MASTER'S DEGREE THESIS

MSc in Statistics and Operations Research

Title: A multi-objective approach to infrastructure planning in the early stages of EV introduction

Author: Andina Rosalya Brown

Advisor: F. Javier Heredia, Cristina Corchero

Department: Statistics and Operations Research

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UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Facultat de Matemàtiques i Estadística

Universitat Politècnica de Catalunya
Facultat de Matemàtiques i Estadística

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Andina Rosalya Brown

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Preface

The work for this project was carried out at the Catalonia Institute for Energy Research (Catalan: *Institut de Reserca de Energia de Catalunya* or *IREC*) as part of the Energy Economics Research Group (EERG) in the area of Electrical Engineering.

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Abstract

The aim of this study is to address the problem of locating fast charging stations for electric vehicles (EVs) in the early stages of infrastructure implementation. While electric vehicles are not a new phenomenon, their development, and the development of their infrastructure, has attracted increasing attention in recent years. With growing concerns over climate change, the quality of air in urban areas, and trade imbalances associated with the EU's dependence on imported oil, there is a drive towards alternative fuel sources for transport in Europe, championed by the European Commission.

Despite existence of successful trials and pilot projects, there are barriers preventing the successful development of a private EV market in its present state; investors are reluctant to invest in infrastructure due to the relatively small number of EV users, and conversely consumers are hesitant about purchasing EVs due high prices and a lack of charging infrastructure. Consequently, it is considered that public sector intervention is necessary for the large scale uptake of electric vehicles to become a reality. It has been identified that introducing fast charging stations can aid this process, in particular by easing users' concerns about running out of charge before reaching their destination (range anxiety).

This study approaches the problem from the perspective of a central planner wishing to install fast charging stations. A multi-objective approach is used to simultaneously consider two conflicting objectives in the optimisation problem. The first objective is to minimise the distance that potential consumers would need to deviate from their normal journeys in order to reach their nearest fast charging station, and thus minimise the associated inconvenience. The second objective is to minimise the set up costs associated with the installation of the stations, which differ according to the number of facilities installed and their location. These objectives are normalised using a function transformation and then combined into a single objective function.

A mathematical model is formulated and implemented using GAMS to obtain results for the case study of Barcelona, building on the existing literature. Using the *weighted sums* method, multiple Pareto optimal solutions are found by solving for different relative weights combinations applied to the two objectives. These solutions are used to depict the Pareto front, offering insight into the nature of the trade-offs between the objectives and aiding the decision making process. This study develops the existing methodology used for the EV infrastructure problem, and shows how the application of a multi-objective formulation can offer useful insight to decision makers, particularly when preferences are unclear *a priori.*

Keywords: Multi-objective Optimisation, Facility Location, Electric Vehicle, Fast Charging Stations, Weighted Sums

Contents

1. Introduction

This study addresses the problem of locating fast charging stations for electric vehicles in the early stages of infrastructure implementation. The primary objectives are to contextualise the electric vehicle infrastructure problem and to subsequently develop the existing methodology found in the literature. In particular, this study aims to design an optimal location model for the infrastructure of fast charging stations for electric vehicles, using the city of Barcelona as a case study.

The most notable contribution is the implementation of a multi-objective model, applying the weighted sums methodology. Whereas previous authors have focussed on a single objective for optimisation, this study combines two separate objectives in a single objective function. Using this approach, multiple solutions can be obtained and used to observe the trade-offs between conflicting objectives, providing valuable information to decision makers.

In addition, an alternative outlook is taken with regards to electric vehicle user behaviour. Previous studies have assumed users to take fixed paths for their journeys, and have therefore optimised the capture of flow along these. Here, however, it is considered that drivers would be willing to deviate from their normal paths in order to make use of recharging facilities. With this in mind, the concept of minimising deviations is introduced into the optimisation problem with an aim to better reflect driver behaviour, and account for all users in the model.

The model is first formulated mathematically and then implemented using the General Algebraic Modelling System (GAMS) to obtain results for a single case study. Data for Barcelona is used to develop the methodology, which could then be applied to other cities or regions.

1.1 Structure

Beyond this initial introduction, the study is organised in the following manner:

Section 2 outlines the context in which the study is undertaken. The notion of electric vehicles is introduced along with a brief history of their development, followed by a discussion of the factors that are currently driving the growth of the electric vehicle market. Both the need for fast charging stations and the need for public sector intervention are explained, with considerable reference to the existing literature on the topic.

The context of the study is expanded in *Section 3 by* identifying some of the existing infrastructure systems for electric vehicle in place across the globe, and introducing the city of Barcelona as a case study. The existing approaches and methodologies that have been applied to the facility location problem are also discussed here.

Section 4 introduces the multiple objective approach to optimisation, and outlines the mathematical model that is later implemented to obtain results, along with an explanation of all relevant notation used.

The data used to implement the model for the case study of Barcelona are discussed in *Section 5,* along with a discussion of methods applied for the manipulation of this data and assumptions made.

Section 6 presents the results obtained using the case study data, and discusses the implications.

Limitations to the study are addressed in S*ection 7* and improvements are suggested.

Finally, *Section 8* provides the conclusions of the study with suggestions for further research.

2. Background Context

2.1 EV Background

Electric vehicles (EVs), and in particular electric cars, have been in existence since the 19th century. Indeed, in the early 20th century EVs were more popular than their petrol fuelled counterparts. Over time however, with vast improvements in the combustion engine and other components, the petrol fuelled car took over the market and private electric vehicles were largely forgotten (Nichols, 2011). In recent decades, the reintroduction of the EV to the domestic market has been a phenomenon of increasing momentum for a number or reasons, notably rising fuel costs, energy sustainability and environmental concerns. In the USA, for example, electric car sales rose "from near zero in 1999 to a high of about 350,000 units in 2007" (Hamilton, 2011).

For the purpose of this study, the terms *electric vehicle* and EV will be used interchangeably to describe vehicles that run at least partially on battery power and are recharged by plugging into the electrical grid. These include both battery electric vehicles (BEVs), with electric motors running entirely on energy stored in rechargeable batteries, and plug-in hybrid electric vehicles (PHEVs) which combine an electric engine powered by a rechargeable battery with petrol fuelled combustion engine (Union of Concerned Scientists, 2013).

2.2 Driving Factors

Reducing carbon dependency and emissions has had increasing global attention, in particular with growing concerns over climate change. In 2010, CO_2 emissions from the transport sector made up 22% of global emissions, with an overwhelming majority attributable to road transport. Given that the World Economic Outlook (WEO) 2012 projects transport fuel demand to grow by nearly 40% by 2035, one of the policy options to limit the emission from this sector is to encourage the use of low-carbon fuels such as electricity (OECD/IEA, 2012). Indeed, a European Commission communication states that "Low-CO_2 alternatives to oil are ... indispensable for a gradual decarbonisation of transport, a key objective of the Europe 2020 strategy for smart, sustainable and inclusive growth" (European Commission, 2013c). The Expert Group of Future Transport Fuels reports that if powered by the EU electricity mix (of 2011), replacing an internal combustion engine vehicle with an electric vehicle would reduce $C0_2$ emissions by approximately 30%, implying a saving of 1 Mt CO_2/year for each 1 million cars (European Commission, 2011a). Note that these figures could be greater yet if a greener electricity mix were employed.

Furthermore, the EU is concerned with the threat that poor air quality imposes on human health and the environment. Since much of the air pollution experienced in the EU is attributable to petrol and diesel burning motor vehicles, a switch to electric vehicles would contribute to the improvement of air quality, as well as reducing noise pollution, particularly in urban areas (European Commission, 2013a).

In addition to environmental concerns, the EU's dependence on imported oil, and resulting trade imbalances associated with "high and rising import bill", motivates the diversification of energy sources for EU transport (*ibid*). In 2012, European transport was 94% dependent on oil, of which 84.3% was imported. A particular cause for concern has been the increasing insecurity of fuel supply, resulting from instabilities in oil producing regions (*ibid*). A transition towards transport run on alternative fuels such as electricity, which is less dependent on foreign imports, could help ease these concerns. Accordingly, one of the goals outlined in the Commission's 2050 Transport Strategy, for a competitive and resource-efficient transport system, is to "halve the use of 'conventionally fuelled' cars in urban transport by 2030; phase them out in cities by 2050" (European Commission, 2011b).

Taking the above concerns into consideration, mandatory minimum infrastructure coverage for electricity, hydrogen and natural gas has been proposed for each EU member state; infrastructure is considered essential for consumer acceptance and further investments and developments from industry. In particular, "member States should ensure that recharging points for electric vehicles are built up with sufficient coverage, at least twice the number of vehicles, and 10% of them publicly accessible, focussing in particular on urban agglomerations", (European Commission, 2013c). Electricity as an alternative fuel is particularly attractive as the infrastructure of electricity distribution is already in place. Key EU objectives on this front include stimulating the market uptake and ensuring interoperability and reliability for the convenience of European consumers, this justifying intervention on a European level (European Commission, 2012).

2.3 The Need for Fast Charging Stations

Two types of current characterise the main types of charging stations used for EV charging: Alternating Current (AC) and Direct Current (DC). The most common form of AC charging station is the standard ("Level 2") type, taking approximately 8 hours to recharge an Electric Vehicle. Fast "Level 3" DC charging stations "can add 60 to 80 miles of range to a light-duty PHEV or EV in 20 minutes" (US Department of Energy, 2013), but with a far greater demand on the electricity system.

It is assumed that the main source of charging for EVs, particularly in urban transport, will be from "slow" AC charging installations in homes and workplaces, since fast charging is not necessary in most travel scenarios; for example, 95% of trips in Great Britain are less than 40 kilometres (Office for Low Emission Vehicles, 2011). In addition to these private installations, there is a need for publicly available charging points. Slow charging stations must be available for those without the necessary conditions for home charging, for example due to the absence of off-street parking. Nevertheless, a network of publicly available fast charging points is also needed to increase the potential range of EVs, combat range anxiety[1] experienced by existing and potential EV users and encourage uptake; it is said that "consumer's purchasing decisions are influenced by the potential to travel further" (*ibid*). Indeed, Van Deventer et al. (2011) report how the installation of fast chargers in Japan is associated with more kilometres travelled in EVs, despite the users rarely needing to use them. That said, the utilisation of Fast EV chargers installed in the US exceeded expectations based on the range anxiety premise, and "appears to dispel the contention that the purpose of … [Direct Current Fast Chargers]... is just a 'confidence builder'" (The EV Project, 2013b). Furthermore, a network of rapid chargers may prove to be essential for recharging taxis, service vehicles, as well as for users facing unexpected travel. This necessary network of fast charging stations will be the focus of this study.

2.4 The Need for Intervention

Unlike in many other emerging markets, in which governments take on a merely regulatory role, it is considered that state intervention is necessary for the EV market's successful development. Experiences to date, in particular successful pilot projects, indicate that electric vehicles are a "viable technological and market option", (European Commission, 2012). However, it is also a reported "lack of alternative fuel infrastructure and of the common technical specifications for the vehicle- infrastructure interface [that] is considered a major obstacle to the market introduction of alternative fuels and consumer acceptance" (European Commission, 2013c).

