 3.12% of total network flow in the model (British mainland). In the regional-only network, this point would not be chosen first – as only 49 flow is recognised (i.e. approximately 5/6 of flow at this point is partial regional flow). The highest demand point in the closed border network on the other hand, would be placed centrally and would capture 2.01%. The same location in the sub-national network would only capture 2.05%. Overall, evaluating the regional-only network provides service for a potential 5.34% of the total national flow if 5 CFs are placed. The sub-national solution however, could provide service to 11.14% of flow with the same number of facilities. If external flows are later considered on the regional network, the solution proves sub-optimal in comparison with only 5.49% of the network flow captured, compared to 11.14% (an improvement of 103%).

Deciding which method to employ may depend on the objective of the model implementer. If the objective is to only service journeys which originate in their region, building the smaller network would suit their purpose. For instance, if a subscription system was utilised – whereby a user pays an annual fee to have access to the charge points – then the regional method would likely be sufficient (users who only occasionally drive into the region are unlikely to pay for the subscription). Similarly, regions with closed borders or standardisation differences could be considered as isolated entities. However, if charge points allow universal access and border movement is possible, consideration of external flows provides a planner with a better knowledge of overall demand and could improve the usage rates if they implemented this design.

5.9   Considering Maximum Deviations

Thus far, the model has been built and solved assuming a maximum deviation of only 2.5 km. This allows a driver to depart from their shortest path and make a minor deviation to a nearby charging facility. The model is constructed such that the BEV has enough capacity allowance to return to the shortest path and continue onward to their destination or the next charge point on their route. As discussed in section 3.5, allowing greater deviations could give the model more locating freedom and could increase the chance of multiple charge zones converging to a single area. Thus, if greater

deviations are incorporated, the model should be able to capture flow at a faster rate – facilities placed on a common shortest path will still be suitable, but the chance of capturing additional flow from nearby paths may be increased.

Using the methodology discussed in section 3.5, this chapter presents results where deviations of up to 7.5km are allowed (based on the parameter definition in section 3.3.4). The deviations are split into distinct bands and the flow from each route is assigned proportionally between them. The three bands considered are: up to 2.5km (minor deviations), up to 5km (medium deviations) and up to 7.5km (long deviations). Flow is assigned such that 100% of drivers are assumed to be willing to deviate up to 2.5km only, 80% up to 5km and 40% up to 7.5km – again, based on the parameter assumptions discussed in section 3.3.4. It is also assumed that deviations are only taken if necessary – i.e. 100% of the flow from a route will be captured if a facility is placed on its shortest path.

As in section 5.2, overlaying all of the charge zones and summing their attributes creates a hotspot map which represents flow as demand across the network. Figure 5-14 shows the charging demand map for the UK where deviations are considered as described above, and only the effect of the SFlow is shown.

Figure 5-14 - UK charging demand map (W0max)

Figure 5-14 shows the charging demand map for the UK considering deviations of up to 7.5km. Similar to W0min (Figure 5-2), a PFlow weighting of 0 has been applied meaning all demand shown is immediately serviceable. As such, the distribution of demand is very similar to W0min with hotspot areas coincident between the two. However, the spread of demand is much wider thanks to the allowance of greater deviation. This means that previous hotspot corridors now

encompass a broader area, and nearby roads carry greater significance, thus providing a wider option of potential sites which could be considered.

This instance of the model is solved for the first 10 CFs and presented in Figure 5-15. The approach used is identical to the solution presented in Figure 5-3. Visual results show that facility location is similar (although not identical) between the two outputs. The first CF in both cases is placed in central London, and subsequent facilities are located on the motorway network around London and towards the North-West of England. However, the flow-capture rate when considering maximum deviations is marginally improved.

UK Charge Network - First 10 Facilities

### Maximum Deviations Allowed, PFlow weighting = 0 (Wmax0)
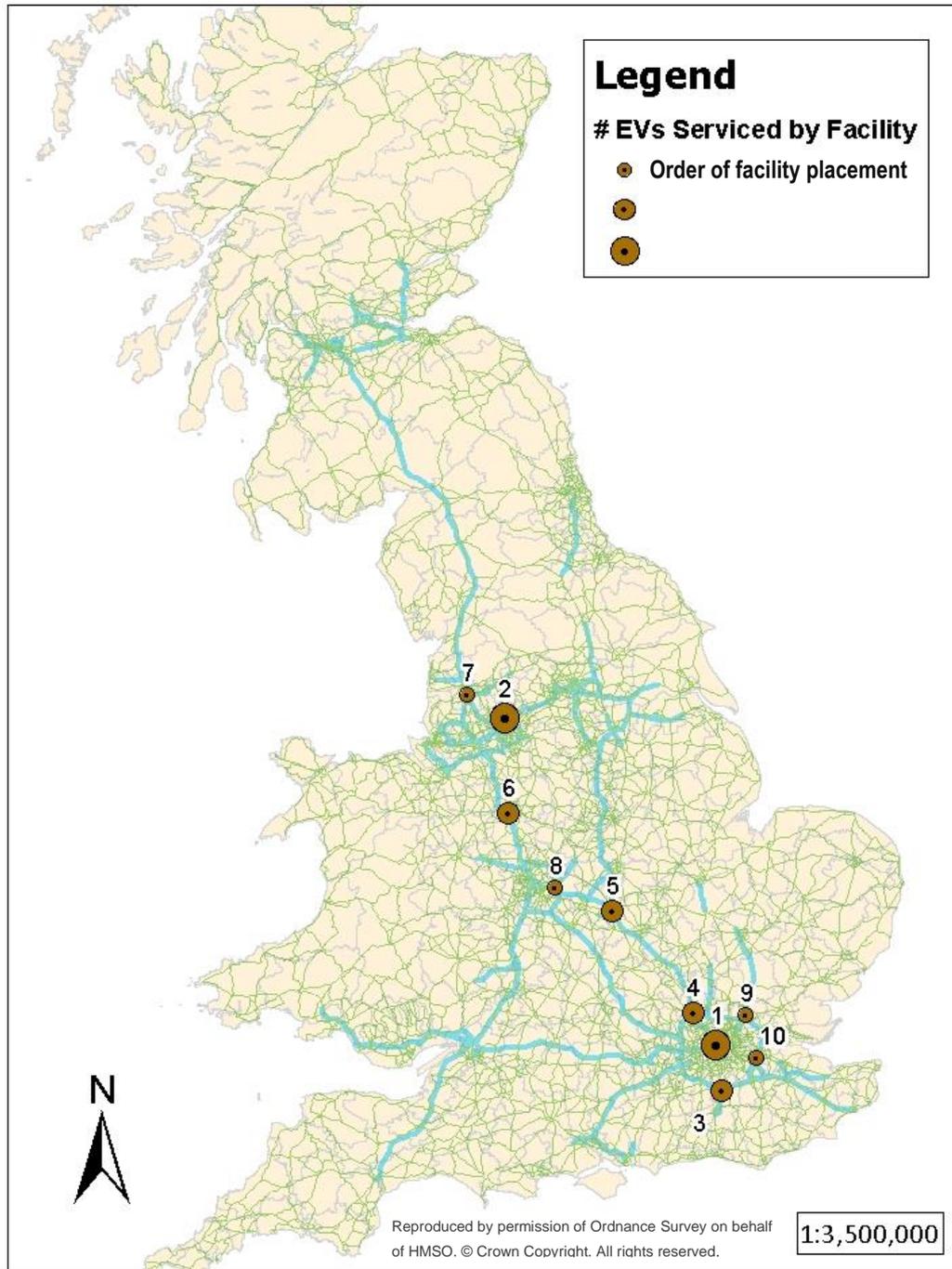
Figure 5-15 - First 10 CF network (W0max)

