

Location and capacity allocation model for the electric vehicle charging stations' network planning in the UK

Abstract

The use of fossil fuels has significant effects on climate change due to greenhouse gas emissions and various environmental pollutions. Thus, many renewable energies have been introduced and are regarded to substitute for fossil fuels in multiple industries, particularly in the transportation industry. According to IEA, the transportation sector accounts for the most significant proportion (approximately 32%) of energy consumption and Green House Gas (GHG) emissions, which has a significant influence on the environment. In order to encourage the electric vehicles uptake, this article focuses on the location and capacity allocation model for the electric vehicle charging stations' network. The practical approach of this study starts with the charging demand estimation according to the population density to determine the number of charging stations. And then, based on the continuous location model and other relevant methods, the location and capacity of charging stations are determined. After that, the construction order of all EVCSs and cost analysis are discussed. The computational experiment is presented through employing the real-world data of DH postcode area in the UK. The result shows the final location and the construction order of EVCSs' network planning in a specific area.

Keywords: *Optimization, Electric vehicles, Electric vehicle charging station, Renewable energy sources, Charging station location planning.*

INTRODUCTION

This section presents a brief overview of the paper. First, the general background and idea of the study are presented, followed by the research aims and objectives in the second part. Research questions are demonstrated in the third part in order to give a better understanding of the study's scope as well as the expected outcomes. Lastly, the outline of the study's structure is presented.

Research Background

Electric vehicles (EVs) have gained rising popularity over the past ten years around the world, with over 5 million electric cars worldwide in 2018, up 63% from the year before (IEA, 2019) (Figure 1). Some essential reasons behind this fact are the growing concerns about environmental pollution and the desire for clean energy. According to IEA (2019), the transportation sector accounts for the most significant proportion (approximately 32%) of energy consumption and Green House Gas (GHG) emissions, which has a significant influence on the environment. In order to achieve more sustainable transportation, EVs are regarded as a green substitution for conventional internal combustion engine (ICE) vehicles, because EVs have considerable advantages in environmental protection with low pollution, emissions as well as low noise (European commission, 2012; Shinde & Swarup, 2016). With these benefits of EVs and urgent concerns for environmental preservation, many governments have taken measures to promote the EV option. For example, the European Union has approved several important policy instruments, including CO₂ emission performance standards for cars and trucks (EU, 2019); China also provides zero-emissions vehicle credits and subsidies (Hongyang, 2018); Korea has expanded the range of national subsidies for all low-carbon vehicles in 2019 (IEA, 2019).

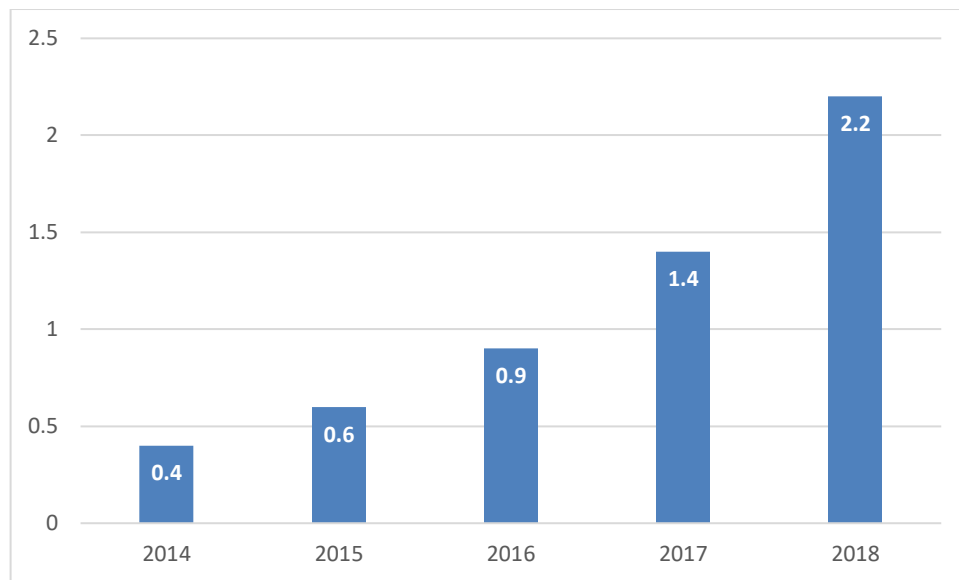


Figure 1: EV-penetration rate in the global market in 2014-2018(McKinsey, 2019)

However, there mainly are two obstacles for EVs to be mass-market adopted: range limitations (Capar and Kuby, 2012; Eberle and Helmolt, 2010; Lim & Kuby, 2010; Wang & Wang, 2010) and the low availability of charging station infrastructure (Shukla, Pekny and Venkatasubramanian, 2011; Wang, 2011; Wiederer and Philip, 2010). The former refers to the mileage that EVs can be driven from a fully charged battery without recharging, and the latter one means the underdeveloped charging station infrastructure which may cause problems including long distance away from charging stations, long queuing time and high charging cost. Finally, these two barriers lead to drivers' fear of running out of power before arriving at an available charging station or their destinations, known as range anxiety (Neubauer and Wood, 2014). To mitigate the impact of range anxiety, a well-planned charging station infrastructure would be essential, considering that it may be challenging to extend driving range significantly in next few-year period (Chung and Kwon, 2015). Therefore, the efficient deployment of charging stations will be critical for EVs to seize the market share.

Research Aims and Objectives

In order to address the electric vehicle charging infrastructure challenge which currently inhibits the uptake of electric vehicles in UK, the 'Scaling On-Street Charging Infrastructure Project' (SOSCI) has been launched, which plans to deliver pilot EV charging point installations to work towards the vision for the 8 million homes without off-street parking to be within 5-minute-walk of an EV charging station. As a major partner, Durham County is expected to identify demanding locations and install charge points (SOSCI, 2020). Based on the requirements of SOSCI, this study plans to

propose an integrated method for determining the optimal location of the charging station network taking into considerations many factors, such as investors' financial cost, EV users' access distance and characteristics of residents. The aims of the study are to develop location-allocation models to support the deployment of Electric Vehicle Charging Stations (EVCSs) in the UK. Then, this paper's practical approach can be applied and verified by the real input data of the DH postcode area to show precise results, the result's discussion, and recommendations.

Research Questions

The primary concern of this study is to provide a comprehensive mathematical model which is essential to determine the optimal locations of EVCSs in the UK. There are three aspects to consider particularly:

- ⑩ How much demand for EV charging in the specific regions?
- ⑩ Where should EVCS infrastructure be placed?
- ⑩ How to determine the optimal capacity and location of EVCS network, taking into consideration financial costs like investment, capital, operation and maintenance?
- ⑩ How to identify the order in which EVCSs should be built in long-term planning?

Regarding these principles, the overview of this project will be clarified as

- ⑩ Which methodology can be used to develop the mathematical model and solve the solution(s) for the particular case study?
- ⑩ What recommendation can be suggested to develop EVCS infrastructures in the UK?

Research Structure

There are six sections in this paper, beginning with a literature review of the principles of facility allocation model in section two, including general definitions, the applications of facility location model in various industries, merits and drawbacks collected from facility location models. Subsequently, facility location models related to the EVCS are reviewed. Section three discusses this study's research methodology, such as the practical research approach, data collection and data analysis techniques. An investigation and analysis of charging demand, classification of postcodes and cost of

charging station are presented in this section. Section four follows by implementing the practical approach, specific problem-solving tools and techniques to examine the EVCSs deployment in the DH postcode area. The study is expected to develop a methodology which is reasonably practicable to address problems in real-life scenarios. Section five analyses result of the computational experiment and the optimal locations of EVCS in the DH postcode area. This section also mentions possible avenues for further research in both DH postcode area and even across the UK. The limitations of the study and suggestions for future research are included. The final section summarises the final conclusions of the paper.

LITERATURE REVIEW

The objective in this section is to review the literature, including the facility location models in diverse objective targets and industries like EVCSs. First, the application of various facility location models in different industries has been presented. Next, the reviews of the relevant publications of facility location models for EVCS systems have been discussed. Finally, the gap and opportunity to apply the facility location models for the design of EVCSs in this project has been concluded.

Facility Location Models

Regarded as the basis of a basic P-Median location problem and modern location theories (Rodrigue, 2020), Alfred Weber developed the location theory to deploy a warehouse for serving several customers with the shortest distance in 1909. Location-allocation models generally cover a broad range of formulation structure, including objectives, variables and constraints, from mixed-integer programming models, network location models to continuous location models (Klose and Drexler, 2005). Klose and Drexler (2005) also broadly classified facility location models into nine types according to different attributes such as single- vs multiple-stage models, single- vs multiple-product models, static vs dynamic models and minsum vs minmax models. Various simulated annealing (SA) can be applied to these models for a specific attribute. For example, SA has been applied to address the P-Median problem to find the shortest distance from a demand/supply location to their nearest facilities (Chiyoshi and Galvão, 2000; Carling et al., 2014). Therefore, because of the practicality, efficiency, great interest in decision-making in the locational process, as well as the manageability of long-period investment in the infrastructure of a specific location issue (Drezner and Hamacher, 2002), many scholars have regarded facility location

models as an effective strategic planning method in many industries (Owen and Daskin, 1998).

the Healthcare System

Strategic deployment of the healthcare system are long-period decisions such as facility sites and capacity determination, and these decisions should be robust in order to cope with possible fluctuation of supply and demand patterns. Besides, considering the high investments, inevitable political impacts, and the hardly reversible results, decision-makers of healthcare facilities need to take future prospects into account to make sure the decisions do not limit prospective choices.

A multi-objective optimisation model was developed by Eaton et al. (1985) to deploy the emergency medical service (EMS) stations in Austin, Texas in order to offer the whole residents the quality service including the shorter response time and a reasonable price, mainly to promote the life-support vehicle's system. And then, aiming at raising the number of choices available to the decision-makers to determine a new site for the blood bank, Price et al. (1986) used the centre of gravity model based on sparse data in Quebec urban community. Notably, there are more and more researchers focusing on the deployment of the necessary healthcare infrastructure in less-developed regions, because the basic healthcare service is not easily accessible to the majority of the population in these regions due to poor geographical accessibility. Rahman and Smith (2000) discussed the application of facility allocation models in healthcare service improvement planning in less-developed countries. They pointed out that most of the studies only developed and analysed the model but failed to claim implementation with unclear reason. They widely divided relevant studies into four types, including finding the optimal site(s) (Patel, 1979; Moore and ReVelle, 1982), deploying facilities in a new region (Berghmans et al., 1984), evaluating the efficiency of locational determinations in the past (Hodgson and Valadares, 1983; Rahman and Smith, 1999) and improving existing systems (Gould and Leinbach, 1966; Mehrez et al., 1996).