The state of the EV market at present can be described as a "chicken and egg" scenario. Private investors are on the whole unwilling to invest large sums of money in EV charging infrastructure, since there are currently too few users to make it a profitable endeavour. This is turn inhibits uptake, since consumers are not willing to purchase EVs without a sufficient infrastructure in place

1 Range anxiety is a term used to describe EV users' concern that they may run out of charge before reaching their destination, thus leaving them stranded.

to combat range anxiety. In addition, the lack of widespread demand inflates the prices of EVs, creating a further barrier to acquisition.

Consequently, investors are faced with a dilemma: Early movers in the market could gain “first mover advantage” and set standards in the industry. Van Deventer et al. (2011) describe this phenomenon using the analogy of TomTom in the mobile navigation market who, having been among the first on the market in the EU, have managed to almost monopolise it. In addition, first movers can often benefit from extra government subsidies which tend to subside as markets develop. On the other hand, acting early also poses greater risks. Early investment implies a commitment to technologies that may become obsolete in the near future, and inhibits a firm's ability to respond to changing demand. In some cases, allowing competitors to enter the market first allows one to learn from their experiences without incurring the attached costs.

EV manufacturers such as Nissan and Tesla, are taking measures to stimulate the market. For instance, the Nissan EV Advantage Program offers a grant of $15,000 to companies or organisations that install publicly available fast charging stations in the USA before January 2014 (Nissan, 2013). Note, however, that Nissan are promoting the installation of charging stations with the ChaDeMo Standard, which, due to a lack of standardisation, are compatible with many, but not all, current electric vehicles. This incompatibility between connection standards creates a yet another barrier to EV market development.

To conclude, although there have been successful demonstrations of how an EV market would function, and the private sector is starting to move, there remains a gap between these trials and a fully developed market, which necessitates intervention from the public sector (European Commission, 2013a). On a European level, the CARS 21 (Competitive Automotive Regulatory System for the 21st century) group stress the importance of a “Union-wide harmonised alternative fuel infrastructure” to take advantage of the potential environmental benefits (European Commission, 2012). For a deeper understanding of the nature of the EV market and the barriers therein, Van Deventer et al (2011) provide a useful discussion.

3. Existing Systems and Approaches.

Many cities and regions around the world have demonstrated a commitment to facilitating electric mobility. Ambitious goals and targets are actively pursued using a variety of different policies and programs, each one tailored to its particular region. Although there are differences in their nature, and thus differences in the tools implemented by local authorities, common practices have been observed across regions. Many cities combine financial and non-financial incentives to encourage the expansion of charging infrastructure and EV uptake (International Energy Agency, 2012). Financial incentives include subsidies, tax credits and discounts for tolls and city parking, etc. Non-financial incentives on the other hand include measures such as preferential parking spaces, special access zones or lanes for EV users, and installation of EV charging infrastructure.

3.1 Global Perspective

While many cities are beginning to introduce fast charging stations, Estonia is the first country to have a nationwide system of fast charging stations for electric vehicles (Vaughan, 2013), and the Netherlands are in the process of installing the "world's largest nationwide fast-charging system to-date" (Tweed, 2013).

In Holland, the private sector takes on a leading role in charging infrastructure, with preconditions set by the national government. In the Dutch city of Eindhoven, public and private institutions have worked in conjunction to develop public charging infrastructure. The Japanese region of Kanagawa, has taken the approach of subsidising companies that install DC fast chargers at service stations, shopping centres, etc.; their target is to have 100 charging sites within the next year (International Energy Agency, 2012).

Berlin on the other hand, contemplated a call for tender system for the infrastructure of charging points, with the aim to find high-performance companies who would develop and operate the infrastructure quickly and efficiently at minimal cost to public services. There is a focus on stepwise implementation and an iterative feedback process that allows for adjustments alongside expanding knowledge and experience (Kunst, 2013). Currently in Berlin, there are two simultaneous test cases in progress, both looking to better understand the nature of the electric vehicle ecosystem. These are both private initiatives, supported by big players in the German utility and automotive industry. The state's role in this case is limited to administrative support and regulation; it mandates, in particular, the interoperability of networks to avoid the monopolisation of charging infrastructure (Philip & Wiederer, 2010).

The guiding principles in London are to provide an equitable base coverage (ensuring all inhabitants have reasonable access to charging facilities) and to target infrastructure in key locations, encouraging EV uptake and providing value for money. The approach has been to first provide a "pan-London coverage", followed by the targeting of potential "hotspots" in which consumers with a high propensity for EV adoption are likely to concentrate. Partner organisations are to play an "important role in the roll-out of fast, and ultimately rapid, charging infrastructure" (Source London, 2009).

Among US initiatives, the private firm ECOtality received government grants to deploy chargers in major cities and metropolitan areas across the United States, working alongside EV manufacturers as part of The EV Project (The EV Project, 2013a). There is a focus on installing fast charging stations at locations where consumers are expected to park for relatively short periods of time, whilst allowing for appreciable recharge, such as convenience stores, service stations, fast food restaurants, etc. (eTEC, 2010). This is found to be justified given the early experiences, which found DC fast charging to be a short time event, with a modal charging duration of 20-25 minutes (The EV Project, 2013b). A separate initiative is the "West Coast Electric Highway", providing fast charging stations along major roadways in the Pacific Northwest of the USA, provided by private companies with the help of state funding. This set up encourages "range confidence" and facilitates intercity travel for EV users (West Coast Green Highway, 2013).

3.2 Barcelona as a Case Study

As we have seen thus far, there is a clear need for some form of public sector intervention to stimulate the EV market, and different regions have taken on different approaches. For this study, the city of Barcelona will be used as a case study, to help better understand the issues and develop a mathematical optimisation model. Currently in Barcelona, there are only two fast charging points.

In principle, companies that fulfil the requirements to be "load managers", who are granted the permission of resale of electricity for EV recharging (Boletín Oficial Del Estado , 2011), will be allowed to install fast charging points at any feasible location, so long as they meet regulatory requirements. This follows the EU Commission (2013c) recommendation that "the establishment and operation of recharging points for electric vehicles should be developed as a competitive market with open access to all parties interested in rolling out or operating recharging infrastructures."

We consider that EV infrastructure will be rolled out in two main phases. In the first phase, the state will ensure a minimum level of coverage for city dwellers. This could, for example, take the form of subsidies to private firms looking to install charging points. In phase two, as EV usage and thus charging demand increases, a competitive market for charging infrastructure is expected to develop. At this stage, the state role will switch to a regulatory one, monitoring for fair competition and interoperability between systems or firms. Since most regions are still in the first phase of EV market development, as is the case of Barcelona, we will focus on the initial coverage problem (phase 1).

As well as ensuring a minimum coverage for inhabitants and commuters, it is also in the interest of planners to consider the associated set up costs. Minimising these costs will reduce the necessary financial contribution of the public sector, as well as encourage involvement of private firms, should their involvement include private capital investment. Although charging points can be installed at any location, costs associated with grid reinforcement are likely to prioritise existing service stations, as was found by Cruz-Zambrano et al. (2013); this work is discussed later in the chapter.

Furthermore, taking into account characteristics of locations could also contribute to encouraging EV demand, enhancing future business prospects as well as social welfare. That is, if a charging station is located near facilities that EV users can take advantage of whilst charging, it expected to attract more consumers, as well as enhance the experience of customers and reduce the opportunity cost of time spent charging.

In developing a strategy for optimal locations, it is worth taking into account the conflicting interests of different stakeholders outlined in Kunst (2013), as shown in Figure 1.

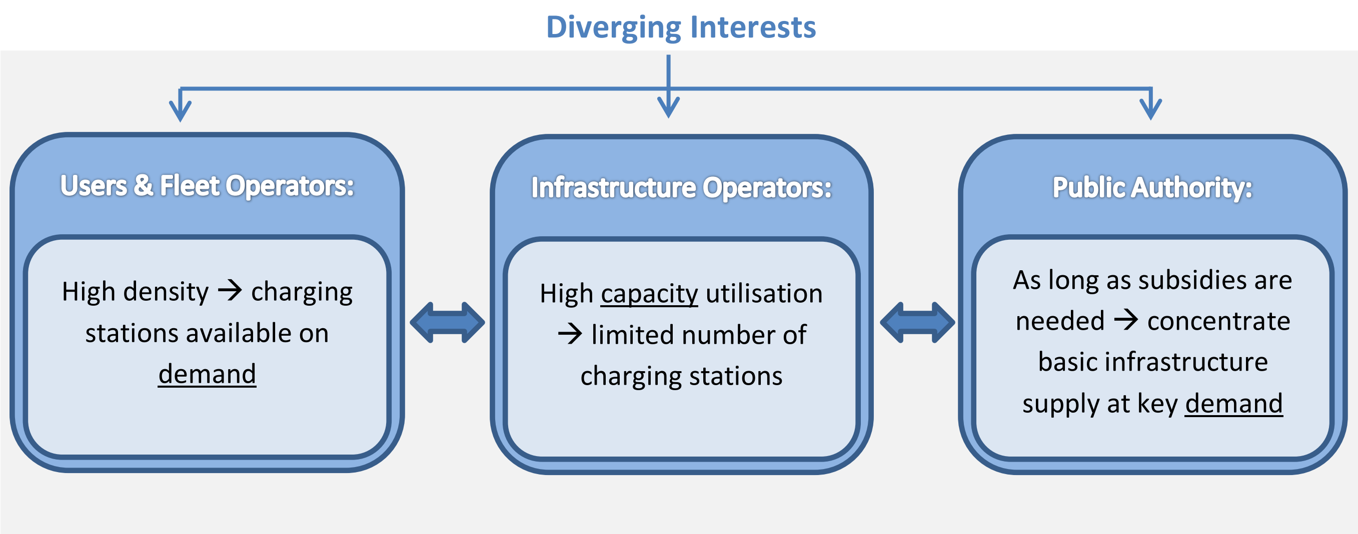


FIGURE 1: Diverging interests of different stakeholders in EV infrastructure

3.3 Existing Methodologies

The optimal location of fast charging stations comes under the umbrella of Facility Location Models within network optimisation. Location models have been studied and implemented for a vast range of applications over the years; a sample of more than 3400 references can be found in Hale (2013).

In traditional location theory, consumer demand is considered to be fixed in space. That is, demand is considered to be at nodes within a network. Regarding facility location, this fixed demand is applied based on the assumption that consumers will travel to facilities from a fixed location such as the home or workplace. With this in mind, Hakimi (1964) and ReVelle & Swain (1970) developed the p-median model, which is often seen in the literature for the allocation of fuelling facilities. In this model, *"p"* optimal locations are found by minimising the overall time or distance travelled by consumers in order to reach facilities. The p-median model can be seen applied to the location of hydrogen refuelling stations in Nicholas and Ogden (2007).