Table 5-7 - Flow-capture performance - W0max vs W0min

| CP# | W0max | Maximum Deviations | CP# | W0min | Minimum Deviations | % Improvement |
	Sflow	% Captured		Sflow	% Captured	
1	4.79%	5%	1	3.75%	4%	1%
2	3.16%	8%	2	3.12%	7%	1%
3	2.66%	11%	3	2.64%	10%	1%
4	2.58%	13%	4	2.45%	12%	1%
5	2.60%	16%	5	2.40%	14%	2%
6	2.38%	18%	6	2.37%	17%	1%
7	2.02%	20%	7	2.10%	19%	1%
8	1.86%	22%	8	1.86%	21%	1%
9	1.85%	24%	9	1.79%	22%	2%
10	1.67%	26%	10	1.66%	24%	2%

Table 5-7 shows the performance of the model when the deviation limit is increased from 2.5km (W0min) to 7.5km (W0max). The captured percentage rates show how much of the network flow has been cumulatively serviced by each stage. The improvement rate shows the amount of additional flow captured by the W0max model compared to the W0min method, as a percentage of total network flow (i.e. Captured % column 1 – Captured % column 2). It can be seen that, compared to the W0min method, assuming greater deviation marginally improves the performance of the output, and could service 1.43% more network flow after the placement of 10 facilities. Additionally, at each stage the W0max method provides a slightly greater cumulative flow total.

Similarly to section 5.5, weighted heuristics are also applied to the solution when considering maximum deviations. The charging demand maps for these outputs, although not shown, follow a similar composition to their minimum deviation predecessors. Roads where long routes are more abundant, such as major highways, are more pronounced than in maps where potential flow is not considered – similar to Figure 5-8. The resultant 10 CF output for these maps is shown in Figure 5-16.

*Figure 5-16 - First 10 CF Network (W0.5max & W0.2max)*
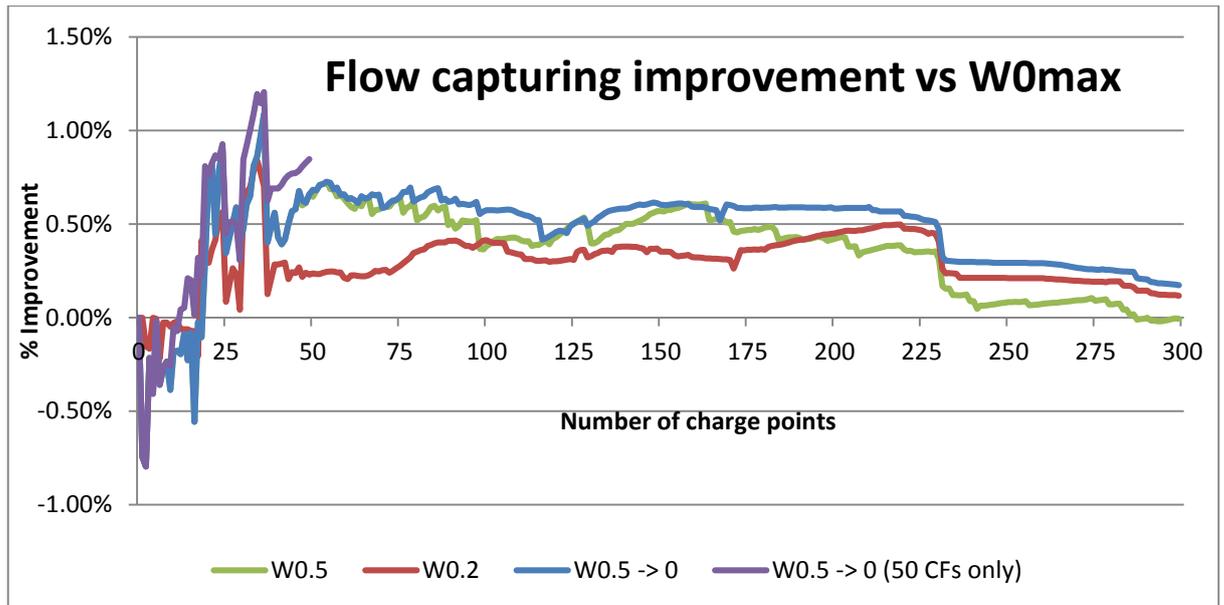
Figure 5-17 - Flow-capturing improvements of weighted heuristics vs W0max