To achieve the best tradeoff between improving access to health service and minimum cost, Mestre et al. (2015) proposed and compared two comprehensive stochastic allocation models for the National Health Service (NHS) in Portugal, but with different assumptions. While the location is regarded as in first model, both location and allocation are considered in first-stage decisions in terms of the second model. As a

result, compared to the first model, the second one has shown to be more adaptable to address the planning issue at hand under uncertain conditions related to uncertain demand for hospital service. As a critical part of the healthcare system, the positioning of emergency medical service (EMS) has gained increasing attention recently, and researchers have proposed various models mitigate the issue (Brotcorne et al., 2003; Li et al., 2011; Maxwell et al., 2010). McCormack, and Coates (2015) presented the optimisation of EMS vehicle fleet assignment and base station sites by applying a genetic algorithm (GA) with an integrated EMS simulation model. To apply this model, actual call information from the London Ambulance Service has to be integrated, and the results have presented that patient survival is increased based on the optimised new base station sites and vehicle fleet without additional resources. However, this paper did not consider the effects of dispatch models, stochastic variation in travel times, as well as time-dependent vehicle routing. In addition, optimum performance can be further examined by investigating the seasonal change in emergency medical demand.

the Transportation System

The demand for transportation services is regarded as a derived demand (Manheim, 1979). The reason is that the demand for the transportation system is created by the requirement to transport people and/or goods from one place to another, not by the inherent desirability of transportation itself (Daskin and Owen, 1999). In a word, transportation is essential only when goods and/or people are not in the place where they are required to. For instance, the majority of commuters do not live in the place where they work, so the demand for transportation services like taking buses and subways is considerable in the morning and evening rushing hours.

Many articles have investigated integer programming models to solve the location decision problem in various forms of transportations like bus, train and aeroplane. For instance, Gleason (1975) formulated zero-one integer programming models in the context of a set covering problem to deploy the location of the minimum number of express bus stops within a specified distance for the satisfactory customer service. The article also presented a modified version of the model to minimise the total distance walked by all boarders. Similarly, based on the airport site selection problem in eastern Turkey, Saatcioglu (1982) developed three mathematical programming models applying various evaluation criteria. The first one aimed at identifying the minimal quantity of airports needed by a fixed number of travellers considering the bus

fares between the cities and airport cost per passenger, which is based on the typical set covering model. The second included both cost-of-travel and total infrastructural cost of airports as criteria; then, it identified the optimum airport locations and the number of travellers requiring moving from the regions without an airport. The criteria of the last model were the annualised airport construction expenditure and the line costs of the air and road between different cities. The model found the optimum locations of the airport, as well as the optimum frequencies of transportation modes among different cities. The result of the last model was totally different from the other two models, which means the information needs of the model, the evaluation criteria applied, procedures of parameter estimation and the structure of the models can result in various solutions to the same issue. Therefore, the availability of information and the formulation of the problem have a great influence on the selection of a model.

Similar to the first two papers, John Hodgson, Rosing et al. (1996) also give real-world data considerable importance, which can be seen from applying the location-deployment model to morning-peak traffic in Edmonton, a city of Canada. The major difference is that they used the flow-capturing location-allocation model (FCLM) to respond to the demand which is presented as passing network traffic, instead of traditional nodes. Next, three solution procedures were applied to the flow-capturing location-allocation model, namely the exact solution procedure, the vertex substitution procedure and the greedy solution procedure. As a result, the greedy solution procedure is examined to be robust; at the same time, a real-world experiment is an essential part of the facility allocation model advancement. Nevertheless, this paper failed to explain how the particular structure of the issue (the traffic congestion during the morning) can enhance the robustness of the algorithm. The effectiveness of the greedy solution procedure is not confirmed in this paper. As a comparison, Cánovas et al. (2007) examined a different situation: the Uncapacitated Multiple Allocation Hub Location Problem (UMAHLP). The dual problem of a four-indexed formulary is proposed and solved by a dual heuristic method. The method is reinforced with several specific subroutines like slackness rectification and multiple horizons use, instead of employing external linear problem solver. The computational results also presented the high efficiency of the method, which is able to solve cases with more than 120 nodes. The major downside is that the high memory is needed to complete the calculation due to the high number of variables in this problem. In other words, the proposed solution may find it challenging to find more than 120 nodes of the whole AP problem.

In addition to bus systems and urban traffic flow networks, Hasany and Shafahi (2018) examined the railroad blocking problem and formulated a mixed-integer programme to determine the optimum path between origins and destinations of each delivery to minimise the shipping and operating costs of running trains. Meanwhile, it has to take the limitations of railroad supply and demand into consideration. A new heuristic is developed and partitions the linearised model into two sub-problems with controllable size on the basis of the general decomposition method. Finally, the computational results are presented using real information from the Iranian railroad network. Nevertheless, this paper neglected the transfer waiting time for shipments through stations, which may be decreased further to achieve the minimised operating and transportation cost (Kang and Zhu, 2017).

the Telecommunication System

As the increasing importance of telecommunications, optimisation issues with relation to the plan and construction of telecommunication systems have gained growing concerns (Yaman et al., 2005). Telecommunications is a critical field of application in combinatorial optimisation (Fortz, 2015). A considerable number of issues confronted by telecommunications operators have close relation with location theories which play an essential role in the telecommunication network design. Related problems are generally categorised into three decision making levels, namely the long-distance or backbone network, the inter-office and switching centre network and the local access network (Balakrishnan et al., 1991). It is clear that these levels are not totally separate, and users may find it necessary to integrate these levels as much as possible. Nevertheless, these decision-making levels are generally treated separately because of complexity and scalability issues. The main location issues are intimately associated with hub location problems (Alumur and Kara, 2008), which started with the pioneering study of O'Kelly, 1986 and O'Kelly, 1987. There are mainly two fundamental kinds of hub networks, including single allocation (Abdinnour-Helm, 1998; Labbé and Yaman, 2004; Skorin-Kapov and Skorin-Kapov, 1994) and multiple allocations (Boland et al., 2004; Contreras et al., 2012; Mayer and Wagner, 2002). They differ in how non-hub nodes are allocated to hubs.

Besides, as the installation of telecommunication networks is costly nowadays, an optimisation phase to minimise costs is required in the planning process. For example, targeting at minimising the entire cost of the system (nodes fixed expenditure and connection expenditure), Carello et al. (2004) formulated a two-dimension local search

formulation in order to address the Hub Location problem in the planning of backbone system. They formulated three different metaheuristics, which are a tabu search, a random multi-start, and an iterated local search. According to computational results, aversion of the tabu search is the most promising metaheuristic. The major downside of this study is that it only considered a generalisation of the HMLC, instead of proposing exact methods. Yaman et al. (2005) examined this problem further. To be specific, they focused on telecommunication systems with complete backbone and star tributary networks and solved the location and dimensioning problems simultaneously. To deal with the specific problem called capacitated single assignment hub location problem with modular link capacities (HMLC), two approaches are presented, namely a branch and cut algorithm and a metaheuristic. Computational experience based on real data presents that the branch and cut algorithm fails to solve cases with large sizes, but it increases the upper bound of the heuristic, as well as discussing the feasibility of the resolution for some problems.

Moreover, some studies presented the application of the zero-one integer linear program in the telecommunication network. For instance, aiming at minimising the cost of terrestrial communication, Helme and Magnanti (1989) transformed a zero-one quadratic facility location problem into an equivalent zero-one integer linear program to deploy satellite homing stations based on distances between two earth stations. Computational experiments based on real information present that the problem-specific branch and bound method is efficient in addressing problems with no more than forty demand points and that results given by this method advance substantially on management generated solutions. Likewise, in order to ensure that an area is offered service by at least one satellite at all time, Drezner (1988) examined the location strategies for satellites orbits in space. Two heuristic solution methods were developed, and the heuristic solutions compare favourably with the lower bounds.

Facility location model for EVCSs

As increasing concerns for sustainable transportation, a large number of studies have focused on the question of how to deploy charging stations on proper locations strategically (Ko et al., 2017). Charging station placement is a problem of identifying optimal locations. Many researchers proposed solutions from different perspectives and facilities location and covering location are two essential parts in this field (Mehar and Senouci, 2013). The optimisation objectives of most studies are considered from these two perspectives, such as financial cost, coverage, population density, time cost,

service quality, et cetera. Regarding research methods, most scholars and researchers focus mainly on optimisation or simulation.

Optimisation

The following three studies are all about solving optimisation problems using mathematical programming algorithms.

Frade et al. (2011) developed a maximal covering model to deploy a set number of charging stations taking consideration of the demand for charging and the coverage of one charging station between 400 and 600 m walking distance. In order to estimate the demand for EV refuelling in daytime and nighttime respectively, a model for the number of vehicles is derived from the regression analysis of the household size, building type, average age, level of education, and employment. Nevertheless, the outdated census data (2001) and insufficient consideration of the penetration rate of EVs may result in inaccuracy to some extent.

Aiming at maximising social welfare related to the coupled power transmission and traffic transportation system, He et al. (2013) adopted a multinomial logit modelling framework for the macroscopic placement of a fixed number of public charging stations in metropolitan areas, taking into consideration of the equilibrium between demand and supply of electricity. The article assumed that drivers tend to consider the availability of charging opportunities, the price of electricity and travel time in choosing destinations. However, the assumption needs to be supported by future empirical research. Besides, this work is not able to determine the specific location of charging stations.

To find more specific positions of charging stations in an urbanised area, Ip et al. (2010) proposed a two-step model that first identified the demand clusters of EVs by hierarchical clustering analysis and then implemented assignment models to allocate charging stations to clusters according to respective demands and capacities. Other similar problems about allocating facilities (e.g., airports and stations) to demand areas can also apply this model since the clustering algorithm involves the characteristics of spatial information. This work, however, assumed that there are many sensors collecting data in the street, while it may be challenging to collect data in some areas.