However, in many cases this fixed demand assumption does not correctly reflect consumer behaviour. For some services, including vehicle refuelling, consumers do not make specific trips but consume "on their way". To account for this type of behaviour, Hodgson (1990) and Berman et al. (1992) independently developed mathematical models denoted the Flow Capturing Location Model (FCLM) and Flow Intercepting Location Model (FILM), respectively. In these models, demand is considered to be along a path rather than at a fixed node, and facilities are located in a way that maximises the amount of flow captured; demand is considered "captured" or "intercepted" when at least one facility is located anywhere on the consumer's path. This model is applied to the optimisation of fast charging stations in Barcelona by Cruz-Zambrano et al. (2013), and also modified to consider set-up costs.

A criticism of the FILM, however, is that it considers fixed paths for consumers (for example, based on mobility surveys), and does not allow them to deviate from these. In many applications (including that of EV charging) it seems reasonable to consider that consumers would be willing to venture away from their otherwise pre-determined paths in order to obtain services if no facilities are directly on their way. Zeng et al (2010) developed the Generalized Flow-Interception Location–Allocation Model (GFIM) to allow for adjustments in the original FILM, depending on characteristics of the problem under consideration. Among these adjustments, one can use the GFIM to allow consumers to deviate from their paths.

A noteworthy alternative approach to the problem of locating fast charging stations in the city of Barcelona is taken by Bernardo et al. (2013). They apply a game of strategic interaction to simulate the entry of fast charging stations for EVs. Although this may be a useful approach for a self-developing market, it is considered here that the barriers discussed above would interfere with such a strategy.

4. Model Formulation

4.1 Considering Multiple Objectives

As discussed in section 3.2, the nature of the fast charging station problem involves the consideration of more than one objective, as is a common for many real life problems. A central planner, such as the municipality in this case, is concerned with minimising set up costs whilst also covering EV drivers' needs. The latter can be targeted by minimising the extra distance EV users must travel in order to use the fast charging station nearest to their routine journeys, denoted the deviation distance. This deviation distance is explained in detail in Section 4.3. In order to account for these potentially (and likely) conflicting objectives, a multi-objective function can be used.

A general multiple-objective optimisation (MOO) problem can be defined as follows (Marler & Arora, 2005):

$$\min_x \qquad \boldsymbol{F}(\boldsymbol{x}) = [F_1(\boldsymbol{x}), F_2(\boldsymbol{x}), \dots, F_k(\boldsymbol{x})]^T \qquad (1)$$

$$\textit{subject to:} \qquad g_j(\boldsymbol{x}) \leq 0\,; \qquad j = 1, 2, \dots, m$$

$$h_l(\boldsymbol{x}) = 0\,; \qquad l = 1, 2, \dots, e$$

where *k* is the number of objective functions, *m* is the number of inequality constraints, *e* is the number of equality constraints, and $\boldsymbol{x} \in \mathbb{R}^n$ is a vector of *n* decision variables.

The *feasible design space* $\boldsymbol{X}$, defined as the set $\{\boldsymbol{x} \mid g_j(\boldsymbol{x}) \leq 0,\ j = 1, 2, \dots, m;$ and $h_l(\boldsymbol{x}) = 0,$ $l = 1, 2, \dots, e\}$ is the set of decision variables that satisfy the constraints of the problem. The *feasible criterion space* $\boldsymbol{Z} = \{\boldsymbol{F}(\boldsymbol{x}) \mid \boldsymbol{x} \in \boldsymbol{X}\}$ is the associated set of objective function values, also known as the *attainable set*.

In addition to considering a single objective as in the FILM or the adjustable GFIM, one can therefore include additional objectives within a single objective function, as described in general terms above. Since a single point that optimises all the objectives simultaneously does not usually exist, different methods have been developed to combine conflicting objectives. Among these is the widely used *weighted sum* or *scalarisation* method (as described in Caramia & Dell'Olmo, 2008), in which a weighted function is used to aggregate the objectives in the following manner:

$$\min_x \quad U = \sum_{i=1}^{k} \omega_i F_i(\boldsymbol{x}) \qquad (2)$$

where $k \geq 2$ objectives are considered and $\omega_i \geq 0$ is the weight assigned to the i^{th} objective function. For the case presented here, $\sum_{i=1}^{k} \omega_i = 1$, and the value assigned to each ω_i reflects the relative importance assigned to each objective function $F_i(\boldsymbol{x})$.

If one has information about the decision maker's (DM) preferences (in this case the planner's), one can assign appropriate weights to the different components of the overall objective function, resulting in a single optimal solution. However, a common feature of multi-objective problems is that these preferences are not known *a priori*; multi-objective programming can be used to help decision makers better understand their options and potentially their priorities in light of solutions presented to them.

Without preference information, one can consider a series of different weights assigned to the multiple objectives, to estimate a set of "Pareto optimal solutions". A solution is considered *Pareto optimal* (also known as "non-dominated") if and only if one cannot improve the value of any of the individual objectives in the aggregated objective function without negatively affecting another (Marler & Arora, 2005).

Formally, a point $x^* \in \boldsymbol{X}$ is **Pareto optimal** iff there exists no other point $x \in \boldsymbol{X}$, such that $\boldsymbol{F}(x) \leq \boldsymbol{F}(x^*)$, and $F_i(x) < F_i(x^*)$ for at least one function (Marler & Arora, 2004).

The weighted sums method always provides Pareto optimal solutions if the objective function increases monotonically with respect to each criterion (Stadler (1988) cited in Athan and Papalambros, 2006). The image of all possible Pareto optimal solutions in the criterion space is denoted the *Pareto front* or *Pareto curve,* and the shape of this curve indicates the nature of the trade-off between the different objectives. An example is given in Figure 2, where all points between $(f_2(\hat{x}), f_1(\hat{x}))$ and $(f_2(\tilde{x}), f_1(\tilde{x}))$ are Pareto optimal solutions and define the Pareto front (Caramia & Dell'Olmo, 2008). $\boldsymbol{C} = \{\boldsymbol{F}(\boldsymbol{x}) \mid \boldsymbol{x} \in \boldsymbol{X}\}$ represents the *feasible criterion space.*

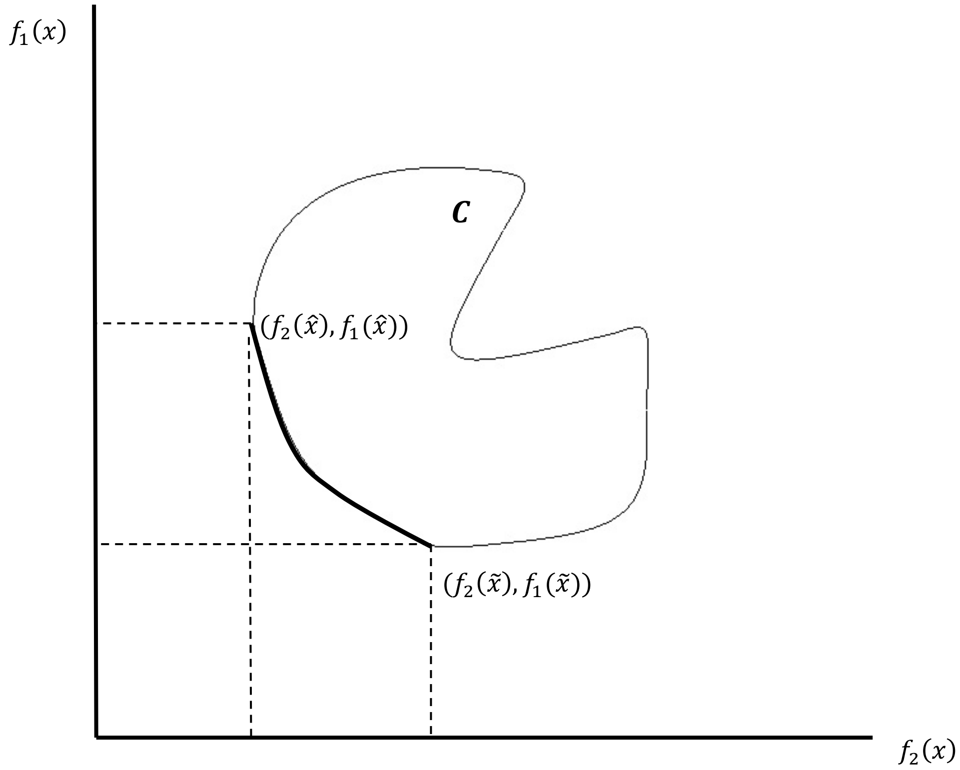


FIGURE 2: Example of Pareto Front

The set of Pareto optimal solutions found using the weighted sums method can therefore be used to estimate this Pareto front, and be presented to a DM, allowing them to directly observe the trade-offs implied when changing the priorities assigned to the different objectives, helping them gain a better picture of the problem they are facing. This approach will be applied for this case study since preference information is not known at the time of implementation.

In this case, we have two measureable objectives: the minimisation of consumer deviations ($F_1(\boldsymbol{x})$) and the minimisation of set up costs ($F_2(\boldsymbol{x})$). Thus, we have a bi-objective problem with $k = 2$.

4.2 Useful Concepts

In order to address the optimisation problem, a graph of the road network for the city or region in question is used. The arcs in the graph represent the main roads, and the nodes are the intersections between them. It is assumed that private vehicle mobility (and thus the mobility of potential or existing EV users) can be modelled using a set of representative journeys that are made on a normal day; information about these journeys is obtained from a mobility survey, as is standard practice. Each different journey within this set is characterised by a fixed origin and destination; using these, a path q traversing different nodes in the road network is estimated for each journey. The set of normal (also denoted "pre-determined") paths taken by potential EV users is entered into the problem as input data, as is the expected *flow* for each one. The flow (f_q) in the model represents the number of people in the survey that took the journey covered by path *q*. It is assumed that mobility survey data is representative of the entire population's travel behaviour on a normal day. Since the optimal location of fast charging stations does not depend on the total population size, and the mobility survey is considered representative, the original flow data from the survey is used directly in the model. That is, it would be possible to estimate the flows for each path for the entire population by taking into account the sample rate used by the survey, but since the optimal location of facilities depends only on the relative flows along the different paths, rescaling the volume of flows is unnecessary. The acquisition of these data and the estimation methods for paths in Barcelona is discussed in Section 5.1.

For this case study, it is assumed that each node (or intersection) in the graph serves as a feasible location for a fast charging station to be installed.

4.3 $F_1(x)$: Minimising Deviations

4.3.1 Estimating Deviation Distances

The first objective ($F_1(\boldsymbol{x})$) under consideration is the minimisation of deviations. Deviation distances are defined as "the extra distance incurred when customers deviate from their pre-determined path", as in Zeng et al. (2010).