Figure 5-16 shows the locations of the first 10 CFs in the network when solved considering maximum deviations and application of the W0.5 and W0.2 heuristics. Similar to previous results, charging facilities are located around London and towards the North-East – showing robustness for this layout. Figure 5-17 shows the results of these two heuristics in comparison to W0max. Additionally, two decreasing weight heuristics are applied, identical to the ones showcased in section 5.6. The heuristic is run to place 300 CFs – such that the PFlow weighting begins at 0.5 and ends at 0 for the 300th CF. Similarly, the model is solved for a limited facility placement of 50. All results show a degree of improvement compared to W0max (except for W0.5 which provides a near identical solution for 300 CFs). The rates at which they do so are fairly consistent with the minor deviation results. The W0.2 heuristic performs relatively consistently, with a minor sacrifice made followed by a steady improvement. The W0.5 heuristic is more extreme, with slight improvements made before a tail-off in the performance gap. The decreasing weight heuristics both provide marginally better solutions for the number of facilities placed.

Overall, results show that consistent flow-capturing improvements are possible if greater deviations are considered, although the improvements observed in this study are marginal. In the case of minor deviations, this allowance enables facilities to be considered just off from a major junction or highway. When allowing for greater deviations, it is possible that a facility can be placed in-between two major routes, thus capturing flow from both paths. However, in a candidate-free setting, the likelihood – given that location siting remained similar – is that a greater deviation simply allowed more routes to reach the same points. This relationship – between applying small

deviations, which don't penalise drivers too much, and greater deviations which allow superior accessibility but penalise drivers more – will thus have to be managed carefully.

5.10 Summary

This chapter looked at the complexity of expanding a network to cover a nationally sized area. Although it was not possible to validate the whole network against empirical usage data at this time, a series of key learning points have been identified which have not previously been reported in the literature. These are:

- Solving techniques were developed to account for a possible weakness in greedy adding approaches used to solve this model. This involved weighting multi-charge routes so that they could be identified in the solving procedure. A series of novel adaptations have been suggested which allow alternative solving heuristics to be implemented, and these were not found to be detrimental to the result.

- Deviation parameters were varied to ascertain if allowing greater deviation tolerances could improve the flow capturing potential of the model at a large scale. Although the use of a greater deviation limit (up to 7.5km) improved the flow capturing result, this increase was marginal. In addition, although the application of both methods was possible, the creation of larger deviation tolerances was found to be more computationally intensive than the smaller ones. Thus, given the high level of uncertainty around deviation tolerance, driver behaviour, and computational intensity, it is recommended that minimal deviations (up to 2.5km) are considered until more concrete data becomes available, given that there was a low level of calculated benefit between the two assumptions.

- To help identify issues around regional infrastructure developments, a network was constructed with a 'closed' border such that only internal journeys were considered. The same area was also evaluated without the border, and the suggested locations from each demonstration were compared. The modelling results suggest that considering a regional network design in isolation from the whole network results in likely sub-optimal location placement, and that consideration of how the region fits within the wider national network is important.

This chapter has demonstrated that the model and methodology in this thesis can be expanded up to national infrastructure level, and that there appears to be a benefit in planning at this level rather than regionally. Depending on the circumstances, minor alterations to the solving procedure might also be considered.

6   DISCUSSION

Chapters 1 and 2 discussed previous methods for locating rapid charging networks and identified key issues and shortcomings in these works. In chapter 3 novel methods were developed to overcome some of the shortcomings in currently published work, and in chapter 4 a practical validation of this research was undertaken by comparing modelled findings with empirical usage data. In chapter 5 the novel location model was tested to consider issues regarding expansion to a national level, with several alternative solving procedures proposed and tested. Within the methods proposed, and for any complex analysis of real world systems, there exist trade-offs and simplifications. In this chapter a discussion into the lessons learnt from this research will be presented which highlights these trade-offs and recommends possible avenues for future work.

6.1   Data Impact on Accuracy

Chapter 3 defined the necessary input data and potential range and variability of alternative values which can be used within the model. The use of these input parameters is primarily application specific, given they can be varied by anyone wishing to implement the model depending on the circumstances of their study. Within chapters 4 and 5, a specific application on the British mainland was chosen to demonstrate the modelling processes involved and validate against empirical data collected within this area. The methods applied appear to work well for this application and the parameters chosen are deemed appropriate given the availability of data. However, there are several inherent assumptions and considerations regarding the method chosen and the data which this requires:

6.1.1   Aggregation of population into an OD network

The aggregation of population into a coverage based network can help ensure realism and inclusion into the modelled results. In other environments this procedure could still be used, but in some cases the layout of the geography may affect how this manifests. For instance, in a more population sporadic environment, setting the aggregation distance to a percentage of vehicle range could result in either a higher number of OD points, or a greater exclusion of the population. In these cases, a trade-off between computational efficiency and desired population coverage for an infrastructure plan must be made.