There are also some studies using optimisation methods based on genetic and greedy algorithms. For example, Mehar and Senouci (2013) proposed an optimised genetic

algorithm named OLoCs (Optimised Location Scheme for electric charging stations) to achieve the minimum investment cost and transportation costs. This algorithm takes into account seven factors and constraints to develop a general model, including area traffic density, investment cost, land cost, infrastructure cost, transportation cost toward the charging station, charging station's capacity and electric grid capability. From the result of the experiments in Cologne (Germany) from 6 a.m. to 8 a.m., this model can get the optimal solution rapidly. The main limitation is that the assumed EV rates may cause some inaccuracy to the experimental results.

As a comparison, Sadeghi-Barzani et al. (2014) did not use any EV related data and constructed a Mixed-Integer Non-Linear (MINLP) model for optimised location and size of the fast-charging stations to achieve minimised total cost of charging station development based on urban roads and geographic information. As fast charging is of extreme significance for widespread acceptance of EVs (Nansai et al., 2001), this research can promote the availability of public fast-charging stations. Zhang et al. (2017) also concentrate on the optimal placement of fast chargers (level 3 chargers), but for highways particularly. They developed a multi-period extension of the Fuel Refuelling Location Problem (FRLP) with capacity constraints and demand dynamics. However, there are some different opinions about definitions of demand dynamics. Anjos et al. (2020), for example, believed that EV drivers might plan to travel to several destinations in terms of demand dynamics, instead of travelling between the same origin and destination in Zhang et al. (2017). To deal with this problem, Anjos et al. (2020) take into consideration of charging demand of drivers' travelling between two locations according to their possibility to do so.

Stimulation

Stimulation-based research does not adopt real-world information, only some data to tune the simulation. The simulation itself generates all the relevant data.

For example, Sweda, T., & Klabjan, D. (2011) presented an agent-based decision support system to recognise characteristics in EV ownership of residents and driving habits to allow the systematic placement of new charging facilities. Even though the study employs real-world information for sales volume and prices of EVs, the majority of parameters are tuned artificially with randomness such as driving patterns, charging state, et cetera. This study implements social interactions among vehicle owners, which enables it probable to simulate the determination to purchase EVs and improve

the number of EVs in the network. Comparing the sales volume of three types of EVs taking into consideration gasoline prices only is another point of the study. The Chicagoland region was adopted as a case study to illustrate this approach, which integrates traffic network information to allow micro-level analyses of the EVs market. The model is assessed through comparing two different formulated charging facility deployments. When contrasting results with the present condition in the Chicagoland region, advancement could be found. This method, however, does not identify new potential sites for the charging station placement; it only examines the deployment offered to it. To be specific, their model failed to simulate traffic and battery usage and was on the basis of the central idea of economic viability which is applied to identify the substitution of traditional vehicles by EVs within a period. Sweda and Klabjan (2015) provided an updated version of the research is provided in a full report.

Hess et al., (2012) took a different simulation-based method to the issue of charging infrastructure deployment in the Vienna using an agent-based traffic simulation of vehicles. They firstly formulated a charging model by characterising battery depletion figures and state-of-the-art ranges and analysed the infrastructure essential to operate them in the urban area. Then, a mobility model for on-demand charging was introduced, which is assumed that vehicles with a low state of charge would choose the closest charging facility before going to the final destinations. Both origins and destinations of vehicles are set randomly in this stimulation. Aiming at minimising the average travelling time including waiting time and recharging time, the genetic programming approach was selected to observe the mobility of EVs. Finally, the virtually optimal deployment of EVCS network would be identified from a group of candidate sites in the smart city. The results of the simulation-based study of synthetic vehicular mobility traces on the city map of Vienna is optimal with statistical certainty.

Unlike the previous research, Viswanathan et al., (2016) did not make any assumption or propose a simple linear charge depletion model. They noticed that previous approaches for deploying charging stations adopt an optimisation approach that fails to consider existing traffic demands and infrastructure. Besides, these methods ignore the dynamics of vehicle motions, such as congestion, traffic flow during peak hours, and time spent in waiting at traffic lights, in terms of determining energy consumption. According to daily traffic patterns and data on the road network, they focused on determining the viability of EVs in urban areas by adopting a nano-scale agent-based traffic simulation. And then, a methodology was formulated in order to make a long-

term plan for charging facility development. The traffic simulation in Singapore has been used to demonstrate this methodology with three major components, including the road network model developed from real positions and postcodes; the electric driver-vehicle unit (DVU) model that simulates vehicle movement, driver behaviour, and energy usage; as well as the traffic allocation model to build realistic traffic patterns in the simulation process from available real-world information. The computational result shows that ninety-nine per cent of the daily traffic requirement in Singapore will be satisfied by existing EVs with a single charging.

In order to find the optimal location and size (e.g., the number of charging spots) of charging stations, Fang and Guowei (2015) formulated a location-sizing model based on FRLM (flow-refuelling location mode) for EVs and the queuing theory considering the demand. The study filled the gap in the queuing phenomenon caused by the limited service. According to the case study, the per cent flows refuelled relevant to the vehicle range, the max average waiting time, the budget fee, as well as the average service period of charging stations. As a result, they believe that directions for future development are to rise the EVs' recharge mileage by advancing the battery of the EVs, and to reduce the charging period of time through developing the power grid technology. Nevertheless, this study did not consider the deviation from the original path to a charging station, considering that the candidate site does not have to be limited in the node that existed in the path in the real world.

To sum up, based on these reviewed research, the diverse types of facility allocation models have contributed enormously to the location decision-making in multiple industries, including healthcare, transportation services, telecommunication networks, retail & distribution, as well as EVCSSs. In most cases, multi-objective programming models, mixed-inter programming models, and centre of gravity or continuous location models are widely adopted in the facility allocation issue. Because of various specific research approaches and different attributes in the models, the mathematical formulation structures are also different in terms of objectives, variables and constraints. The target of the facility location models differs from profit maximisation, total distance minimisation, coverage maximisation, total cost minimisation, customer service level maximisation, waiting time minimisation to market share maximisation.

As for the deployment of EVCSSs, range anxiety is widely recognised as one of the most significant difficulties left to cope with in terms of raising EV adoption, and it is directly relevant to the advancement of EV charging facilities. Although the recharge

mileage of most EVs is nominally enough for commuters travelling within a city, potential EV customers may not purchase an EV because of their familiarity with the existing gas station infrastructure. There are many researchers focusing on this condition and proposing some solutions. For instance, deploying charging facilities along the highway close to existing gas stations since there is fundamental infrastructure (Sathaye and Kelley, 2013). Another main difficulty in terms of the charging facility placement is the capacity of power grid systems. The number of EVs is presumed to increase, which could result in significant issues because the electricity demand might be higher than the supply. Both Masoum et al. (2011) and Abdalrahman & Zhuang (2017) developed a method to the EVCS deployment considering previous limitations, such as the decreased power loss in distribution networks. The last challenge would be the problem of long-period planning for charging infrastructure advancement. Considering the expensive capital costs and long period of time taken to construct charging stations, both the sites and the construction order of charging infrastructure is essential to determine in the initial plan.

METHODOLOGY

Various types of research methods have been developed because of different requirements of information, changing patterns of demands and complicated time availability (Cooper and Schindler, 2006). In order to undertake productive research and present a well-structured study, it is essential to comprehend the specific methods applied to undertake research, comprehend the chosen subject, as well as understanding and interpreting the results (Sekaran and Bougie, 2010). This section, therefore, would focus on the research methods, including the type of research and practical research approaches, and finally the collection and analysis of the data and information so as to complete the calculation of research's method.

Research Type

The study has decided to adopt the mixed methods research which is regarded as an acceptable and desirable approach for business research because it is able to address the enormous scope of research problems and provide sufficient support for the conclusion (Johnson and Onwuegbuzie, 2004). The mixed methods are regarded as autonomous and softening attitudes of feminist towards quantification methods. Nevertheless, all these merits do not mean that mixed methods research is inherently superior to mono-strategy or mono-method research (Bryman and Bell, 2015). Bryman

and Bell (2015) also categorised mixed methods research into nine categories in terms of the priority decision and the sequence decision (Figure 2). Based on the classification, the QUAL->quan method would be applied in this paper; in other words, the quantitative research performs an action in formulating the essential sections of the paper in the qualitative environment.

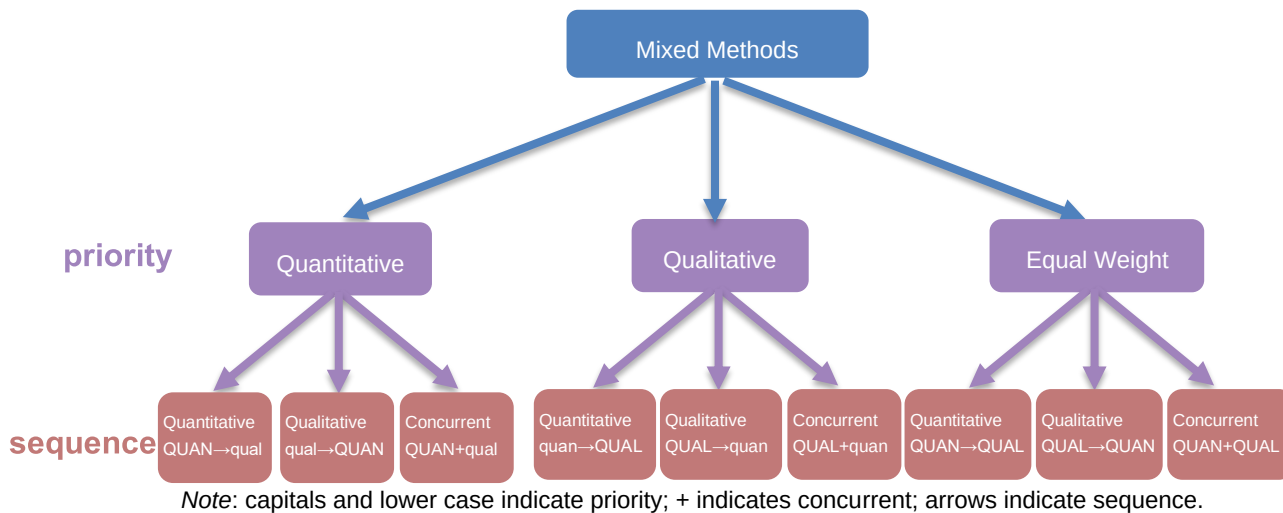


Figure 2: Classifying mixed methods research based on priority and sequence

Moreover, this study also adopted the case study, an increasingly common and popular method in academic studies (Eisenhardt and Graebner, 2007). Many researchers have employed the case study to advance a wide range of topics such as group process (Edmondson et al., 2001), internal organisation (Galunic and Eisenhardt, 2001; Gilbert, 2005), and strategy (Mintzberg and Waters, 1982). However, there are several challenges faced by case studies such as case selection, subjectivity and potential bias. In order to mitigate these very legitimate challenges, scholars may find it efficient to use accurate language and achieve elaborate research design: careful justification of case collection, theoretical sampling of cases, eliminating informant bias, a clear statement of theoretical arguments, as well as effective presentation of evidence in tables and appendixes (Eisenhardt and Graebner, 2007). The case of the paper is a real geographical region: DH postcode region in the UK. Based on the recommendation of Yin (1994), there are mainly four stages of undertaking case study methodology. The first stage is to design the case study, including identifying the researched case(s) and determining the logic of the case study. And then, researchers need to conduct the case study through collecting evidence at the second stage, followed by analysing the case study evidence. The

final stage is to develop the conclusion, recommendations and implications based on the previous three stages. All these stages and data would be designed and examined in the next two sections.