It is assumed throughout this work that potential EV users take the shortest possible route between the origin and destination of their journeys. In line with this, it is assumed that consumers needing to divert from their normal path to reach a fast charging station would choose the shortest possible route from their origin to the facility, and from there the shortest route to their destination. The deviation distance between a given pre-determined path and a potential facility location is therefore calculated as the difference between the sum of the two diversion journeys' distances and original origin-destination distance. Shown graphically in Figure 3:

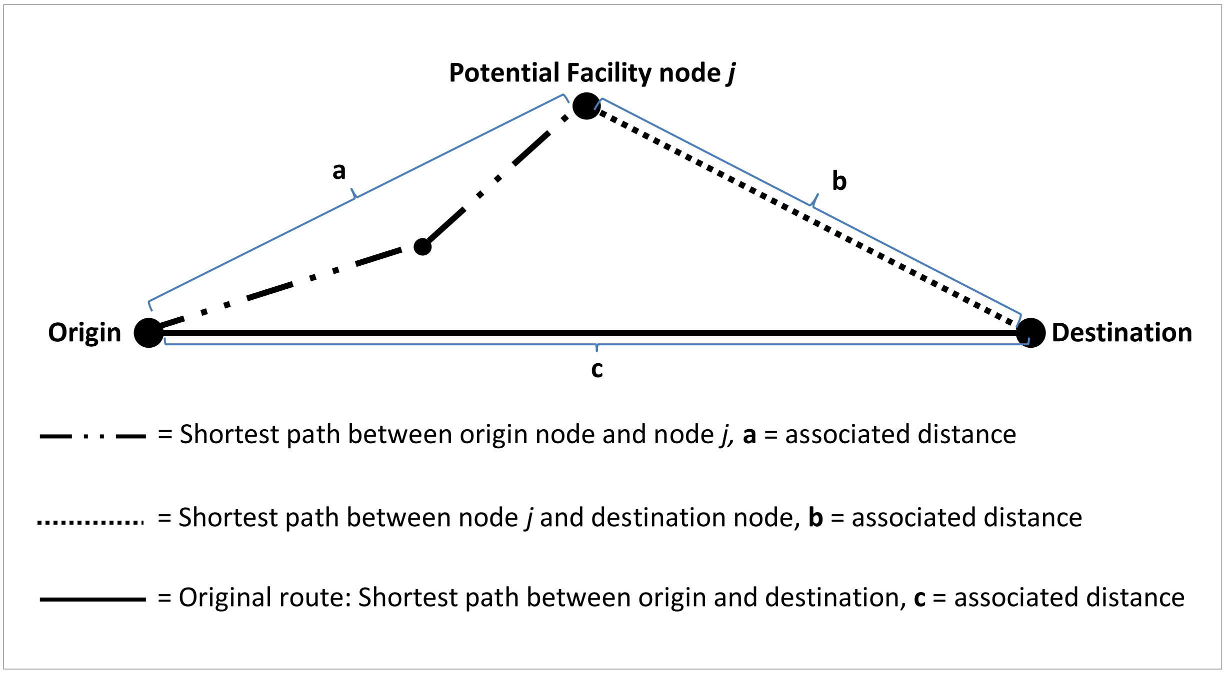


FIGURE 3: Diagrammatic example of deviation distance calculation

Deviation distances are calculated for each path-node pair, denoted d_{qj} in the optimisation model, where q is a pre-determined path used by consumers and j is a potential facility location. If q is the Origin-Destination path shown above, $d_{qj} = a + b - c$.

4.3.2 Mathematical Formulation

The mathematical formulation for $F_1(\boldsymbol{x})$ is based on the Generalised Flow Interception Model introduced in Zeng et al. (2010). Applying the GFIM to the minimisation of deviation distances, the model takes the following form:

$$min \qquad F_1(\boldsymbol{x}) = \sum_{q \epsilon Q} \sum_{j \epsilon N_q} f_q \cdot d_{qj} \cdot X_{qj} \tag{3}$$

s.t.

$$\textstyle\sum_{j \epsilon N_q} X_{qj} = 1, \qquad \forall q \epsilon Q \tag{4}$$

$$X_{qj} \leq Y_j, \qquad \forall q \epsilon Q, j \epsilon N_q \tag{5}$$

$$0 \leq X_{qj} \leq 1, \qquad \forall q \epsilon Q,\ j \epsilon N_q \tag{6}$$

$$Y_j \epsilon \{0,1\}, \qquad \forall j \epsilon J \tag{7}$$

where

$Q =$ the set of non-zero flow paths indexed by q

$J =$ the set of potential facility sites containing all nodes in the graph, indexed by j

$N_q =$ the subset of nodes j capable of intercepting the flow along path q, $q \in Q$

$f_q =$ the flow volume along path q, $q \in Q$

$d_{qj} =$ the deviation distance between path q and node j, $q \in Q$, $j \in J$

$X_{qj} =$ the proportion of flows on path q intercepted by a facility at node j, $q \in Q, j \in J$

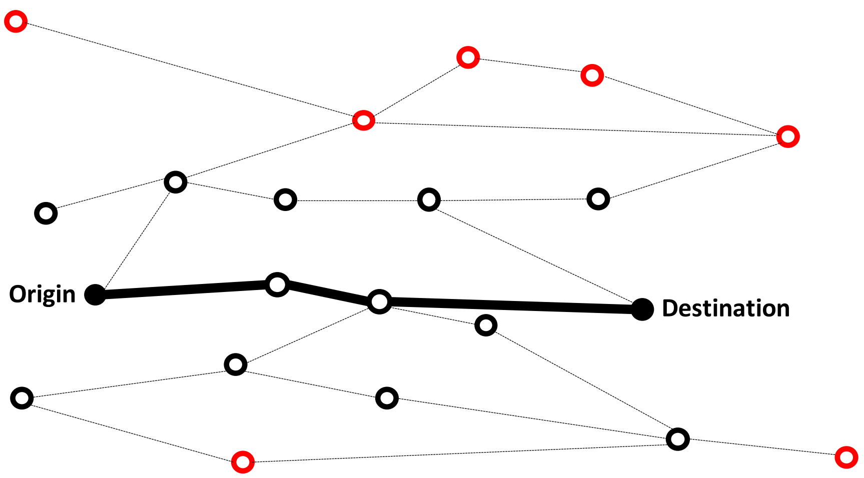
$Y_j \begin{cases} = 1 & \text{if there is a facility located at node } j, \ \ j \in J \\ = 0 & \text{otherwise} \end{cases}$

$\boldsymbol{x} = \begin{bmatrix} X_{qj} \\ Y_j \end{bmatrix}$ the vector of decision variables, $q \in Q, j \in J$

$F_1(\boldsymbol{x}) =$ the objective function, the total deviation distance travelled by all consumers

In this formulation, the objective function (3) is aimed at minimising the total deviation distance necessary for all consumers to reach a charging point. The first set of constraints (4) ensures that 100% of flows along each path q are captured by facilities in N_q. Constraint (5) ensures if a path q is served by a facility located at node $j \in N_q$, this facility must be open. Constraint set (6) represents the bounds on variable X_{qj} and (7) defines the decision variable Y_j as binary. Note that decision variables X_{qj} will behave as a binary variable in all cases except where there are two open facilities are equidistant from a path q, in which case the flow could potentially split. Note also that the upper bound enforced on these variables in (6) is not strictly necessary since it is already covered by constraint set (4) but has been included here for clarity.

A subset of candidate nodes N_q is defined for each path $q \in Q$. This set contains the nodes j from the set of all nodes in the graph (J) that are considered capable of capturing the flow along path q. In the FILM, N_q is essentially the set of nodes on path q, since flow is only captured if a facility directly intercepts a path. In the GFIM however, one can choose how to define N_q according to the characteristics of the problem (Zeng et al., 2010). For this problem, one could consider allowing all nodes to be candidates for all paths, since we are assuming there are no restrictions on the locations at which facilities can be placed. In this case there would be no need for the subset N_q since the set J could be used directly. However, one of the main motivations for installing fast charging stations is to tackle the problem of range anxiety; this would not be achieved if solutions that require some EV users to travel far out of their way in order to reach their nearest facility are allowed. The nodes in J that are allowed to service each path $q \in Q$ are therefore restricted for this problem, taking into account the extra distance d_{qj} needed to reach them from the different paths. Figure 4 shows a simple example of a road graph with an example path q to help visualise this restriction.



Path q, the shortest path between the origin and destination

Nodes allowed to serve path q

Nodes that are not allowed to serve path q since the deviation distance d_{qj} exceeds the chosen criteria for the restriction of N_q

FIGURE 4: Example road graph demonstrating generic restriction of N_q

In Figure 4, a path q is shown between the origin and destination of a journey within the road graph. The black nodes are those that are allowed to serve path q and thus belong to the subset N_q. The red nodes are the nodes that belong to the entire set of nodes J, but that are considered too far from path q to serve it. This sketch is provided in order to help the reader understand the mathematical formulation; the explicit deviation distance criteria that have been chosen to restrict N_q for this problem are discussed at length in Section 5.2.

In the original formulation presented by Zeng et al. (2010) there is an additional constraint setting $\sum_{j\epsilon J} Y_j = p$, ensuring that exactly *p* facilities are located. For our application, however, we do not fix *p,* since we are interested in seeing how changing priorities affects not only the location of facilities, but also the number of facilities opened. Omitting this original constraint set out by Zeng et al. (2010) means that this problem has a trivial solution when presented alone as it is above; one can ignore the Y_j variables and separate the problem by paths.

In this case, for each path $q \in Q$:

$$X_{qj} \begin{cases} = 1 & \text{for the index } qj \text{ with the minimum deviation } d_{qj} \\ = 0 & \text{otherwise} \end{cases}$$

That is, each path is served by the facility that offers the minimum deviation distance. If this minimum deviation distance is observed for more than node j, the optimal solution would be to assign the flows of path q to any of these nodes, or to distribute the flows between them. Since we do not restrict the number of facilities that can be opened here, it is always possible to open at least one facility at a node j that lies on each path q, with a zero deviation distance d_{qj}. Therefore, the optimal solution with $F_1(\boldsymbol{x}) = 0$ would be obtained by ensuring that at least one fast charging station is installed on each path q. Having obtained the optimal values for all X_{qj} , one can then obtain the values of Y_j directly. For each node $j \in J$:

$$Y_j \begin{cases} = 1 & \text{if } X_{qj} > 0 \text{ for some q} \in \text{Q} \\ = 0 \;\; or\ 1\ interchangeably & \text{if } X_{qj} = 0 \text{ for all q} \in \text{Q} \end{cases}$$

Although this problem appears trivial here, it is no longer the case when incorporated into the multi-objective model, since the consideration of set up costs limits the number of facilities that are opened. The deviation minimisation problem has nevertheless been presented firstly in isolation in order to get a clear picture of the separate components of the final multi-objective model.

4.4 $F_2(x)$: Minimising Set up Costs:

The second objective function minimises the cost of setting up charging stations, including grid reinforcement where necessary (costs are described in more detail in Section 5.3).

The minimisation of this objective takes the following form:

$$min \qquad F_2(\boldsymbol{x}) = \sum_{j \epsilon J} c_j \cdot Y_j \tag{8}$$

s.t. *constraints (4) to (7)*

where

$c_j =$ the cost of setting up a facility at node *j*, $j \in J$

$F_2\ (\boldsymbol{x}) =$ the objective function, the total cost of setting up facilities in all chosen locations.