6.1.2 Road network

In the methodologies described in chapters 4 and 5, it is assumed that people take the shortest (time) path between two points. Although this assumption is consistent with previous work, the application of this method is dependent on declared road speeds and congestion levels. A key shortcoming of the implemented method is that road speed is fixed for each road type. This results in a skew of assumed traffic towards routes where speeds limits are higher than the speeds which might be achieved on these roads in practice. This is highlighted in Figure 5-2, which shows a high potential demand through London. In this implemented case congestion is not considered, and so a route through the city is deemed faster than one around it. To help assess this process, traffic count data was compared with expected route flows (discussed in section 4.3.4). These results suggest that traffic assignment to A-roads was not as good as to motorways (since road speed varies considerably across A-roads, unlike the majority of motorways). However, the use of traffic count data might not perfectly represent expected flow along routes. This is because, in the model, journeys less than ½ of the vehicle range are not considered. Thus, when implemented (given the set parameters) only journeys greater than 50km are acknowledged. The majority of traffic from the count however, will likely be undertaking trips less than this distance. As a result, some routes might have a higher proportion of short trips compared to other routes. To overcome these general issues, ideally each road would be accompanied by a bespoke speed limit and congestion levels. However, as discussed in section 2.2 and 3.2.2, the inclusion of stochastic elements such as congestion may make the model more difficult to implement, given the likely increase in computational intensity that would result.

6.1.3 Route flow assignment

Within the implementations of the developed model in this work, a gravity model was used to assign traffic flow across the network. Although travel-to-work statistics were used to improve this implementation, a general shortcoming of gravity models is that they estimate journey needs based on node attraction and generation, and the distance between them. In addition, Census data used to populate implementations of this model were derived from the 2001 UK Census, and as a result the currency of the data is likely to have affected the results. In practice, traffic systems and journey choices are more complex than the one modelled in this thesis. Although an 'all-or-nothing' assignment is deemed appropriate to avoid unmanageable combinations in the model, a more accurate representation of traffic flow could be used. Origin-Destination networks, with pre-

populated routes can be bought or commissioned from many private companies or government organisations (such as the network available for Scotland produced by (National Records of Scotland Web, 2013)). The flow assignment technique used within this body of work was chosen as a means to demonstrate the developed methods within the financial constraints of the PhD. It is likely that a commercial package could produce different results, but the assumptions inherent in these networks (such as aggregation scales) may not be publicly available, and as such, may not be adaptable for an electric vehicle infrastructure application. An issue with commercially available OD networks, and the one presented in this thesis, is that they are built based on the travel patterns and geographic distribution of ICEVs. However, attributes of early BEV adopters, such as income level, environmental awareness, or niche travel patterns, may not be consistent geographically and across the whole population. Although this consideration is not currently incorporated into the results presented, this factor could be included within the research if data became available. The aim of including this would be to lead to a time dependent location strategy with uptake. Allowing early user needs to be met while ensuring that future users are catered for at the same time without too much cost penalty.

6.1.4 Parameters

Parameters which can be inputted into the model can vary depending on changes in time of day, temperature, road topology, driver behaviour, land availability, land cost, and electrical network capacity as discussed in section 3.3. The choice of these parameters is likely to impact on model implemented accuracy. The parameters chosen in the demonstrations of this model appeared to represent an effective set in conjunction with the model to allow validation of the approach. In general however, it is likely that results will vary depending on these parameters in the following ways:

- Range: In previous models, increases in range resulted in fewer locations being needed to capture flow in the network (where capacity wasn't assumed a constraint).
- Deviation willingness: Increases in deviation willingness presented within this thesis appeared to provide a slight increase in the amount of routes which could be serviced with a given number of locations. However, as discussed in section 6.3, it would be beneficial to test this relationship further.
- Candidate site selection: A novel approach in this thesis is the ability to quantify demand throughout the network and evaluate candidate sites for any location. In practice, additional site constraints will also apply (see section 6.2 for a wider discussion on this). As a

consequence, the results produced by this model will vary greatly depending on the candidate options chosen, but in all cases, the method will recommend the best sites (in order) from the given input set.

- Capacity at sites: In the modelling procedure, capacity can be set as a limiting constraint on any site. Given the variability in capacity constraint this is likely to have an effect on the output if the data is known (see section 6.2 for a wider discussion on this). In the solving procedure, a capacitated site could be placed and, depending on the capacity constraint, could only capture a portion of the flow in that area. As such, at a later point in the procedure a site nearby to the original location might be recommended to help service all of the demand in that area.

6.1.5 Inherent assumptions

One inherent assumption in the modelling approach is that it is expected drivers will wish to minimise the number of times they need to recharge on a route. This may not accurately represent driver behaviour under all situations, but without data to this effect, this assumption is deemed appropriate.

The modelling technique developed in this thesis assumes that drivers will choose a recharging site based purely on their journey/range needs. However, in actuality drivers may not always choose sites in relation to their location. Additional ancillary services at sites may draw in customers who then charge. Alternatively, drivers may choose a charging site based on a perceived range need (such as when their state of charge falls below 50%) even if an alternative combination, which may allow them to recharge fewer times, exists.

Additionally, it is assumed that vehicles start long journeys with 100% state of charge in their battery. This possibility is evidenced by findings from the CABLED trial (see section 3.3.2), but due to the size of the sample this assumption might not apply in all other cases. As suggested in section 1.7.3, it is likely to be more applicable to BEV owners who can charge at home. As a means of handling variations in this assumption, conservatism was added to the range. In doing so, it is likely in some cases where a vehicle does not start with 100% range their journey needs could still be handled by the model.

Although not an inherent assumption, in the implementation of the model in chapters 4 and 5 routes requiring 4 or more charges are excluded. This could impact the provision for these routes in the future, however as suggested in 3.3.1 there is unlikely to be significant demand for these journeys (possibly representing 0.07% of all trips (Department for Transport UK, 2013f)).

6.1.6 Validation data

Empirical rapid charging usage data was reported by a number of operators and collated by the regional infrastructure manager, Cenex. Within this data there existed slight data anomalies. Following discussion with the operator, the majority of these errors were identified as data recording issues (where charging took place but no data was recorded), and corrected for accordingly in the analyses. However, variations in driver behaviour and the billing mechanisms in place may also have introduced deviations in expectations.