Research's Practical Approach

To determine the number, optimal locations and capacity of the EVCSs network, the framework of the research practical approach is established as the following main steps:

- 1) Estimation of the charging demand
- 2) Postcode area's population data classification
- 3) EVCS facility's locations decision
- 4) The cost analysis of the EVCS network

Estimation of the Charging Demand

Aiming at supporting the stability of the electrical power system, it is important to determine the number of charging stations, which is relevant to the charging time, the number of populations in the area and the number of EV owners (Wannawit et al., 2018). For the charging times, it is normally determined by the level of EVs charging, the sizing of battery packs and the State of Charge (SOC) of EVs. Generally, EV charging technologies can be categorised into three levels: Level-1 (opportunity charging), Level-2 (primary charging) and Level-3 (fast charging) (Shareef et al., 2016). Opportunity and charging technologies take about ten hours to complete a recharge due to the low-power charging capacity (normally less than 6.6 kW). Consequently, opportunity and charging technologies are suitable for charging overnight or at parking lots for a prolonged period of time. The Level-3 charging refers to DC fast-charging technologies which can complete a recharge in not over an hour, because DC fast-charging technologies have a high-power charging capacity (typically 50-200 kW) (Rahman et al., 2016). It might be the most popular type of the charging station for EV customer in the future, so this study focuses specifically on the Level-3 charging but cost the most to build currently. Meanwhile, in order to reduce computational load and model solving difficulties, it can be assumed that the charging demand is initiated from the fixed locations within a traffic network. Therefore, the charging time of an EV can be estimated as the *Equation 1* (Leeprechanon et al., 2016).

$$t_{ev} = \frac{kWh_{EV} \times (SOC^F - SOC^{TH})}{P_{CH} \times eff_{CH}} \quad (1)$$

Where

t_{ev} = charging time of each EV (hr.)

P_{CH} = the rated power output of the charger (kW)

eff_{CH} = the efficiency of the charging (%)

kWh_{EV} = the battery capacity of the EV (kWh)

SOC^F = the final state of charge of the EV (%)

SOC^{TH} = the threshold state of charge of the EV (%)

Subsequently, the number of charging station (M) can be estimated through the *Equation 2* (Phonrattanasak and Leeprechanon, 2012).

$$M \geq \frac{population \times pEV}{sh \times ncp \times nst} \quad (2)$$

Where

$population$ = the population of an area

pEV = proportion of EV owner per the number of populations in an area

sh = the number of service hour of a charging station in a day

ncp = the number of charging pump in a charging station

nst = the number of services in an hour of charging pump or $\frac{1 \text{ hr}}{t_{EV}}$

Postcode Area's Population Data Classification

According to Brimberg et al., (2008), considering that the application of a continuous location model needs large amounts of input data about coordination points, the mass-scale location problem normally adopts a pre-processing step to reduce the computing time by scaling down the data into a smaller subset. Notably, the scaling down region does not considerably affect the whole problem (Marlin, 1981). The paper, therefore,

has been determined to scale down the entire individual postcodes in the UK into several postcode regions. The number of postcodes per postcode region is substantially smaller than total postcodes in the UK, leading to the higher computing possibility of the designed method in the study. Subsequently, all 124 postcode regions in the UK can duplicate these approaches to design the EVCS network (MRS, 2020).

The total number of populations in the postcode area would be classified into clusters according to the number of charging stations in the network by the K-means method. The K-means algorithm was proposed in 1960s (Duda and Hart, 1973; Lloyd, 1982), and is regarded as the most well-known and most straightforward partitioning clustering algorithm because of its easiness in the implementation, relatively low computational cost and straightforward parallelizability (Capó et al., 2020). There are two major stages of the K-means algorithm: 1) Initialisation, where researchers need to set the initial number of group centroids; 2) the iterative stage, also known as Lloyd's algorithm (Lloyd, 1982), where the initial group centroids would be placed in the place, followed by allocating each instance to its closest centroid, then the locations of the group centroids will be updated after all instances are allocated. In the end, the procedures of assigning group instances and recalculating centroid points will not stop until the centroids are no longer changing (Kodinariya and Makwana, 2013). As a consequence, the minimal dissimilarity among members in the same clusters can be found (Priya and Ghosh 2012), that is to say, the distance between every instance point and its centroid is minimised. The calculation process of k-means algorithm is presented in figure 3. However, the main weakness is the problem of initialisation, which requires users to determine the number of clusters. The final result is highly dependent on the initial number of clusters. Therefore, it is essential to run the algorithm several times with the different number of clusters in order to achieve a reliable result.

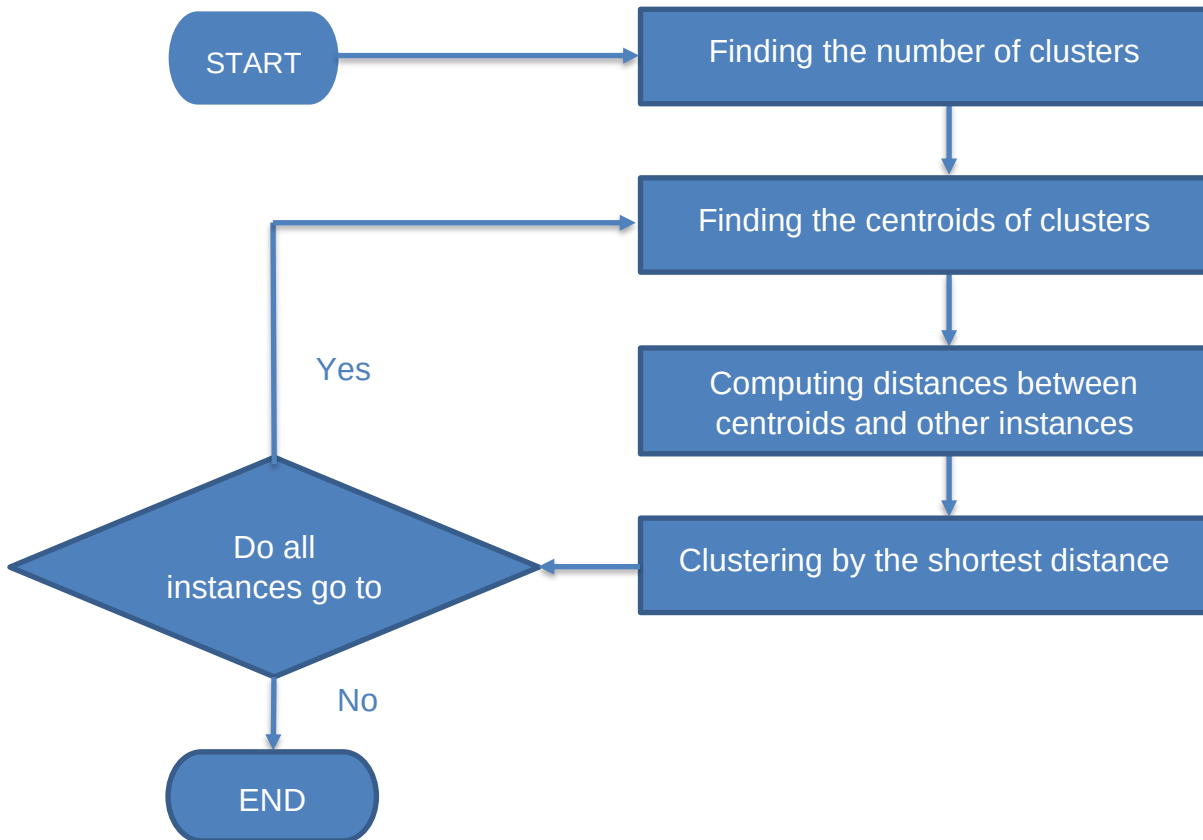


Figure 3: The calculation process of the k-means algorithm (Kodinariya & Makwana, 2013)

The study has been determined to apply the K-means clustering method to partition the whole individual postcodes of each postcode region into clusters by using 'SPSS 26' software. The individual postcodes are regarded as the set of consumers of each charging station in the cluster. The number of groups indicates the number of charging stations at the postcode study area. The number of clusters or the number of charging stations is determined by the previous part. The relevant parameters in the implementation of K-means clustering in the paper have been presented as below table:

<i>variables</i>	<i>= Latitude and Longitude of the individual postcode</i>
<i>Number of Clusters</i>	<i>= Total number of charging stations in a system</i>

<i>Label Cases by</i>	<i>= The individual postcodes</i>
<i>Method</i>	<i>= Iterate and classification</i>
<i>Maximum Iterations</i>	<i>= 30</i>
<i>Convergence Criterion</i>	<i>= 0</i>
<i>Save</i>	<i>= Geographical coordination of charging stations</i>

Table 1: paraments of K-means clustering

3.2.3. EVCS Facility's Locations Decision

In order to find the optimal solution for EVCS's network planning in the study area, the location decision of EVCS consists of two steps. The first step would minimise the sum of the weighted Euclidean distance between an individual postcode to its charging station in the system, and then the second step would rank all possible locations in order of priority according to several factors like crime rate and average income.