Note here that the number of installed facilities will depend on the definition of N_q, the set of nodes allowed to service path q. For instance, should $N_q = J$, when considering set up costs alone the optimal solution would be to open a single facility to serve all paths, in the cheapest possible location.

4.5 Multi-objective Model

Combining the two objectives outlined by applying the formulation in (1) to the case study results in the following model:

$$min \qquad \omega_1 \cdot F_1(\boldsymbol{x}) + \omega_2 \cdot F_2(\boldsymbol{x}) \tag{9}$$

$$= \omega_1 \left[\sum_{q \epsilon Q} \sum_{j \epsilon N_q} f_q \cdot d_{qj} \cdot X_{qj} \right] + \omega_2 \left[\sum_{j \epsilon J} c_j \cdot \mathrm{Y_j} \right] \tag{10}$$

s.t. *constraints (4) to (7)*

where

$\omega_1 =$ the weight factor for the consumer deviations

$\omega_2 =$ the weight factor for set up costs

4.6 Function Transformation

As is common for multi-objective problems, $F_1(x)$ and $F_2(x)$ are measured in different units and have significantly different orders of magnitude. This can be problematic for depicting the Pareto optimal set, since the aggregated function may be dominated by one or more objectives within it. A function transformation can be used to normalise the different objective functions. Different approaches to this transformation have been applied in the literature, a selection of which have been evaluated in detail by Marler & Arora (2005). Of those assessed, the *upper-lower-bound approach*, is found to be the most effective and robust transformation method. This method has therefore been chosen to transform the two previously described objective functions. F_i^{trans} is the term used to describe the i^{th} transformed function and is defined in the following manner:

$$F_i^{trans} = \frac{F_i(\boldsymbol{x}) - F_i^o}{F_i^{max} - F_i^o} \tag{11}$$

where $F_i^o = \min_x \{F_i(\boldsymbol{x}) \,|\, \boldsymbol{x} \in \boldsymbol{X}\}$ is the minimum feasible value of the i^{th} objective function, obtained by minimising $F_i(\boldsymbol{x})$ subject to the problem's constraints without taking into account the other objectives. F_i^{max} represents the 'maximum' value of $F_i(\boldsymbol{x})$. For the application to multi-objective optimisation, it is not the absolute maximum of $F_i(\boldsymbol{x})$ that is of interest, but the maximum value attainable within the Pareto optimal space, otherwise known as the *Pareto maximum*. In general terms, F_i^{max} is defined as $\max_{1 \le j < k} F_i(\boldsymbol{x}_j^*)$, where $\boldsymbol{x}_j^*$ is the point that minimises the j^{th} objective function. That is, F_i^{max} is the maximum value of $F_i(\boldsymbol{x})$ obtained for solutions that minimise all functions $F_j(\boldsymbol{x})$ where $j \neq i$. For the bi-objective case therefore, F_1^{max} is obtained by minimising $F_2(\boldsymbol{x})$ subject to constraints (4) to (7) or, equivalently, setting $\omega_1 = 0$, $\omega_2 = 1$ and minimising the weighted sum formulation outlined in (9). This can be directly applied to the original untransformed objective functions, since the solution found is unaffected by transformations for the 0-1 weights case. The value of $F_2(\boldsymbol{x})$ found for this solution also provides F_2^o. The same process is used to obtain F_2^{max} and F_1^o, reversing the values of ω_1 and ω_2.

Using the type of transformation outlined in (11) will yield a value between 0 and 1 for F_i^{trans}. For some applications of this function transformation it may not be possible to obtain accurate values for F_i^{max} and F_i^o, and thus values calculated for F_i^{trans} may lie outside the 0-1 bounds. However, this does not apply here since these parameters can be accurately obtained using the methods outlined above. Marler & Arora (2005) found the application of (11) using the Pareto maximum for F_i^{max} to be a relatively robust approach to function transformation. In particular, unlike in other approaches, the denominator is guaranteed to be positive, and therefore does not face the potential problem of division by zero. Furthermore, the *lower-upper bound approach* is the only transformation method that constrains both the upper and lower limits of F_i^{trans}; alternative approaches focus on the *upper bound* or *lower bound* only. Using this method therefore effectively mitigates the problem of differing orders of magnitude, impeding any single objective from dominating the aggregated weighted sum function.

4.7 Final Model

The function transformation outlined in (11) is applied to multi-objective function formulated in (9). The resultant model to be implemented in GAMS therefore becomes:

$$min \qquad \omega_1 \left[\frac{\sum_{q\epsilon Q}\sum_{j\epsilon N_q} f_q \cdot d_{qj} \cdot X_{qj} - d^o}{d^{max} - d^o}\right] + \omega_2 \left[\frac{\sum_{j\epsilon J} c_j \cdot \mathrm{Y_j} - c^o}{c^{max} - c^o}\right] \tag{12}$$

Subject to

$$\sum_{j\epsilon N_q} X_{qj} = 1, \qquad \forall q\epsilon Q \tag{13}$$

$$X_{qj} \le Y_j, \qquad \forall q\epsilon Q, j\epsilon N_q \tag{14}$$

$$0 \le X_{qj} \le 1, \qquad \forall q\epsilon Q,\ j\epsilon N_q \tag{15}$$

$$Y_j \epsilon \{0,1\}, \qquad \forall j\epsilon J \tag{16}$$

where

$Q =$ the set of non-zero flow paths indexed by *q*

$J =$ the set of potential facility sites indexed by *j*

$N_q =$ the set of nodes capable of intercepting the flow along path *q*, $q \in Q$

$f_q =$ the flow volume along path *q*, $q \in Q$

$c_j =$ the cost of setting up a facility at node *j*, $j \in J$

$d_{qj} =$ the deviation distance between path *q* and node *j*, $q \in Q$, $j \in J$

$\omega_1 =$ the weight factor for the consumer deviations

$\omega_2 =$ the weight factor for set up costs

$X_{qj} =$ the proportion of flows on path q intercepted by a facility at node *j*, $q \in Q$, $j \in J$

$Y_j \begin{cases} = 1 & \text{if there is a facility located at node } j, \quad j \in J \\ = 0 & \text{otherwise} \end{cases}$

$d^{max} =$ the *Pareto maximum* value of the total deviation distance travelled by consumers to reach their nearest charging point

$d^o =$ the minimum feasible value of the total deviation distance travelled by consumers to reach their nearest charging point

$c^{max} =$ the *Pareto maximum* value of total set up costs

$c^o =$ the minimum feasible value of set up costs

5. Data

As in Cruz-Zambrano et al. (2013), mobility data was taken from the 2006 "Encuesta de Movilidad Cotidiana" (EMQ, 2006), a quinquennial everyday mobility survey conducted by the Barcelona Metropolitan Transport Authority. Within the survey, the city of Barcelona is broken down into 63 different zones.

Although the greater Metropolitan Area of Barcelona is considered in the survey, this study looks only at the city. Taking into account the entire metropolitan area would lead to more precise results, since traffic flows would be better observed for both the inner city and its surroundings. However, this study's primary concern is the development of methodology, and expanding the area covered would not result in additional insights to this effect. As this expansion would require considerably greater computational resource, the area is limited in in order to relieve the computational burden. It is worth noting that despite this limitation, the journey data does incorporate commuters who make their journeys within the city but enter from the greater metropolitan area. The zones in which these commuters enter the city are used as the origin zones for their journeys.

Respondents of the survey are asked to outline the origin, destination, time and transport mode for all journeys made during the day prior to questioning; in this work, only journeys made by private vehicle are considered. Rather than appointing a unique node to each origin or destination, journey beginnings and ends are aggregated by zones and assigned to a centroid point, again easing the computational strain of the problem. Centroid points were assigned by Cruz-Zambrano et al. (2013) to the node that best represented the set of journeys that originated and/or terminated in each zone in a centralised manner, making use of urban characteristics.

5.1 Consumer Paths

In order to implement the optimisation model, we need to define a set of paths taken by the potential consumers, i.e. the population of Barcelona. A simplified roads graph with 940 nodes and 2552 edges is used, originally published by the Generalitat de Catalunya.

Given the origin and destination of the trips recorded in the mobility survey, we are able to estimate each path taken using information on distances contained within this graph, as well the amount of flow (or number of consumers) that uses each path. It is assumed that potential consumers will take the path with the shortest distance between their origin and destination. Thus for each Origin-Destination pair a path $q \in Q$, defined by the set of nodes it passes, is estimated using Dijkstra's shortest path algorithm, implemented using MATLAB. Using this information, the length of each path *q* can be calculated.

As previously discussed, it is considered that consumers will deviate from their pre-determined path in order to access fast charging services. Since one of the main goals of the infrastructure planning is to make fast charging as convenient to users as possible, we minimise the average necessary deviation distance. The calculation of the deviation distances between paths $q \in Q$ and nodes $j \in J$ also makes use of Dijkstra's shortest path algorithm. For each path-node pair (*qj*) the algorithm is used to estimate the shortest path between path *q*'s origin and the node *j*, as well as the shortest path between node *j* and path *q*'s destination. Having obtained these shortest paths, their distances are determined and used in conjunction with the length of path *q* to compute the deviation distance d_{qj}, as described in Section 4.3.1.

5.2 Calculating N_q

As introduced in the model formulation, a set N_q containing candidate nodes is defined for each path $q \epsilon Q$. One might consider allowing all nodes to be candidates for all paths, in which case the set up costs could be minimised by opening only one fast charging station, but at great expense to the convenience of EV users. In Section 4 it was established that such a solution would be unsatisfactory, since many EV users would have to go far out of their way to use fast charging stations, and thus range anxiety would not be effectively targeted. Furthermore, the computational size of the problem is large, involving the calculation of 940 binary decision variables related to the 940 nodes in the network, as well as over 2 million continuous variables; restricting the nodes able to service each path reduces the number of feasible solutions to the problem and can therefore ease the computational strain. The candidate nodes $j \in J$ that can service each path $q \in Q$ are therefore restricted here using the deviation distance d_{qj} to establish the restriction criteria.

A first approach considered was to restrict the allowed deviation distance as a function of the path length. Using this approach N_q would be defined in the following manner:

$$N_q = \{j \mid d_{qj} < length(q)\} \qquad q \in Q$$

where $length(q)$ is the shortest path distance between path *q*'s origin and destination.

That is, if the deviation required to access node *j* from path *q* is greater than the distance normally travelled to traverse path *q*, node *j* is too far from path *q* to be considered as a candidate. The reasoning behind this approach is that consumers making longer journeys will be willing to deviate further to recharge their EV. The result of restricting N_q in this way is that no consumer would have to more than double their normal journey distance in order to recharge.

However, this restriction means that greater importance is given to consumers making short journeys when calculating a solution. For example, if a path *q* of 500 metres exists, say, in order to satisfy the constraints of the model, the solution would be forced to place a charging station within 500 metres deviation distance from *q*, regardless of its flow, or the flow of neighbouring paths.

Note that if one were to enforce a limit on the number of facilities to be opened (as is done in the original GFIM where exactly *p* facilities are opened) an over restrictive definition of N_q could yield the optimisation problem infeasible.