For instance, driver behaviour was likely influenced by the free-at-point of use scheme available for these rapid chargers. It was noted within the data that some users took advantage of this and appeared to charge with a regularity not normally associated with long journeys. In future, such billing systems might be replaced by pay-at-use schemes, and if so different usage patterns might be expected.

In addition, the cohort of people using these sites was relatively small (given <1% of passenger vehicles are BEVs in the UK (The Society of Motor Manufacturers and Traders, 2014b)). As such, certain points could have received greater usage simply because they happened to be convenient for one or two drivers. In future, the skewing effect on charge point usage is likely to be less, and as such an approach to control for this was introduced into the analysis (see section 4.2).

The use of models and data within this thesis are derived from different sources with varying levels of accuracy. Although not perfectly representative, it has still been possible to validate this work in a novel way, and the method of modelling appears to stand up to scrutiny given these constraints. However, further validation on a national scale with more data, and with higher usage rates would offer a stronger validation case. The ultimate validation approach would be to design a network, build and install it as per the modelled recommendations, and then gather sufficient data regarding usage of the network.

6.2   Practical Considerations

The aim of this research was to 'determine a method for locating a network of rapid chargers to enable extended BEV journeys in order to assist research and development into encouraging uptake and usage of BEVs.' Given this, an appropriate application of this research is for infrastructure developers to use as a planning tool. Such that the model recommendations can be considered fit for purpose, several practical considerations will have to be implemented by the planner. An advantage of the approach developed in this research is that the model can be implemented candidate-free. Given this, a planner can introduce many constraints and factors and determine the best set of sites given these considerations.

6.2.1   Land availability and cost

The main practical constraint for an infrastructure developer is the availability of land. Because of the flexibility of the approach developed within this thesis, available sites could be chosen in one of two ways. Firstly, a planner may have a set of defined sites that they have access to, and may wish to place charging facilities at some of these sites. In this scenario, the model could be restricted to choose only from these sites and recommend the ones most likely to receive higher BEV usage. Alternatively, in a more open-plan approach a number of filters could be applied to the network that could restrict the site options based on a variety of options. In these cases the model can be used to recommend a selection of sites, with which the planner may choose to develop based on land availability or cost. In addition, if suitable parameters are assigned, the model could be used to suggest likely numerical demand at each site, which in turn could be used to form a possible expected revenue stream (assuming charging is billed for). As such, a cost vs revenue trade-off could be determined by the planner and used in the decision making process.

6.2.2   Site specific constraints

As discussed in section 3.3.6, capacity at a site could vary depending on electricity network constraints or the number of drivers who could be serviced each hour. In the modelling procedure capacity is handled by assigning a limit to the number of BEVs who can be served at any site. Because the precise nature of these constraints is not known, a fixed parameter was not set in the model implementations in chapters 4 and 5. However, in reality this constraint could be applied

either as a fixed limit across the network, or individually as per the capacity at each site. This would depend on the local electricity network constraint, which may be defined by transformer or cable thermal ratings and the cost of re-enforcing these if required at a location. To include this type of data an electricity network model would need to be interfaced with the current model (which could be possible within GIS software). Most electricity constraints occur at peak time – so the capacity could be set to account for this. In addition, it may be beneficial for the infrastructure supplier to provide a booking scheme for their charging points. This may help avoid some temporal demand situations where queues could form.

6.2.3 Existing sites and competition

The idea of competition was not specifically considered in this research as the aim was to provide charging services to as much of the population as possible. However, it is likely that competition between operators might exist (especially as the market expands). A degree of competitive advantage may be achieved through pricing and business models (i.e. if the charging provided is cheaper than a competitor). However, a tenet in this research is that location matters, and given that this form of charging may be infrequent for some drivers, it is likely that convenience and range need satisfaction will be the principal motivators in their choice. Given this, being able to provide a service that suits the range needs of its customers may be key. As such, the location model in this research could be used by a planner to seek a competitive advantage, in terms of customer service provision, compared to its rivals. This could be achieved by loading existing sites into the location model (as in chapter 4) and identifying areas that are either under-provisioned, where service could be improved, or in locations that might 'take' users from a competitor.

In this section, practical constraints were discussed which would need to be considered if the developed method were used in an applied setting. These include a planner being aware of, and having data for, electricity network constraints, land availability and cost, and knowledge of competitors or other sites in the network. In the next section directions for future research progression in relation to this work are discussed.

6.3   Directions for Future Work

As discussed at the start of chapter 2, a trade-off exists in location modelling between accurately representing real world systems and managing the inherent complexity of optimising a large, complex non-linear system with many constraints that are not easily defined by simple mathematical definitions. This means it can be difficult to formulate a method and optimise its results under all scenarios. This section uses the understanding gained from this research to suggest areas for further research to help build increasingly robust models and methods for location determination of rapid charging stations.

In order to improve the robustness of the methodology, a future research program investigating different aspects which impact the method and its validation is suggested below. These suggestions are subdivided into: Accuracy of parameter determination, Modelling strategy, Collaboration with other research fields, and Progressing BEV take up.

6.3.1   Accuracy of modelling inputs

In this research a complex location model was developed with flexibility in mind. Given this, the model can be replicated by any practitioner and used on a different OD network with inputs and parameters set depending on their requirements. To demonstrate this process however, the model was run on a particular network with several parameters chosen. Depending on availability of data/known behaviour, these parameters or assumptions could be varied and/or improved in several ways:

- Deviation preferences applied in this research are based on survey results from a cohort of real-world electric vehicle users. To fully understand peoples' tolerances and behaviours, it would be desirable to have empirical data about drivers' true willingness to deviate. For instance, the method currently considers deviation in threshold bounds – but, perhaps the penalty function for deviation is more continuous in nature (similar to (Kim and Kuby, 2012)). The impact of this could be evaluated and compared to the current method.
- All long distance journeys are assumed as likely as those in ICE cars. Long range travel patterns in BEVs are likely to be different, but there is currently little data to show this. If data becomes available, it could be included with the research and compared to ICE behaviour to understand the difference and limitations regarding network planning.