Step 1: calculating the minimised distance

After classifying the individual postcodes into clusters based on the geographical coordination, charging facility sites are presumed to be anywhere of the DH postcode region, and the charging requirement of each household is at the same level in daily life. The sites of charging infrastructures have been examined by the application of P-median problem with continuous location model. Aiming at minimising the sum of the weighted Euclidean distance between an individual postcode and its charging station of the system, the following mathematical model is developed (*Equation 3 and 4*):

$$\text{Minimise } \left\{ q = \sum_{n \in N} \sum_{m \in M} s_{mn} d_{mn} \right\} \quad (3)$$

where

$$d_n(x, y) = \sqrt{(x - a_n)^2 + (y - b_n)^2} \quad (4)$$

q = the weight sum product of the total Euclidean distance for all EVCSs in the system

s_{mn} = the number of households of postcode n which requires to charge EV at charging station m

n = index of postcodes

N = the number of postcodes in the cluster

m = index of EVCSs

M = the number of EVCS in the system

d_{mn} = the distance from the EVCS m location coordinates (x, y) to postcode n which is located in (a_n, b_n)

In this study, Excel Built-In Solver, an optimisation software, has been used to solve the mathematical formulation (Fylstra et al., 1998).

Step 2: ranking the candidate locations

Apart from population distribution and distance between households to charging station, there are many other factors influencing the EVCS deployment like the economy, land use, transportation and charging habits (Liu et al., 2018). From the view of energy usage, electricity consumption during peak and valley periods, energy structure, incentive policy, distribution of the load and scheduling strategy will impact EVCS allocation. Meanwhile, from the view of user characters, education background, charging habits, crime rate, the employment rate of EV owners and so on, also have effects on the charging infrastructure deployment. The influential components of charging facility deployment, thus, should be integrated into a comprehensive network to examine the essential factors. In accordance with the division principle of the system boundary, Liu et al., (2018) categorised the components influential to the EVCS into four subsystems, namely user subsystem, society subsystem, energy subsystem and scheduling subsystem. Due to the limited data, this study would focus on the user subsystem consisting of the income level and unemployment rate. According to a study in the UK, early adopters of EV are normally found to have a higher income than average income (Campbell et al., 2012; Hidrue et al., 2011). By contrast, the unemployment rate tends to affect the growth of EV number adversely (Frade, I. et al., 2011). The final evaluation value of one factor is the ratio of each candidate location's data to the mean value. Both the income level (w_1) and

unemployment rate (w_2) are specific numbers, so it is not difficult to evaluate these two factors.

Therefore, the model of location evaluation is formulated as *Equation 5*.

$$W_m = w_1 - w_2 \quad (5)$$

where

$$w_1 = \frac{w_{1m}}{\bar{w}_1}; w_2 = \frac{w_{2m}}{\bar{w}_2} \quad (6)$$

m = index of EVCSs

W_m = the evaluation value of the candidate location m

w_{1m} = the income level of the candidate location m

$\bar{w}_1$ = the average income level in the study area

w_{2m} = the unemployment rate of the candidate location m

$\bar{w}_2$ = the average unemployment rate in the study area

the Cost Analysis of EVCS's Network

The cost analysis targets to the analysis of EVCS's network instead of a single charging station. Based on the study of Serradilla, J. et al., (2017), the total costs of the EVCS's network consist of the initial capital expenditure (CAPEX) and the annual operating costs (OPEX). First, CAPEX refers to the cost which is incurred before operations begin, including the installation management, charger purchase and delivery, site preparation, commissioning and new power connections. According to RCN (2014), each fast charger costs about 38400GBP for the initial capital expenditure on average, and the charger purchase and delivery accounts for 54.7% of the initial capital expenditure, which is 21004.8GBP. Second, OPEX is mainly related to the operation and maintenance of chargers, including electricity cost (9.8 p./kWh), maintenance insurance (3% charger cost per year), unexpected maintenance (4% charger cost per year) (RCN, 2014)). Therefore, the total cost is formulated as *Equation 7*.

$$C = CAPEX + OPEX \quad (7)$$

Where

$$CAPEX = 38400 \times ncp \times M \quad (8)$$

$$OPEX = 9.8 \times p_{CH} \times ncp \times M \times 24 \times \frac{1}{100} + 7\% \times 21004.8 \quad (9)$$

Therefore, the total cost is estimated as the following formulation (*Equation 10*):

$$C = 38400 \times ncp \times M + 2.352 \times p_{CH} \times ncp \times M + 1470.336 \quad (10)$$

where

ncp = the number of charging pump in a charging station

M = the number of EVCS in the network

P_{CH} = the rated power output of the charger (kW)

Data Collection and Analysis

There are two forms of information and data collection system techniques in the research setting, namely secondary data collection and primary data collection. (Cooper and Schindler, 2014). Data can be collected through primary data sources or secondary data sources or through a combination of both. The main form of required data of this study is secondary written data, and the saturation of information has a significant influence on the decision making of qualitative secondary analysis (Fusch and Ness 2015). As a consequent, the author has focused mainly on information collection from reference sources and reliability of the essential information such as the accurate geographical coordination of individual postcodes, the number of households of each individual postcode, size and population in the area, information of fast chargers and EV diffusion. The aim of this sector is to find essential data to complete the research's practical approach. The following data would be gathered and discussed:

- 1) the number of populations and its geographical coordination point
- 2) the diffusion and trend of EVs
- 3) charging demand estimation

4) income level and the unemployment rate of candidate locations

The Number of Populations and its Geographical Coordination Point

There are approximately 1.7 million individual postcodes in the UK and MRS (2018) classifies all postcodes into 124 postcode areas according to the first two letters of the postcode. For instance, there are around 8,986 active individual postcodes with 309,030 residents in DH postcode area (Doogal, 2020). Therefore, www.doogal.co.uk, which provides data in accordance with the 2011 UK's census, can be used to collect the total number of residents per postcode address in different postcode areas. In addition, the individual postcode's geographical coordination (latitude and longitude) is also freely available from this database, which can be applied to identify the centroid point of each cluster and calculate the transportation distance.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Postcode	In Use?	Latitude	Longitude	Constituency	Population	Households	Built up area	Lower layer super output area	Rural/urban	Region	Altitude	Average Income
2	DH1 1AB	Yes	54.786659	-1.530113	City of Durham	17	8	Durham	County Durham 028B	Urban city and town	North East	90	43600
3	DH1 1AD	Yes	54.786726	-1.531325	City of Durham	63	27	Durham	County Durham 028B	Urban city and town	North East	88	43600
4	DH1 1AE	Yes	54.78715	-1.531616	City of Durham	26	11	Durham	County Durham 028B	Urban city and town	North East	86	43600
5	DH1 1AF	Yes	54.790099	-1.5297	City of Durham	115	51	Durham	County Durham 028C	Urban city and town	North East	78	43600
6	DH1 1AG	Yes	54.788869	-1.529979	City of Durham	9	6	Durham	County Durham 028D	Urban city and town	North East	81	43600
7	DH1 1AH	Yes	54.791248	-1.527012	City of Durham	110	46	Durham	County Durham 028C	Urban city and town	North East	75	43600
8	DH1 1AJ	Yes	54.792324	-1.52642	City of Durham	1	1	Durham	County Durham 028C	Urban city and town	North East	74	43600
9	DH1 1AL	Yes	54.789333	-1.529056	City of Durham	98	44	Durham	County Durham 028D	Urban city and town	North East	80	43600
10	DH1 1AN	Yes	54.789939	-1.527851	City of Durham	23	10	Durham	County Durham 028C	Urban city and town	North East	78	43600
11	DH1 1AP	Yes	54.787522	-1.530181	City of Durham	34	16	Durham	County Durham 028D	Urban city and town	North East	85	43600
12	DH1 1AQ	Yes	54.79137	-1.52827	City of Durham	85	35	Durham	County Durham 028C	Urban city and town	North East	76	43600
13	DH1 1AR	Yes	54.787321	-1.529359	City of Durham			Durham	County Durham 028D	Urban city and town	North East	85	43600
14	DH1 1AS	Yes	54.788772	-1.528067	City of Durham	82	41	Durham	County Durham 028D	Urban city and town	North East	81	43600
15	DH1 1AT	Yes	54.790696	-1.526054	City of Durham	86	37	Durham	County Durham 028D	Urban city and town	North East	77	43600
16	DH1 1AU	Yes	54.792393	-1.525661	City of Durham			Durham	County Durham 028C	Urban city and town	North East	74	43600
17	DH1 1AW	Yes	54.787988	-1.53002	City of Durham	39	18	Durham	County Durham 028D	Urban city and town	North East	83	43600
18	DH1 1AY	Yes	54.792567	-1.524259	City of Durham	2	1	Durham	County Durham 028C	Urban city and town	North East	74	43600
19	DH1 1AZ	Yes	54.792867	-1.525222	City of Durham	70	32	Durham	County Durham 028C	Urban city and town	North East	73	43600
20	DH1 1BA	Yes	54.793205	-1.524205	City of Durham	44	21	Durham	County Durham 028C	Urban city and town	North East	72	43600
21	DH1 1BB	Yes	54.792686	-1.527135	City of Durham	24	10	Durham	County Durham 028C	Urban city and town	North East	73	43600
22	DH1 1BD	Yes	54.793659	-1.523096	City of Durham	45	18	Durham	County Durham 028C	Urban city and town	North East	72	43600
23	DH1 1BE	Yes	54.791776	-1.524284	City of Durham	1	1	Durham	County Durham 028C	Urban city and town	North East	75	43600
24	DH1 1BF	Yes	54.780447	-1.546008	City of Durham			Durham	County Durham 029A	Urban city and town	North East	91	32400
25	DH1 1BG	Yes	54.791222	-1.524971	City of Durham	6	5	Durham	County Durham 028C	Urban city and town	North East	76	43600
26	DH1 1BJ	Yes	54.785844	-1.531009	City of Durham	33	12	Durham	County Durham 028B	Urban city and town	North East	92	43600
27	DH1 1BL	Yes	54.791337	-1.52441	City of Durham	48	30	Durham	County Durham 028C	Urban city and town	North East	76	43600
28	DH1 1BP	Yes	54.791631	-1.523804	City of Durham	10	4	Durham	County Durham 028C	Urban city and town	North East	76	43600
29	DH1 1BQ	Yes	54.789226	-1.527094	City of Durham	137	55	Durham	County Durham 028D	Urban city and town	North East	80	43600
30	DH1 1BW	Yes	54.781392	-1.568666	City of Durham			Durham	County Durham 030E	Urban city and town	North East	92	29800
31	DH1 1DA	Yes	54.782988	-1.543092	City of Durham	29	12	Durham	County Durham 028E	Urban city and town	North East	90	43600
32	DH1 1DB	Yes	54.782484	-1.541253	City of Durham	43	25	Durham	County Durham 028E	Urban city and town	North East	90	43600

Table 2: information of DH postcode area from the doogal.co.uk

the Number and Trend of EV

According to the Department for Transport (2020), ultra-low emission vehicles (ULEVs) sales continue to increase substantially in the UK, presenting an increase of 26% on 2018 and 52% on 2017, and the percentage of all vehicle registrations grew from 0.05% in 2013 to 0.55% by 2018. The majority types of ULEVs are battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV). During 2019, there were 79,747 ULEVs registered for the first time in Great Britain, an increase of 26% on the previous year, and ULEVs made up 2.7% of all new registrations. The proportion of ULEV in Durham County has a relatively lower level than that of England, which is 0.25% in 2018 (Figure 4). However, this is much lower than the countries which have been succeeded in increasing ULEV uptake, such as Norway at 55.93% Iceland at

22.60% and the Netherlands at 15.14% in 2019 (IEA, 2020). The ‘Central scenario’ of Committee on Climate Change (CCC, 2018) envisages EVs accounting for approximately 30% of the total vehicle by 2030 in the UK. The pEV , thus, is defined at 30% in order to satisfy the charging demand in 2030.