In order to account for the problem caused by short paths (and also ensure that very large deviations are not allowed), upper and lower bounds can be set to allow more elements *j* in N_q for short paths, and fewer for the longest paths. In early stages of this study, this approach was tested, using the 10th and 90th percentiles of all the path lengths as limits. In this case, N_q was constructed in the following manner:

$For\ any\ q \in Q\ do$

$\quad N_q \coloneqq \emptyset$

$\quad For\ any\ j \in J\ do$

$\quad\quad if\ \ length(q) < \ 10^{th}\ percentile\ length\ then$

$\quad\quad\quad if\ \ d_{qj} < \ 10^{th}\ percentile\ length\text{:} \quad N_q \coloneqq N_q \cup \{j\}$

$\quad\quad else\ if\ \ 10^{th}\ percentile\ length \leq \ length(q) \leq \ 90^{th}\ percentile\ length\ then$

$\quad\quad\quad if\ \ d_{qj} < \ length(q)\text{:} \quad N_q \coloneqq N_q \cup \{j\}$

$\quad\quad else\ if\ length(q) > \ 90^{th}\ percentile\ length\ then$

$\quad\quad\quad if\ \ d_{qj} < \ 90^{th}\ percentile\ length\text{:} \quad N_q \coloneqq N_q \cup \{j\}$

$\quad End\ do$

$End\ do$

Here, if the length of a path *q* is smaller than the 10th percentile of path lengths, membership of N_q is no longer determined by the length of *q*; a node *j* is allowed in N_q if d_{qj} is smaller than the 10th percentile length. Similarly, if the length of a path *q* is greater than the 90th percentile of path distances, a node *j* belongs to N_q only if d_{qj} is smaller than the 90th percentile distance.

Although applying these limits mitigates the problem of consumers with extreme path lengths, for those who have paths lengths lying between the 10th and 90th percentiles, the ones with shorter paths are still in effect given more importance when solving the optimisation problem; again, limiting N_q according to path lengths effectively enforces stricter constraints on the locations that are allowed to serve shorter paths. It is therefore considered that a more equitable methodology is to apply a fixed permissible deviation distance as the N_q membership criterion for all paths, regardless of their length. Using this membership criterion ensures that all potential users will have a fast charging station within the same fixed deviation distance from their paths.

To apply the multi-objective optimisation problem, a distance limit of 3km, approximately equal to the 25th percentile path length, was chosen to determine N_q . That is, $N_q = \{j \mid d_{qj} < 3km\}$. Using this restriction ensures that for any solution found, at least 75 percent of consumers would not have to deviate further than the length of their normal path, and no consumers would have to deviate more than 3km. Using this value reduces the computational requirements of the problem, while still allowing sufficient flexibility to effectively optimise the objectives. A second N_q with a deviation distance limit of 2km was also tested for some values of ω_1 and ω_2 to explore the sensibility of the results with respect to the definition of N_q.

It should be noted that should the decision maker wish to enforce a specific maximum deviation distance for *all* consumers, and it was known *a priori*, this could be achieved by limiting N_q , without needing to add an extra constraint in the mathematical model.

5.3 Estimation of Set up Costs

The costs used for the optimisation problem use estimates for costs with and without the need for grid reinforcement, associated with the presence of service stations and their existing facilities. These costs are taken from Cruz-Zambrano et al. (2013), who adapted costs found in Schroeder & Traber (2012). The cost estimates categorise the 940 candidate locations into four types, each with differing characteristics and estimated set up costs; these can be seen in Table 1 with their associated cost estimates.

TABLE 1
Set up costs by type of candidate location

	Type I	**Type II**	**Type III**	**Type IV**
	Petrol station with car wash	Petrol station with more than 10 pumps	Petrol station with less than 10 pumps, Hypermarket or Mall	Other
Material cost (€)	40,000	40,000	40,000	40,000
Grid Reinforcement (€)	-	25,000	50,000	50,000
Cost of Land (€)	-	-	-	13,484
Total (€)	**40,000**	**65,000**	**90,000**	**103,484**

The material costs are assumed to be the same for all candidate locations. No grid reinforcement is needed in the presence of a car wash at a petrol station, and reduced grid reinforcement is needed where a petrol station has more than 10 pumps. The cost estimates by Cruz-Zambrano et al. (2013) assume no land cost for existing petrol stations and malls. The assumption here is that the fast charging stations at this type of location would be installed by, or in collaboration with, the existing facility providers. For nodes without existing facilities, the cost of land was calculated using average land prices for Barcelona. Cruz-Zambrano et al. (2013) sourced information regarding the location of petrol stations, hypermarkets and malls online from the Spanish Ministry of Industry, Tourism and Commerce.

6. Results

Each Mixed Integer Linear Program (MILP) tested solves for 2,244,720 continuous variables and 940 binary variables with 2,245,660 constraints; there are 4,489,440 bounds associated with the x_{qj} variables. All MILPs were formulated using the General Algebraic Modelling System (GAMS), and executed using the CPLEX solver with default options. The execution time depended on the values of ω_1 and ω_2 used and the limits used when defining the set N_q, varying between 33 minutes and 24 hours; all executions were run in Microsoft Windows on standard desktop PCs. In total, the final model was executed 48 times to obtain the results presented here.

First, the objective function outlined in (10) is minimised subject to constraints (4) to (7), without applying the transformations found in (12). This is applied for $\omega_1 = 0,\ \omega_2 = 1$ in order to find values for d^{max} and c^o and for $\omega_1 = 1,\ \omega_2 = 0$, to obtain c^{max} and d^o. Equivalently, one could say the problem (3) – (7) is minimized to find d^{max} and c^o, and the objective function (8) is minimised subject to constraints (4) – (7) to find c^{max} and d^o. Having calculated these parameters, the model outlined in (12) – (16) (in which the objective functions are transformed) is solved for different weights, varying between zero and one, subject to the condition $\omega_1 + \omega_2 = 1$.

6.1 Primary Results

Table 2 shows the optimal values $F_1(\boldsymbol{x}^*)$ (Total Deviations) and $F_2(\boldsymbol{x}^*)$ (Total Set up Costs) for each of the weights combinations tested, for N_q using a fixed deviation limit of 3km as defined in Section 5.2. Only ω_2 (the weight associated with set up costs) is shown (in column 1) for ease of reading, where ω_1 is the complement weight.

The value of total deviations represents the extra travel distance required for all consumers to reach their nearest fast charging station once. For a more intuitive representation, this value has been divided by the total volume of flows (i.e. the total number of responses in the survey sample), to find the Average Deviation Distance, in the following manner:

$$Average\ Deviation\ Distance = \frac{\sum_{q\epsilon Q}\sum_{j\epsilon N_q} f_q \cdot d_{qj} \cdot X_{qj}}{\sum_{q\epsilon Q} f_q}$$

This average deviation represents the average deviation distance that each consumer must travel every time they wish to recharge their EV at a fast charging facility.

The final column of Table 2 shows the total number of facilities opened for each solution found. This is defined as follows:

$$Number\ of\ Facilties\ Opened = \sum_{j \in J} Y_j$$

The value of the collective objective function is not presented here, since applying the function transformation described in section 4.6, as well as the different weights, means that it does not have a meaningful interpretation. In addition, it is worth noting that the values presented in Table 2 reflect the values of $F_1(\boldsymbol{x}^*)$ and $F_2(\boldsymbol{x}^*)$ without transformation; although their orders of magnitude appear significantly different here, the transformation applied deals with this difference before the problem is optimised, and therefore curbs potential computational problems.

TABLE 2
Solution Values for N_q limit fixed at 3km

ω_2	Total Set up Costs (EUR)	Total Deviations (m)	Average Deviation Distance (m)	Number of Facilities Opened
0	87,448,424	0.00E+00	0.00	865
0.1	4,424,972	3.85E+07	0.15	47
0.2	3,714,520	1.30E+08	0.51	39
0.3	3,998,004	3.27E+08	1.29	42
0.4	3,170,132	1.04E+09	4.1	34
0.45	2,886,196	1.83E+09	7.21	32
0.5	2,913,164	1.95E+09	7.68	32
0.55	2,719,228	2.49E+09	9.83	31
0.6	2,719,228	2.61E+09	10.32	31
0.65	2,619,228	3.88E+09	15.30	31
0.7	2,550,744	4.41E+09	17.41	29
0.75	2,318,776	5.52E+09	21.76	27
0.8	2,048,776	9.55E+09	37.68	24
0.85	1,908,776	1.08E+10	42.66	23
0.9	1,661,808	1.63E+10	64.24	20
0.91	1,481,356	2.34E+10	92.42	19
0.92	1,183,936	3.41E+10	134.53	17
0.93	1,183,936	3.41E+10	134.53	17
0.94	1,183,936	3.41E+10	134.53	17
0.95	1,080,452	4.09E+10	161.31	16
0.96	1,080,452	4.09E+10	161.31	16
0.97	990,452	5.05E+10	199.41	15
0.98	770,000	8.29E+10	327.21	13
0.99	666,968	1.08E+11	426.83	11
0.999	653,484	1.32E+11	522.25	11
0.9999	653,484	1.39E+11	549.19	11
1	653,484	3.26E+11	1288.02	11

Note that for the two cases in which a zero weight is allowed (in the first and final row), there is no guarantee that the solution found is Pareto optimal, since the model ignores the value of the objective function *i* with $\omega_i = 0$ outright; this phenomenon is discussed in Steuer (1986, p.167). Thus, although the solution in the final row of Table 2 finds the best possible value for set up costs, it may be that for this same level of set up costs, it is possible to improve the value of the deviations. This would imply finding an alternative solution for which $F_2(\boldsymbol{x}^*) = 653484$ and that yields a value of $F_1(\boldsymbol{x}^*) < 3.26\text{E} + 11$, which is feasible since CPLEX terminates after finding the first solution that minimises the global objective function, and when $\omega_1 = 0$, the value of $F_1(\boldsymbol{x})$ is ignored. Such points can be described as *weakly Pareto optimal,* since it is not possible to move from one of these points to another that improves all objective functions simultaneously (Marler and Arora, 2010). It may be that there is a different combination of facilities with the same set up cost that is better distributed in space; i.e. yielding the same value for $F_2(\boldsymbol{x}^*)$ but different values for one or more Y_j, in such a way that the total deviation distance for all consumers is reduced. Changing the values for Y_j inherently changes the values of the path-facility allocation decision variables X_{qj}, and in doing so could improve the optimal value $F_1(\boldsymbol{x}^*)$. Alternatively, it may be a better value of $F_1(x^*)$ can be found for the same set of Y_j decision variables, but with different values for one or more X_{qj}.

In addition to the extreme points, there are some solutions in Table 2 that are not strictly Pareto optimal. For example, the solutions found for $\omega_2 = 0\ .55$ and 0.6 give the same value of set up costs, but different deviation distances. This can be explained by the fact that not all solutions were found using an optimality gap set strictly equal to zero. For some cases where this was observed, the results were re-computed with a zero optimality gap and the solutions found no longer contradicted the notion of Pareto optimality. This was not however repeated for all weights combinations since it would imply a significant computational burden, and it is considered that the results obtained are satisfactory for demonstration purposes.