- As mentioned previously, electrical or temporal capacity may be a determining factor in location choice. Research which combines the modelling techniques within this thesis with a detailed Network dataset (where ratings are known for every relevant transformer), and information about demand profiles throughout the day would be beneficial.

Similar to previously published location models, inputs for this research are mainly deterministic in nature (although the model is run several times with different solving procedures). Future research could look in more detail at a stochastic approach. There are two variations of this that could be considered:

- Stochastic data – Vehicle range varies with a number of factors including battery chemistry, vehicle manufacturer, driving behaviour, road topology, and weather conditions. A means which could assign variable range across the network, such as seasonal change, would enable a wider set of scenarios to be investigated and the differences between them could inform future field trials or input to inform facility location guidance. Since this research proposes a method that generates a demand surface, stochastic flows could be used to generate a more complex demand surface – with different instances of vehicle range perhaps weighted according to available data. Other inputs that could be treated in this manner include flow distribution, or deviation tolerance.
- Static data but with run model several times – for example, repeating the process undertaken in this research with a higher BEV range to simulate improved battery technology and also with a minimum range to simulate an inefficient driver in winter with a degraded battery. This would allow the variation in locations due to extreme conditions to be compared and analysed.

The use of more formal optimisation techniques could lend themselves to the addition of constraints within this method. Research could look at including, for example, electricity network constraints, space constraints, traffic conditions, geographical consideration, investment and operating costs.

6.3.2 Modelling strategy

There are three main methods of improvement which are felt could be promising avenues for future modelling strategy: better models based on existing data, changing the model to solve in a different way, and expanding the model to deal with additional constraints.

For instance, agent based modelling could be a promising avenue for future research and may provide a more realistic solution – as BEV behaviour could be varied to reflect real-world differences. However, more in-depth information would be needed regarding BEV charging patterns/desires, travel habits etc. Results from trials like CABLED could be used to infer these patterns and variations, but since rapid charging was not available, the inference of long-range travel would be difficult. ICEV patterns could be used as an alternative – but again their use as a direct proxy to BEVs would need to be explored. Additionally, agent based modelling can be computationally intensive, since every BEV (or small set of BEVs) must be modelled. The planning of a rapid charge network requires a macro level approach, which is not currently believed to be suitable for agent-based modelling application.

Alternative approaches to infrastructure location strategy could also be developed. For example, the exact formulation and success of the method relies on the input from an OD network. Figure 5-4 shows that a relationship could exist between charge point placement, population density and major highways. Potentially therefore, these patterns could be used to inform candidate selection – possibly by identifying road sections with a high traffic count. A comparison of the two methods as part of a future research program would provide insight and recommendations could be used to inform general siting strategy and policy.

Currently, the model developed has several tasks which are carried out exogenously. Although most processes are automated, the integration of them into one program would be beneficial from a usability point of view. Such a development could be used to make the method available for other users. In addition, the development of a universal model and method as described previously to help analyse different methods and models could be beneficial.

Another option could be to expand the areas where demand is considered. In the method proposed in this research, the model finds the finite dominating segment for each OD path. In doing so, the

minimum number of facilities needed to refuel a path can be considered. However, in some cases this may not represent the minimum number of points which can refuel a network. Consider Figure 6-1.
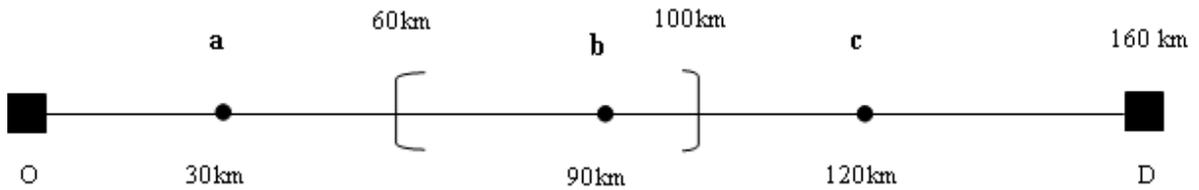

Figure 6-1 - The finite dominating set for a route

For a path 160km in length where facilities exist at O and D, the finite dominating segment for vehicles with 100km range is between 60km and 100km. Thus, a facility placed at b (or anywhere within the segment) would refuel the path with the minimum number of facilities possible. However, if facilities happen to get placed at positions a and c – placed because they serve other paths – then a facility at b is technically not needed. With a and c in place a vehicle can traverse the whole round trip successfully, even though it needs to stop and charge once more than might be necessary. To manage this with the methodology, it may be necessary to dynamically update the sizing of charging zones as the heuristic progresses. For instance, if a point gets placed at a, then the charging zone could be extended to the 130km limit. This would mean that a later point, placed anywhere between 60km and 130km, would enable the route to be captured.

Due to the complexity of the algorithms, the model was solved using a greedy algorithm as a traditional and reliable method along with the addition of weighted heuristics. Since a problem of this size and complexity is NP-hard, finding the truly optimal solution is difficult. However, other solving techniques could be explored and compared in an attempt to improve the output performance. With these methods comes the difficulty of formulation and time span to solution. An alternative solving procedure that has been used in other field is genetic algorithms. Genetic algorithms may provide a better solution, but the intensity of choosing sites from a set >120,000 and computing subsequent permeations, may prove too exhaustive. A greedy adding method with substitution (where initial site recommendations are substituted out) may also avail a better result and could feasibly be managed within the current method. However, its use may have to be restricted to cases where a restricted set of sites is used, rather than an open candidate network as developed in this work.

6.3.3 Collaboration with other research fields

The work undertaken in this thesis has the potential to impact and inform other fields of research to enhance understanding across the field. Several examples of how this research could be used within other fields of research are described below.