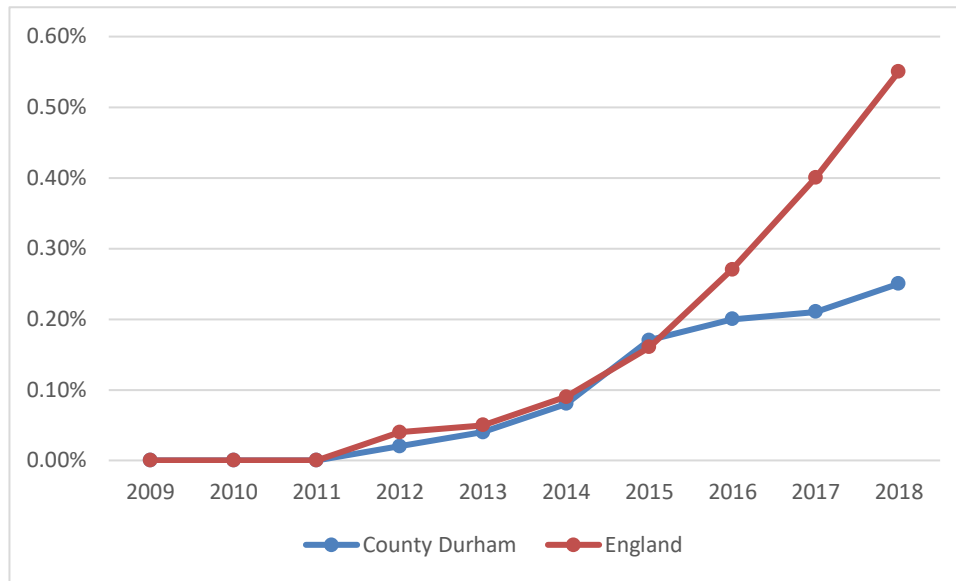


Figure 4: ULEV registrations of all vehicle registrations (%)

Charging Demand Estimation

The mobility pattern of EVs is presumed that each EV attends to its closest charging station in close to linear in twenty-four hours, and the average battery capacity of EVs is estimated to be 40 kWh around the world according to Statista Research Department (SRD, 2020). Because fast-charging technologies can charge an EV to 80% state of charge with 1p an hour (Serradilla et al., 2017), SOC^F and SOC^{TH} of EVs are presumed at the same level for all EVs, which are 30% and 80% respectively. The population of DH area is 309,030 (Doogal, 2020), and the number of charging pumps is defined as five considering the grid capacity. Other parameters related to estimating the quick charging station are presented in Table 3.

Variables	Parameters	Variables	Parameters
kWh_{EV}	40	<i>population</i>	309,030
SOC^F	80%	pEV	30%
SOC^{TH}	30%	<i>sh</i>	24

P_{CH}	240	ncp	5
eff_{CH}	95%	nst	11.4025
t_{ev}	0.0877		

Table 3: parameters related to estimate the quick charging station

income level and the unemployment rate of candidate locations

This step would be too time-consuming since the data has to be collected from different sources and then organised manually one by one. After finding all candidate locations of EVCS, the exact address of these locations can be obtained by inputting longitudes and latitudes into the www.latlong.net. According to Doogal (2020), the average income in the DH postcode area is 36,120.70 pounds per year, and the income level of each postcode is also presented in Table 2. As for the unemployment rate, Plumplot (2019) reported that the average unemployment rate in DH area is 5% in 2019, which is slightly higher than the UK average rate at 3.8%, and the specific data of each postcode are available at postcodearea.co.uk.

COMPUTATIONAL EXPERIMENTS

To assess the viability and applicable of the proposed practical approach, this section would perform computational experiments under the condition of the DH postcode region, located in the northeast of the UK. The assumptions and parameters have been analysed and adopted to calculate the number of EVCSs and possible locations in the DH area. Subsequently, the importance of candidate locations is evaluated in terms of the income level and unemployment rate. Finally, the cost analysis of the EVCS network, including installation management, charger purchase and delivery, site preparation and electricity cost, has been computed and presented.

Estimation of the Number of EVCSs

The DH postcode area is used to illustrate the computational experiments because the volume of relevant data in this region is suitable for the research study time like the number of populations and coordinates of individual postcodes in this area. Furthermore, ~~SOSCI~~ (2020) also plans to deploy EVCSs in this region in the next few years. Thus, this study considers the DH postcode area as a case study to develop a robust EVCS's network. There are 8,986 active individual postcodes and 309,030 residents in DH postcode area. In the computational experiment, the minimal number of EVCSs in the network is 68 with 340 fast chargers under the case of meeting the

charging requirement in DH postcode area by 2030. Nevertheless, for the current EV proportion in the DH postcode area, the minimal number of EVCSs in the network would be much smaller than the number in 2030. This is because the proportion of EV in the DH area in 2020 is only approximately 0.3% while the proportion of EV in 2030 is estimated at 30% in 2030 (CCC, 2018). The number of clusters in the K-means algorithm is also determined which would be completed in the next process. Besides, the computational experiments also employed the following parameters which can be found in the previous section.

- ⑩ The rated power output of the charger (P_{CH}) and its charging efficiency (eff_{CH}) are 240 kW and 95% respectively, which means the actual output of a charger would be 228kW in the DH postcode area.
- ⑩ The battery capacity of most EVs (kWh_{EV}) is estimated to be around 40 kWh. The charging time of each EV (t_{ev}) is 0.0877 hr. and the number of services in an hour of charging pump (nst) is 11.40 services.
- ⑩ The number of charging pump (n_{cp}) and service hour of a charging station in a day (sh) are assumed to be 5 pumps in a charging station and 24 hours a day, respectively.
- ⑩ The initial capital expenditure (CAPEX) of one fast charger is 38400GBP in the UK and the average electricity cost is 9.8 p./kWh in the UK

Population's Classification in DH Postcode Area

According to the process of K-means algorithm (Figure 3), 8,986 individual postcodes have been assigned to 68 groups through SPSS 26 software in accordance with the minimised distance. The detail geographical coordination points (longitude and latitude) of each EVCS candidate locations, as well as the number of postcodes served by one EVCS has been presented in Appendix A. From the results of K-means clustering, there is a difference between clusters in terms of the number of individual postcodes in each cluster. To be specific, there are 471 individual postcodes in No. 65 cluster, while only two postcodes are assigned to No. 24, No. 36 and No.39. If all individual postcodes in the DH postcode area are equally allocated to 68 clusters, each cluster will have 132 individual postcodes. Figure 5 illustrates the distribution of postcodes and candidate locations of EVCSs in the DH postcode area. Every individual postcode in the DH postcode area is represented by a single grey point, and

blue points in Figure 5 present candidate locations. From this figure, it is not difficult to see that candidate locations of EVCSs tend to be located in the population centres.

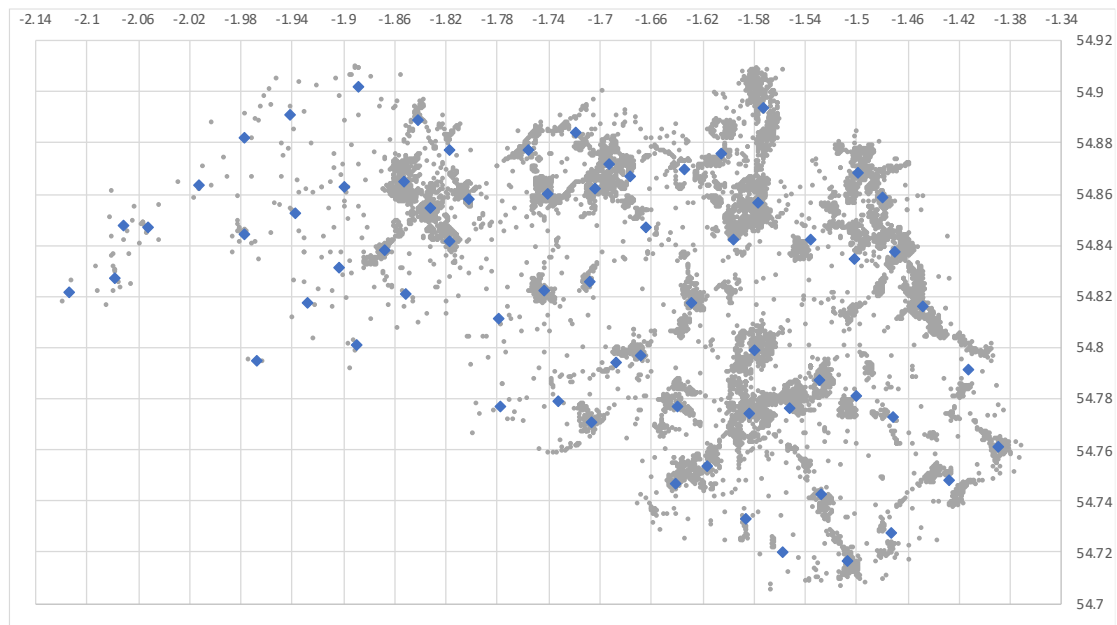


Figure 5: the distribution of postcodes and candidate locations by K-means

EVCS Facility's Locations Decision

The first step is to calculate the minimised Euclidean distance of all 68 EVCSs in the DH area. Excel Built-in Solver has been used to calculate the mathematical formulation on the basis of the continuous location models (*Equation 3 & Equation 4*). According to the computational result, the minimum weighted sum product of the total Euclidean distance of all EVCSs in the DH area is 1,184.47. Due to the conception of the weighted sum, the EVCS sites have the tendency to be close to the region with relatively high population density so as to reduce the travelling time. The EVCSs' addresses from www.latlong.net can be seen from Appendix A. The second step to rank the candidate locations in terms of other two factors, namely the income level (w_1) and unemployment rate (w_2), and this step is also completed by Excel Built-in Solver. Figure 6 presents the top 10 (triangles) and the last 10 (points) candidate locations of EVCSs in the DH postcode area after evaluating the income level and unemployment rate. The full results are presented in Appendix A.