Since the collective function minimised in (12) is a linear combination of two convex functions, with non-negative coefficients, it is itself convex. This is used to find Pareto optimal points using weights combinations as described previously. The solutions found are used to depict the trade-off between the contrasting objectives, shown in Figure 5. Here the average deviation distance, as defined above, is plotted against the value of $F_2(\boldsymbol{x}^*)$, the total set up costs. Note that although the convention is to plot the values of the objective functions against one another, it is considered that the interpretation of the average deviation per consumer is more intuitive. Should the total deviation distance $F_1(\boldsymbol{x}^*)$ be on the x-axis however, the shape of the graph would not change. Note also that the solution found for $\omega_1 = 1,\ \omega_2 = 0$ (represented in the first row of Table 2) is not included on the graph; in this solution 865 facilities are opened, resulting in total set up costs almost 20 times greater than for the next solution found, where $\omega_1 = 0.9,\ \omega_2 = 0.1$. Including this point on the graph would not add a great deal to the interpretation, but would however inhibit a clear representation of the remaining results. Figure 6 provides the same results as figure 5, but omitting the solution found for $\omega_1 = 0,\ \omega_2 = 1$, to allow a closer look. Some solution points have been labelled with the value of ω_2 for viewing clarity.

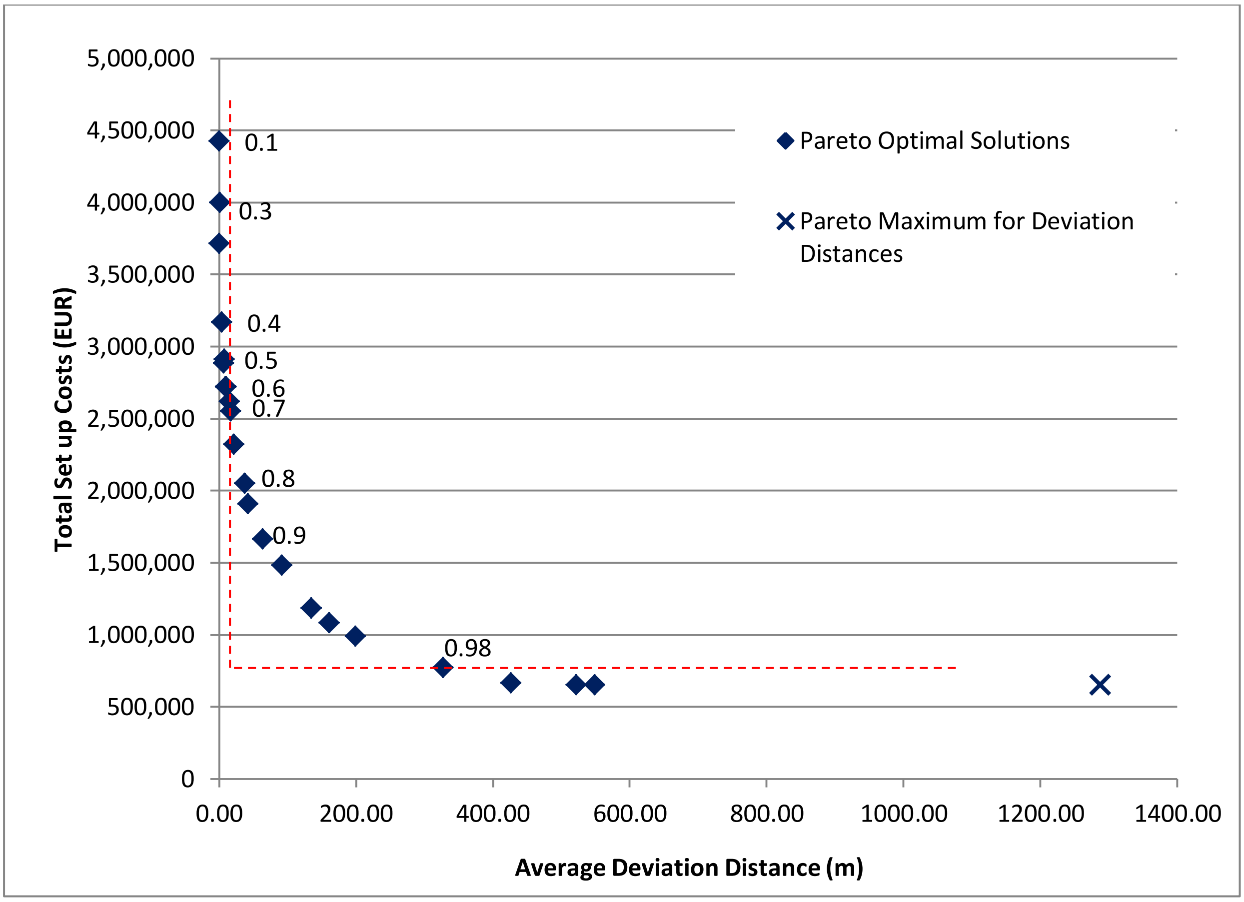


FIGURE 5: Trade-off curve for Set up Costs and Average Deviations

Initially, solutions were found for $\omega_1 = 0.1, 0.2, \dots, 0.9$ with the complementary values for ω_2. It was found that for higher values of ω_1, i.e. where a greater weight was applied to deviation distance minimisation, the difference in the average deviation distances for the different solutions was relatively small. As can be seen in Table 2, even for $\omega_1, \omega_2 = 0.5$ the average deviation distance is below 10 metres. This can be explained by the fact that in this solution, 32 facilities are opened, and thus many consumers may have facilities directly on their pre-determined path. As ω_1 decreases, fewer facilities are opened and thus more consumers will have to deviate from their path.

In Figure 5 it can be seen that until ω_2 reaches 0.8, the solution points appear close to one another on the deviations scale. That is, small sacrifices in deviations can achieve large reductions in set up costs. In order to observe the nature of the trade-off implied as deviation distances increase, solutions were found for additional values of ω_1 and ω_2 at 0.05 intervals for $\omega_2 > 0.4$, and yet more weights combinations for $\omega_2 > 0.9$; 11 solutions are found for ω_2 between 0.9 and 1. In total, 27 solutions were found for this definition of N_q. Using these weights combinations has enabled the picture depicted in Figure 5. This demonstrates that even having applied the function transformation described in Section 4.6, using uniformly distributed weights does not necessarily lead to a clear depiction of the trade-off curve; Marler and Arora (2004) describe this phenomenon as one of the shortcomings of the weighted sums approach, stating that "varying the weights consistently and continuously may not necessarily result in an even distribution of Pareto optimal points and an accurate complete representation of the Pareto optimal set". This problem has been addressed here by solving for more weights combinations within certain intervals.

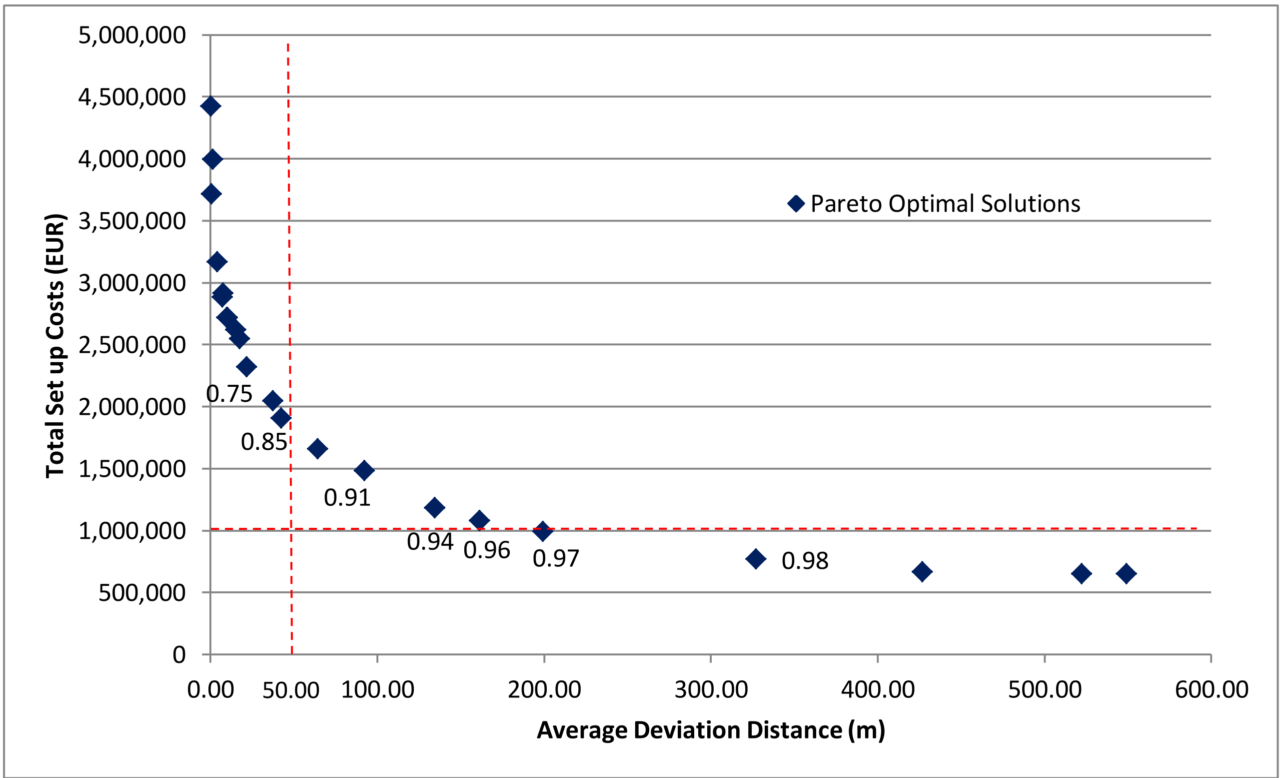


FIGURE 6: Trade-off curve—Pareto Optimal Solutions Only

It is also worth highlighting that trade-off graphs such as these help decision makers avoid applying weights based on misinformed judgements. Since the objective functions have been transformed to address their different orders of magnitude, a DM valuing set up costs and deviations equally might reasonably assume that applying a weight of 0.5 for each objective would yield a solution that reflects their preferences. However, it is clear from Figures 5 and 6 that setting $\omega_1, \omega_2 =$ 0.5 places significantly more importance on the minimisation of deviations.