The issue of infrastructure provision is often referred to as the 'chicken and egg' problem (Browne et al., 2012). Without charge points in place consumers are loathed to commit to a technology which isn't necessarily sufficient for all their needs. Similarly, infrastructure providers are reluctant to invest in a market that is not currently established. The pitfalls of doing so are exampled by Better Place, who invested heavily in building a recharging/battery swapping network, but were unable to make a return through customer usage (Reed, 2013). Hence, it is prudent to plan an infrastructure roll-out carefully, and consider when and where the likely market will come from. In this research, demand is assigned to routes based on likely journey requirements, but it should be noted that the demand cannot manifest itself unless appropriate charge facilities exist. Thus, if the overall take-up of vehicles is *dependent* on the roll-out of infrastructure, then a lag from infrastructure provision – to market confidence – to actual take-up of vehicles may be observed. The economics and logistics behind the roll-out is an example where results from this research impact on areas of other research such as economics, planning, and logistics who need to understand the relationship between charging stations, numbers of users and likely locations of user demand to best impact policy.

Work on likely demand/location patterns of electricity usage could also be used to inform researchers into smart grids and demand side management to understand if rapid chargers can be integrated into the smart grid. Ideally this should be quantified with real world data. This data could also help researchers into battery technology to understand issues such as capacity fade (both calendric and usage based).

6.3.4 Progressing BEV take up

The ultimate aim of the research is to help towards alleviating range fears of BEV drivers and encouraging take-up to reduce CO_2 emissions. To make this happen the research needs to continue in line with this aim. Additional further research to help towards this aim includes:

- Continued work to address some of the barriers to BEV uptake mentioned in chapter 1, such as purchase cost and battery development.
- Continued research into electricity network decarbonisation, which if implemented, will strengthen the CO_2 case for BEVs.
- Research into the provision of slow charging, which could be used in conjunction with this work. In particular, solutions which allow adequate charging for drivers who cannot charge at home should be sought.
- Development of common data collection, security and storage strategies of field trial data (both existing and new) to enable real field trial validation across wide platforms.
- Encouraging user and vehicle recovery participation in projects to understand specific issues that may influence location such as history of incidences of running out of battery charge.

Mentioned here are a few suggestions of where this research could expand, and be used in conjunction with other work to help meet the overall aim of reducing CO_2 emissions. The next chapter provides a conclusion to this thesis and assesses how the research fits within the wider research, and global, field.

7 CONCLUSION

Given the need to reduce emissions in road transport, alternatives to the status quo are presented within this thesis. One such alternative, the BEV, has the potential to contribute towards reduction targets in line with a decarbonisation of the electricity grid. Currently however, despite the fact many models are available in the market, sales are still low suggesting barriers to their uptake exist. Based on the reported findings from several real-world trials the main barriers to uptake and usage were identified as cost, range, and charging. For BEVs to become a viable alternative it is seen as key that their cost comes down. Forecasts suggest that this is likely to happen over the coming years, and as such it is important that other barriers to BEV use are addressed by this time. Following an extensive literature search undertaken as part of this research the range of a BEV and the need to recharge were found to be intrinsically linked, and thus an improvement in either is deemed likely to minimise the problems of both. Given this, one method, which is the focus of this research, is to expand charging provision in order to enable long range journeys in BEVs.

In the context of charging and journeys, two main needs were identified. The first can be classified as non-time critical replenishment (such as at home or work). This form of charging could be sufficient for most needs, but for long journeys a different provision is needed. One form of charging which could satisfy these journey needs can be classified as range extension. This describes the need for recharging when the immediate range of a BEV is insufficient to carry out a long journey. Solutions which allow for this include rapid charging and/or battery swapping as they can provide additional range capacity in a short period of time. Within the UK, a number of rapid chargers have already been installed through public grant schemes and business and public sector consortia. To maximise the benefits of public spending in this area, it is desirable to locate rapid chargers as part of a more cohesive strategic plan so that investment is tied to locations which will offer high utilisation and value for money. To help achieve this it was necessary to determine a method of locating rapid chargers that is relevant to current and future BEV drivers' usage patterns, and is expandable to cover national areas. The focus of this research was therefore based on the need to extend the immediate range of BEVs.

7.1 Meeting the Objectives

Given the need to provide a method to help enable BEV journeys, this research addressed the issue of determining an appropriate location strategy for a recharging network with the following aim:

- • Determine a method for locating a network of rapid chargers to enable extended BEV journeys in order to assist research and development into encouraging uptake and usage of BEVs.

Based on the needs of this aim, the developed method incorporated the following features:

- Geographically representative: The approach taken allowed the model to be representative, consider variations in population spread, and be adaptable for any region.
- Expandable: The model was tested and developed at a large scale, with slight adjustments recommended to make this feasible (such as application of a raster grid to represent demand, and minimisation of the number of OD points).
- Consider range and habitual journey patterns of BEVs: This approach identified the types of journeys which are likely to require rapid charging, and devised formulae to suggest where on routes charging demand could occur.
- Realistic and applicable to real-world networks: The method in this research was demonstrated on a large, realistic network and could be applicable in similar cases. Although the direct implementation of the OD network was not perfect, due to lack of sufficient data, based on the findings of the traffic count data analysis, it was found that certain improvements could have been made, such as assigning road speeds and average congestion levels to each road segment separately.

To achieve the aims and needs of this study, the following objectives were addressed:

Objective 1: Understand how location modelling has previously been applied for similar purposes, and identify the assumptions and short comings inherent in these methods.

Objective 2: Develop a model and appropriate methodology to recommend sites for a charging network, and overcome issues with previous work in this area.

Objective 3: Apply this model to a real world network and analyse its outputs against current charging usage.

Objective 4: Demonstrate differences in modelling outcomes based on comparison between national infrastructure plan and a smaller regional like plan.