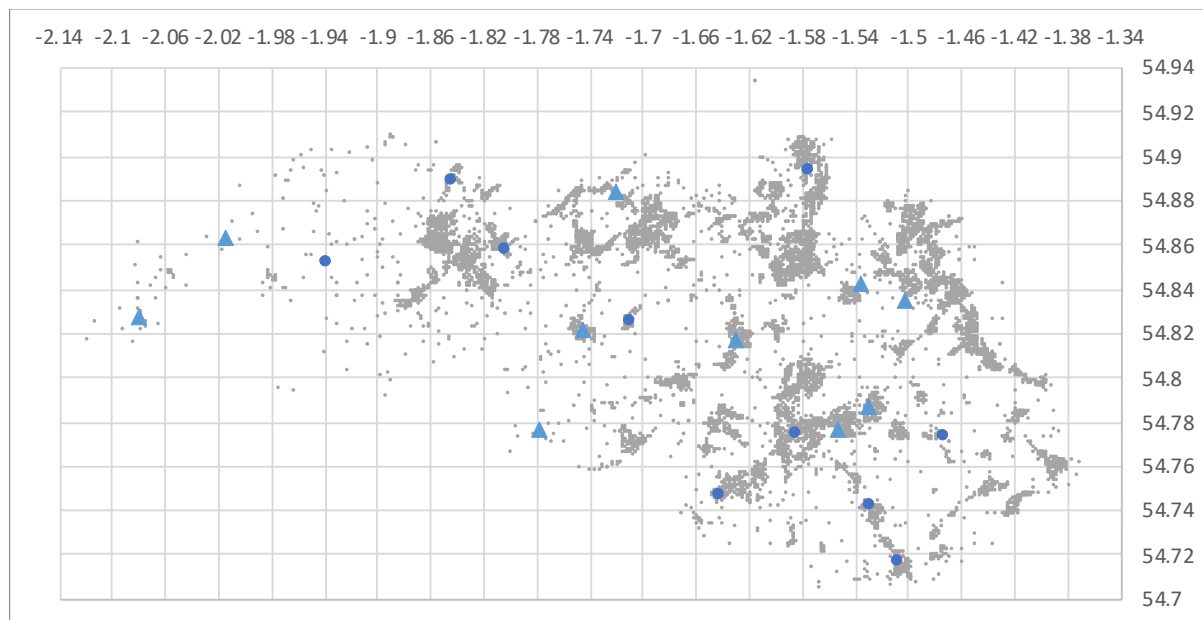


Figure 6: the top 10 (triangles) and the last 10 (points) candidate locations of EVCSs in DH

Cost Analysis of the Total EVCSs' Network

From the previous parts, there are two parts in the cost analysis, namely CAPEX and OPEX. The CAPEX of the entire EVCS network is 13.056 million GBP, and the OPEX of the entire EVCS network is approximately 0.2 million GBP per year. Therefore, the total cost of EVCS network is estimated to be at around 13.256 million GBP in the first year with 0.2 million GBP annual maintenance cost. Nevertheless, it is challenging to build all EVCS in one year in terms of the budget and construction time. As an alternative, all candidate locations can be allocated to the next ten year based on the rank of candidate location evaluation. To be specific, those locations with higher evaluation values are generally close to higher income groups, as well as the communities with a lower unemployment rate. Therefore, the EVCS network should be started with these locations with higher evaluation values in accordance with the rank of candidate location evaluation. The annual cost of EVCS network in the DH postcode area from 2020 to 2029 has been presented in Table 4, from which can be seen that the CAPEX of each year is the same value (about 1.3 million) but with steadily increasing OPEX over time.

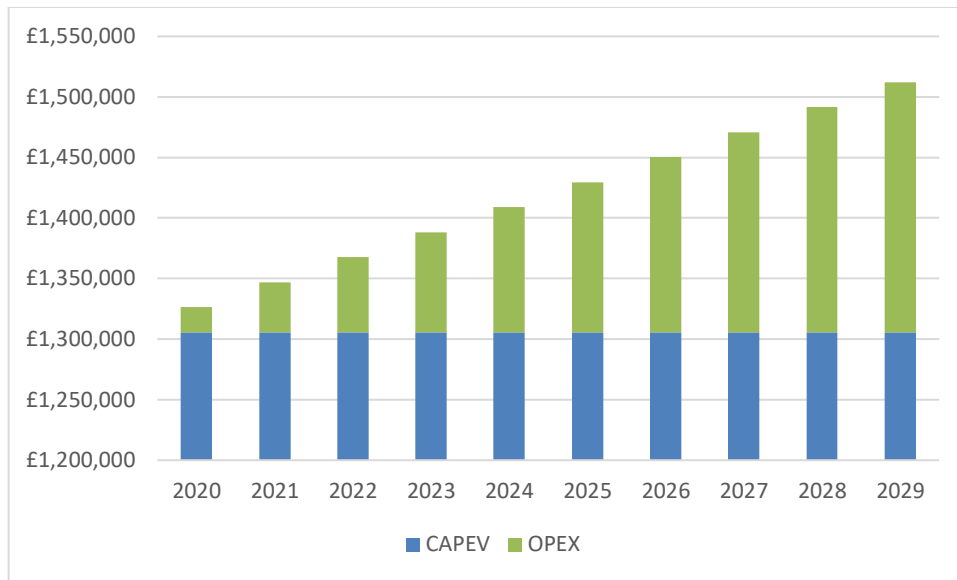


Table 4: annual cost of EVCS network from 2020 to 2029

RESULT AND DISCUSSION

In order to give a better understanding of the computational results, the key finding of this study would be described, and sufficient discussions would be provided to come to conclusions of EVCS system in the DH postcode area. The interpretation of the relations among charging demand, the number of EVCSs and evaluation of candidate locations have been discussed. Finally, the recommendation for EVCS network in DH postcode area is clarified in the last section in this section.

the Charging Demand in Relation to the Number of EVCSs

In this study, the charging demand is estimated by the population density in an area, rather than the traffic flow or distribution of origins and destinations. There have been a large number of articles focusing on these two factors, while a few articles concentrate on the distribution of the population. According to Connected Car Magazine Team (2020), more than 60% of EV owners choose to complete the majority of their recharging overnight near their home, instead of charging in the workplace in the daytime. As a contrast, there are only 5% EV owners doing most of recharging at work. In other words, most EV owners require charging infrastructure close to the place where they live, rather than the place where they work. In order to make sure the deployment of EVCSs closing to the demand points, this study decided to focus on the population density to estimate the charging demand of EVs in the DH postcode area. Another important point is the determination of the EV penetration rate, which have a significant influence on the final estimated number of EVCSs. This is because there are a lot of uncontrollable factors in terms of the EV market, such as policy, subsidy,

petrol price and environmental awareness of the public. The EV penetration rate is changing all the time, so it is difficult to predict the accurate rate in the following years. Thus, there is always a gap between the actual EV penetration rate and predicted EV penetration rate. If the actual rate is higher than the predicted rate, EV owners may face the problem of lacking charging infrastructure, resulting in more internal combustion engine (ICE) vehicles on the road, and even less and fewer EV adopters in the long run. However, if the actual rate is lower than the predicted rate, there would be a massive waste of investment and charging infrastructure, and companies operating EVCS business may face an operating loss. The deployment of EVCS is regarded as long-term planning for both governments and organisations since it costs huge funds and a long period of time. It is obvious that higher charging demand means a larger number of EVCS, but the difficulties are how to determine the specific demand and how to solve the inevitable gap between reality and expectations.

the Evaluation Criteria in Relation to the EVCS Site Determination

The deployment of EVCSs should be considered from comprehensive perspectives, including economy, environment, society and technology. Each perspective consists of multiple factors. For example, economic perspective consists of construction cost, operation and maintenance cost, update and removal cost, charger salvage value, inflation rate and discount factor, et cetera; environmental perspective consists of destruction degree on vegetation and water, ecological influence, electromagnetic interference and so on. Thus, researchers may find it challenging to take everything into consideration when determining the site of EVCSs. Even if all factors are taken into consideration, another problem is the importance of each factor related to EVCS allocation, which determines the weight given to each factor.

Recommendation for EVCS Strategy Network Planning

As mentioned at the beginning of this study, the low availability of charging station infrastructure is one of the main barriers of increasing EV adoption. In order to solve this problem and bring EV to become mass-market adoption, the facility allocation model can be an effective technique to address this issue. Most EVCS are designed to serve the postcodes close to them in accordance with the principle of K-means clustering. This study, including literature review, methodology, computational experiment and results, presented that facility allocation problem of EVCS in DH postcode region could be analysed through adopting the continuous location model

and other applicable methods. As a consequent, the advancement of EVCS strategical system plan in the DH postcode region would be able to make some changes to the DH area from the many ways, such as systematic management of the EVCS network, the shortest travel cost to charging infrastructure as well as environmental protection. It is therefore recommended that in the DH postcode area, EVCS should be located at geographical coordination locations: (54.774458, -1.583892), (54.863635, -2.013246), (54.88216, -1.977475), (54.863006, -1.898897) and so on (Appendix A). Each EVCS was supposed to have five charging pumps with the rated power output of 240 kW in 24 hours.

Limitations of the Study

The study of the EVCS system in the DH postcode region of the study is a plan on a strategic level. Even though this research has achieved its aim and objectives, there are several limitations. Firstly, the DH postcode area is chosen as case study to conduct this approach, because the volume of input data in this area is suitable for the study period of time. Users may have to spend a large amount of time in collecting the income level and unemployment rate of all candidate sites in the area with great charging demand, which can be extremely time-consuming. Besides, areas differ in terms of their framework conditions, like the availability of charging in the off-street parking, and the question of how many charging stations is required cannot be answered equally for all areas in the UK. Second, the geographical coordination of EVCS site applying the continuous location model produces the result on the basis of the computational program. These specific locations, however, may not available for CS construction, because there is some possibility of locating in houses, rivers or private lands. Third, the minimised distance refers to the Euclidean distance between the centroid of the individual postcode to its closest CS, which is different from the actual travel distance.