To meet these objectives it was necessary to conduct original and novel research, especially in regards to objectives 2, 3, and 4 where the following key areas of contribution to knowledge included:

- Development of a location model specific to battery electric vehicles (objective 2)

- Development of a methodology to allow the location model to be applied in a practical context (objective 2/3)
- Validation of the model and method using empirical data (objective 3)
- Understanding scaling issues between regional and national size models (objective 4)

Based on the needs of **objective 1**, location modelling was identified as the primary tool to help recommend rapid charging networks. Of the various types of location model available, flow-based modelling was recognised as the most suitable means to represent non-stationary demand (such as vehicles) – since, unlike fixed demand models, flow modelling can quantify and represent demand at several locations throughout a network (which is key to understanding range and habitual journey patterns of BEVs). Application of these models is reliant on Origin Destination networks as these provide an awareness of full route distance, which is important in the context of range limited vehicles. However, models of this type have not previously been validated with empirical usage data or real world behaviours. In addition, based on the identified shortcomings in these published works novel requirements for the modelling process were defined.

Modelling Objective a: Develop a method to represent source/destination areas in the model, such that OD aggregation scale is considered and accounted for in the modelling procedure.

Modelling Objective b: Represent demand for charging across two-dimensions, such that a potential demand *surface* can be generated.

Modelling Objective c: Create a modelling procedure which relaxes the need for an input candidate set, instead choosing from the continuous plane.

Modelling Objective d: Employ solving heuristics to ensure the method is computationally manageable on a large scale (where suitable solving heuristics are applied to maximise the number of extendable BEV journeys, given a number of facilities to be placed).

Within this thesis a method was defined which allowed necessary location modelling to be undertaken and developed. Key to this (modelling objective a) was the development of a method to integrate aggregation error into the model. Furthermore, a novel method of generating a solution that is not bounded by candidate sites was developed to improve flexibility and represent charging demand across 2-dimensions (modelling objectives b and c). Additional contributions looked at how the model can be solved heuristically, given different priorities and with more complexity (modelling objective d). In this regard, it is felt that **objectives 1 and 2** have been addressed sufficiently, with identified shortcomings overcome through the proposals in this thesis. In

addition, the developed method has allowed the relevant needs to be met as described above (geographically representative, expandable, conscious of BEV journey needs, and applicable in realistic settings).

In relation to **objective 3**, to test the efficacy of the developed model, an important aspect of the work was the validation of the model and method behind its use. Previously published literature in this field has not been validated with real world data, and as such the proposals in this thesis represent a significant novel contribution. The method of validating the model was achieved by comparing empirical rapid charging usage data with modelled results. As such, **objective 3** was achieved by comparing the ranking of model evaluated locations against used locations as reported by rapid charging operators. It was found that the modelled outputs can provide a good approximation to the observed usage data, and can even identify possible discrepancies in the data itself (such as underreported usage). In addition, the model was implemented without constraint over the same region to identify differences in the approach. The findings suggest that the proposed model can recommend similar locations to current sites which observed high usage. Based on this, alternative networks could be planned in any area, with levels of demand estimated. The alternative network recommended in this thesis may not be practically implementable, but the demonstrated methodology indicates the sort of coverage that might be suitable and could potentially be used as a benchmark from which a feasible solution could be generated.

The final part of this thesis **(objective 4)** looked at the complexity of expanding a network to cover a nationally sized area. Based on these findings, a series of key learning points were identified which have not previously been reported in the literature:

- Solving techniques were developed to account for a possible weakness in greedy adding approaches used to solve this model. This involved weighting multi-charge routes so that they could be identified in the solving procedure. A series of novel adaptations are suggested which allow alternative solving heuristics to be implemented – based on desired strategy, and these were not found to be detrimental to the result.
- Deviation parameters were varied to ascertain if allowing greater deviation tolerances could improve the flow capturing potential of the model at a large scale. In regards to these tests, and development of further heuristics, slight improvements in the performance of the model were observed. These were found to be computationally manageable in the tests undertaken (thus meeting modelling objective 4), but the improvement in performance is not deemed significant given the trade-off in computational effort (for deviations).

- To help identify issues around regional infrastructure developments, a network was constructed with a 'closed' border such that only internal journeys were considered. The same area was also evaluated without the border, and the suggested locations from each demonstration were compared. The modelling results suggest that considering a regional network design in isolation from the whole network results in likely sub-optimal location placement, and that consideration of how the region fits within the wider national network is important. As such, **objective 4** is deemed to have been met, but it is recommended that further tests are undertaken to identify the impacts on policy decision.

7.2   Achievements of the Research

Based on the summary in the previous section, it is felt that this research has met the original objectives necessary to meet the aim 'to determine a method for locating a network of rapid chargers to enable extended BEV journeys in order to assist research and development into encouraging uptake and usage of BEVs'. Key to this have been some innovative developments in this research field, including:

- Improvements to location modelling specific to electric vehicle charging infrastructure, such as:
- Integration of aggregation scale into a developed model such that realistic range and journey options can be considered.
- Allowing demand to be represented across areas, such that evaluation can be considered at any point in the network.
- Facilitating a candidate-free approach that can be used to consider siting options with increased freedom.

In addition, the application and demonstration of the model developed within this research has allowed:

- The determination of insight into the complexity around model expansion and scaling.
- Validation of the location modelling process against empirical usage data, indicating that the developed model is fit for purpose.

Given the achievements of this research, it is hoped that the methodologies developed can be used to assist further research work. In addition, it is felt that the practical implementation of this model could be used to inform effective charging network layouts, which in turn may allow for greater

journey satisfaction for electric vehicles. In line with other developments in this sector, this research contributes towards improvements for the viability of electric vehicles, which in turn could encourage uptake and usage. This transition towards electrification in transport will help reduce emissions, and in turn be beneficial for peoples' health and the environment.

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