Suggestions for Future Research

Considering that this study focuses mainly on the EVCS planning in DH postcode area from the macro strategic perspective, so further research or study at the operational level still need to be clarified in detail. For example, in order to make sure the availability of candidate sites of EVCS network, it is essential to conduct the land surveying. The EVCSs shall be located at the closest site of those candidate sites as much as it is possible to be constructed when the lands of candidate sites are not

available. Moreover, this study focuses on the initial stage of EV adoption, presuming that the proportion of EVs in the DH postcode area is relatively small. Nevertheless, with the increasing number of EVs, it is imperative to examine further the congestion effect of traffic flow resulting from charging demands on road traffic. In addition to the heavy traffic, the distribution of the EVCSs would put relatively considerable pressure on the local power grid when the EV diffusion moves into a mature stage. As a consequence, further research should take the power factor into consideration.

CONCLUSION

The use of fossil fuels has significant effects on climate change due to greenhouse gas emissions and various environmental pollutions. Thus, many renewable energies have been introduced and are regarded to substitute for fossil fuels in multiple industries, particularly in the transportation industry. Moreover, high population densities in urban areas are resulting in rising congestion and various environmental problems. A large-scale transition to E-mobility would be widely required for constructing sustainable cities in the near future, and the advancement of EV charging facility is the prerequisite for the large-scale transition. EVs are identified as one of the most promising solutions to solve the fossil fuel energy crisis and other various pollutions, but still in an early market phase in almost all markets. In the initial process of EVCS installation, location-allocation performs an important role in its entire lifecycle. Because of the real advantages for various kinds of business of the facility allocation model, the facility allocation model has been adopted by the planning of the EVCS locations. This strategic planning has examined the EVCS facilities deployment problem in the DH postcode area of the UK through applying the continuous location model and other relevant techniques. Furthermore, in order to produce an accurate order in which EVCSs should be built in the next ten years, both the income level and unemployment rate of candidate locations are taken into consideration. Then, the computational experiment presented useful results for the DH postcode area.

In conclusion, the facility location model of fast charging stations constructed in this study comprehensively considers various factors, such as charging demand, the investment cost, EV owners' characteristics, and comprehensively reflects the problems of installing charging infrastructure. There are plenty of available opportunities in the advancement of EVCS system so as to develop the EV-charging industry and EV market in the UK. Even if the computational experiment has only been employed to the DH postcode area in the UK instead of other areas, this study can be

an early phase for EV adoption and charging infrastructure planning organisations through following the research approach and adopting suggestions in the paper. It is supposed to apply the generic practical approach in this study to all postcode areas in the UK for strategic design of EVCS facility network.

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APPENDIX

Index of EVCS	latitude	longitude	number of postcode	address of EVCS	income level	unemployment rate (%)	w1	w2	W
65	54.774458	-1.583892	471	DH1 4QQ	54900	1.4	1.5199	0.28	1.2399
7	54.863635	-2.013246	5	DH8 9PG	45800	2	1.268	0.4	0.86797
32	54.88216	-1.977475	9	DH8 9SB	45800	2	1.268	0.4	0.86797
37	54.863006	-1.898897	18	DH8 9TG	45800	2	1.268	0.4	0.86797
45	54.891273	-1.941707	14	DH8 9RW	45800	2	1.268	0.4	0.86797
60	54.852811	-1.937457	14	DH8 9EF	45800	2	1.268	0.4	0.86797
27	54.754232	-1.616726	162	DH7 8RG	54900	3.3	1.5199	0.66	0.8599
49	54.79959	-1.579304	289	DH1 5PJ	50700	2.9	1.4036	0.58	0.82363
10	54.822569	-1.744157	130	DH7 0HT	41300	1.9	1.1434	0.38	0.76339
26	54.801038	-1.8894	5	DH8 9HP	41300	1.9	1.1434	0.38	0.76339
3	54.787849	-1.52944	237	DH1 1AW	43600	3.2	1.2071	0.64	0.56706
52	54.842569	-1.596789	209	DH2 3TN	35400	2.1	0.98	0.42	0.56005
20	54.781636	-1.501052	124	DH6 1EY	36300	2.5	1.005	0.5	0.50496
17	54.761506	-1.390374	135	DH6 2LN	30400	2	0.8416	0.4	0.44162
63	54.716828	-1.50742	149	DH6 4SZ	36800	3.1	1.0188	0.62	0.39881
21	54.720361	-1.557896	21	DH6 5LE	39400	3.5	1.0908	0.7	0.39079
13	54.864872	-1.852756	317	DH8 0LR	40100	3.8	1.1102	0.76	0.35017
4	54.884397	-1.719505	108	DH9 9UE	39800	3.9	1.1019	0.78	0.32186
33	54.831405	-1.904116	11	DH8 9DD	33200	3	0.9191	0.6	0.31914
35	54.821358	-1.85186	15	DH8 9HG	33200	3	0.9191	0.6	0.31914
36	54.794955	-1.967416	2	DH8 9DX	33200	3	0.9191	0.6	0.31914
42	54.817608	-1.928208	6	DH8 9DS	33200	3	0.9191	0.6	0.31914
28	54.733492	-1.587099	38	DH6 5HA	39400	3.9	1.0908	0.78	0.31079
15	54.86867	-1.499332	303	DH4 7LL	36300	3.6	1.005	0.72	0.28496
53	54.816732	-1.448073	320	DH5 0BG	31800	3.2	0.8804	0.64	0.24038
41	54.794588	-1.688356	45	DH7 9FF	37000	4	1.0243	0.8	0.22434
57	54.858928	-1.479974	239	DH4 4YB	36900	4	1.0216	0.8	0.22157
62	54.747231	-1.641663	119	DH7 8TG	32100	3.4	0.8887	0.68	0.20869
48	54.85455	-1.832818	297	DH8 5LD	34500	4.3	0.9551	0.86	0.09513
5	54.842681	-1.535891	157	DH3 4DR	37900	5.1	1.0493	1.02	0.02926
34	54.779105	-1.732785	33	DH7 9EB	37000	5.2	1.0243	1.04	-0.0157
8	54.827492	-2.078775	14	DH8 9UP	35900	5.1	0.9939	1.02	-0.0261
14	54.847199	-2.052645	11	DH8 9PZ	35900	5.1	0.9939	1.02	-0.0261
16	54.844577	-1.977786	17	DH8 9NQ	35900	5.1	0.9939	1.02	-0.0261
24	54.821958	-2.114429	2	DH8 9UL	35900	5.1	0.9939	1.02	-0.0261
2	54.834647	-1.501996	200	DH1 1QQ	32400	4.7	0.897	0.94	-0.043
1	54.777301	-1.778113	13	DH7	36400	5.3	1.0077	1.06	-0.0523
55	54.811972	-1.779816	19	DH7	36400	5.3	1.0077	1.06	-0.0523
38	54.847847	-2.071033	8	DH8	31720	5	0.8782	1	-0.1218
44	54.902065	-1.888581	13	DH8	31720	5	0.8782	1	-0.1218

19	54.841718	-1.817249	141	DH8 7EW	32700	5.2	0.9053	1.04	-0.1347
66	54.742678	-1.528144	137	DH6 5ER	39400	6.2	1.0908	1.24	-0.1492
18	54.877188	-1.817925	73	DH8 6QS	40100	6.4	1.1102	1.28	-0.1698
67	54.889151	-1.84219	60	DH8 0QL	40100	6.4	1.1102	1.28	-0.1698
51	54.837985	-1.470301	319	DH5 8LR	34200	5.6	0.9468	1.12	-0.1732
59	54.826081	-1.708536	52	DH7 0AG	41300	6.8	1.1434	1.36	-0.2166
68	54.773303	-1.472022	59	DH6	32760	5.7	0.907	1.14	-0.233
9	54.817586	-1.628823	237	DH7 6NE	35400	6.2	0.98	1.24	-0.26
23	54.791394	-1.413126	144	DH6 2TW	35700	6.5	0.9884	1.3	-0.3116
11	54.727581	-1.473012	78	DH6 4QU	36800	6.9	1.0188	1.38	-0.3612
47	54.797396	-1.66921	119	DH7 9QH	37000	7	1.0243	1.4	-0.3757
12	54.856669	-1.577342	449	DH3 3YJ	30100	6.1	0.8333	1.22	-0.3867
25	54.748725	-1.428488	196	DH6 3AR	28900	6.2	0.8001	1.24	-0.4399
40	54.867437	-1.676851	139	DH9 6UY	33800	7.4	0.9358	1.48	-0.5442
43	54.771469	-1.707223	111	DH7 9HZ	35200	7.9	0.9745	1.58	-0.6055
30	54.869937	-1.634746	126	DH9 6SU	33400	8.2	0.9247	1.64	-0.7153
46	54.838519	-1.867749	118	DH8 8DE	33200	8.2	0.9191	1.64	-0.7209
61	54.858278	-1.802001	140	DH8 7RT	32700	8.2	0.9053	1.64	-0.7347
64	54.893822	-1.573483	384	DH3 2LP	32800	8.5	0.9081	1.7	-0.7919
58	54.877613	-1.756062	139	DH9 9AL	29300	8.2	0.8112	1.64	-0.8288
54	54.876071	-1.605206	219	DH2 1EW	33400	9.5	0.9247	1.9	-0.9753
31	54.860062	-1.740394	278	DH9 8JY	29300	9.1	0.8112	1.82	-1.0088
56	54.847617	-1.664943	58	DH9 6EN	29000	9.2	0.8029	1.84	-1.0371
22	54.77757	-1.63954	188	DH7 7LN	36100	11	0.9994	2.2	-1.2006
39	54.934641	-1.615103	2	DH98	32500	10.6	0.8998	2.12	-1.2202
29	54.862178	-1.704744	203	DH9 7AG	30200	11.1	0.8361	2.22	-1.3839
6	54.776949	-1.552091	256	DH1 2EY	32400	12.7	0.897	2.54	-1.643
50	54.872062	-1.692547	252	DH9 0DJ	29000	13	0.8029	2.6	-1.7971