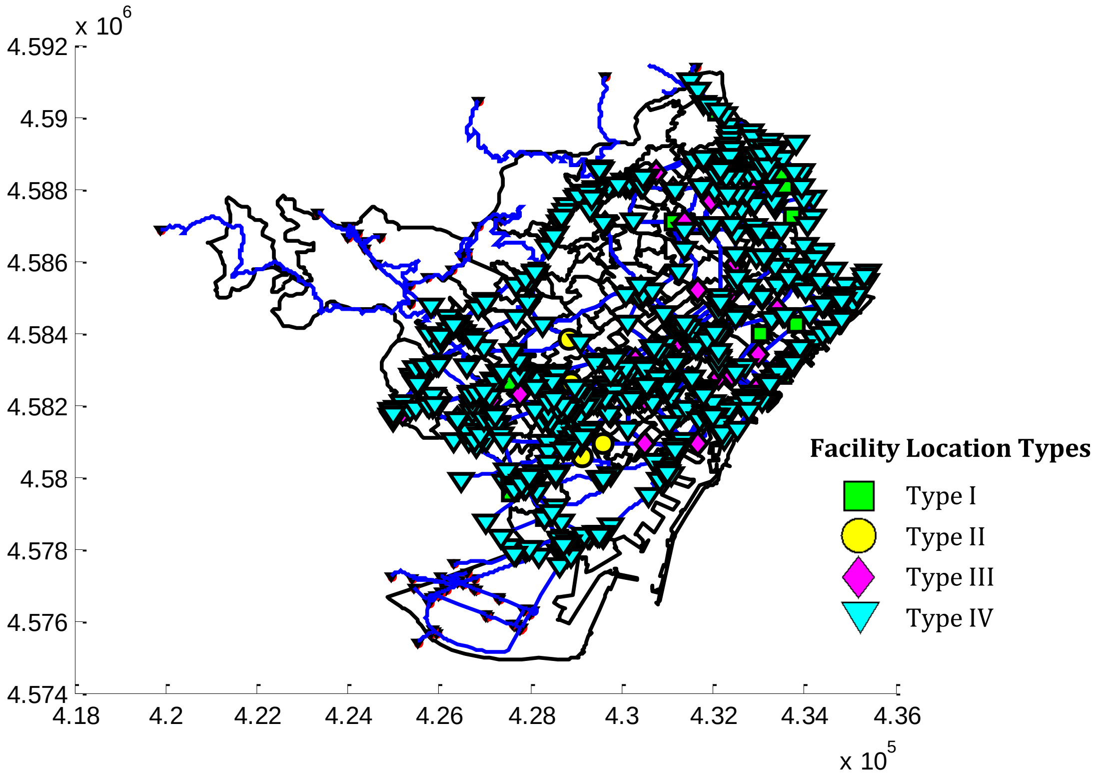
As expected, and as could be deduced from Table 2, there is a negative trade-off between total set up costs and the amount consumers must deviate from their pre-determined paths: set up costs are depicted as a monotonic decreasing function of deviation distances. Figures 5 and 6 allow the decision maker to observe the shape of this trade off, and see how much they would need to sacrifice one objective in order to improve the other. It can be seen that this trade-off relationship is non-linear, with the trade-off represented by a steep collection of points on the left hand side of Figures 5 and 6, gradually becoming shallower as ω_2 approaches 1.

Depending on the decision maker's preferences, any point on these graphs (or any point found as a solution of other weight combinations) could reasonably be chosen as the optimal solution, since every point is efficient in terms of simultaneously optimising the two contrasting objectives. However, the purpose of producing these results is to help a DM observe their options and better understand their preferences. For example, from Figure 6 it can be seen that for any weight $\omega_2 < 0.85$, the average deviation distance in the solution found is less than 50 metres, and limiting the average deviation distance below 50 metres implies a significant increase in set up costs. Similarly, the solution found for $\omega_2 = 0.96$, gives a total set up costs value of €1,015,452; attempts to reduce the set up costs to values bellows €1 million imply an increasingly large sacrifice in terms of deviations. The red dotted lines have been drawn to help the reader observe these results; the vertical line marks an average deviation distance of 50 metres, and the horizontal line marks €1 million set up costs.

From looking at the results in Figure 5, it seems reasonable to suggest that the most cost effective solutions, in terms of deviation distance to set up costs trade-offs are found for values of ω_2 between 0.7 and 0.98 (outlined by the red dotted line). It could be suggested that a solution should be chosen from this region since these solutions represent the best "value for money" in terms of deviation reductions. However, it may be the case that the DM's preferences are reflected in solutions outside this region, in which case the choice of an alternative solution would be equally valid.

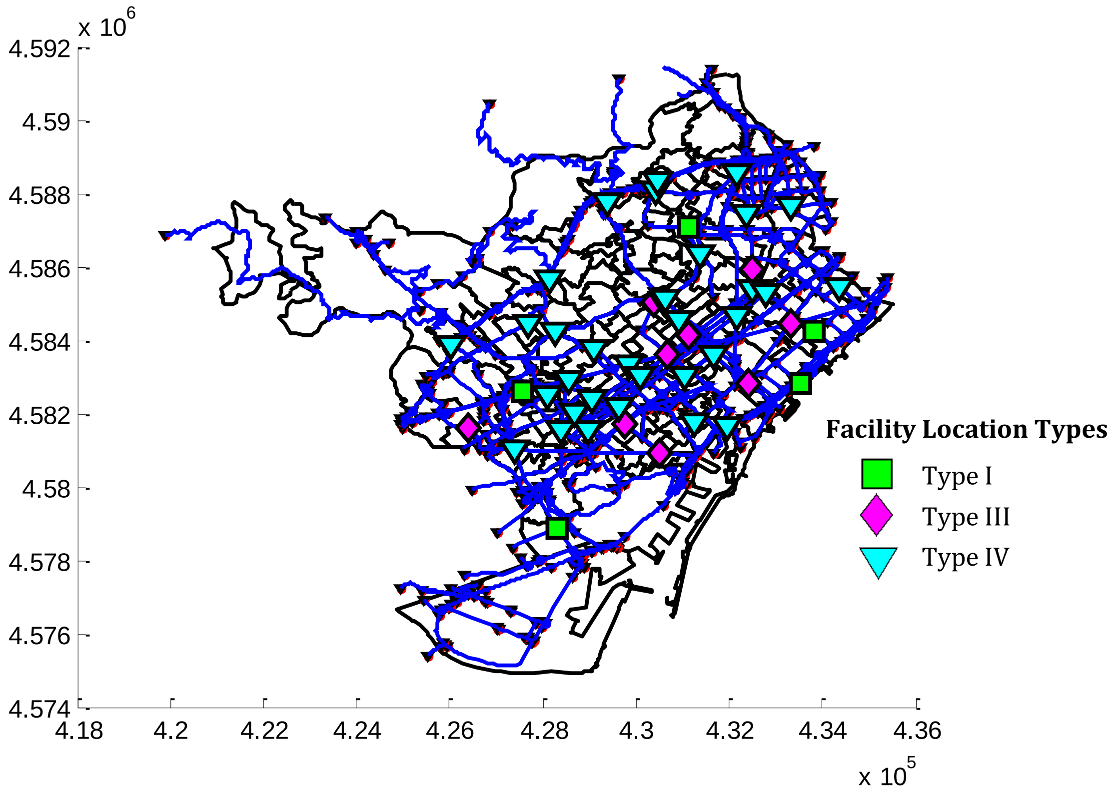
In addition to the information already provided, solving the MILP for each combination of weights returns not only the number of facilities to be opened but the location of these facilities. Using the roads graph described in section 5.1, the solutions can be presented on a map of Barcelona, implemented using MATLAB graphing software. The blue lines on each of the maps that follow represent the main roads that are used as arcs in the calculation of paths.

Figures 7 and 8 show the solutions found when $\omega_1 = 1$ and $\omega_1 = 0.9$, respectively.



Total Set up Costs: € 87,448,424 **Average Deviation Distance:** 0.00 m

FIGURE 7: Optimal location of Fast Charging Stations when $\omega_1 = 1$ $\omega_2 = 0$

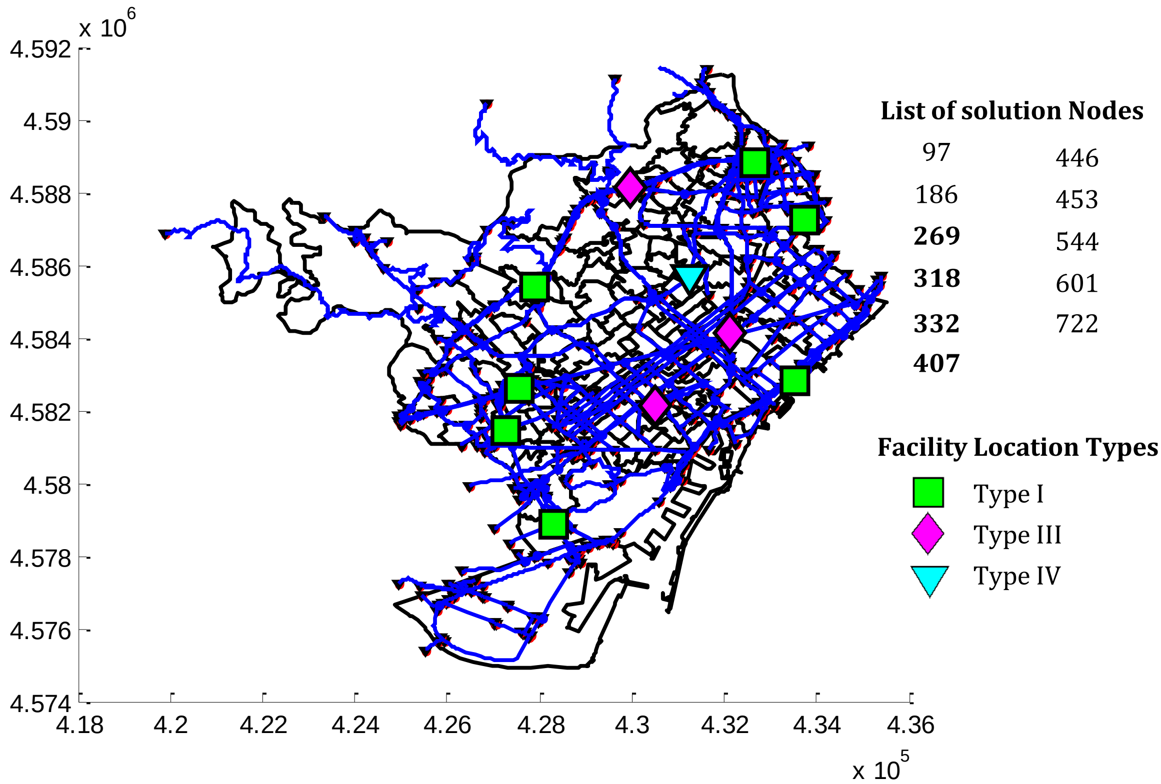


Total Set up Costs: € 4,424,972 **Average Deviation Distance**: 0.15 m

FIGURE 8: Optimal location of Fast Charging Stations when $\omega_1 = 0.9$ $\omega_2 = 0.1$

While it is clear that no central planner would choose to employ the solution found in Figure 7, the difference between these two figures highlights the usefulness of the multi objective approach. Even if a DM's most pressing priority were to ensure that deviations were as small as possible, it is shown here that applying even a small weight to the set up costs objective vastly changes the solution, at minimal expense to the average deviations value. For the solution represented in Figure 8, the Average Deviation Distance has only increased from 0 to 0.15 metres, whilst set up costs have fallen from approximately €90 million to approximately €4.5 million.

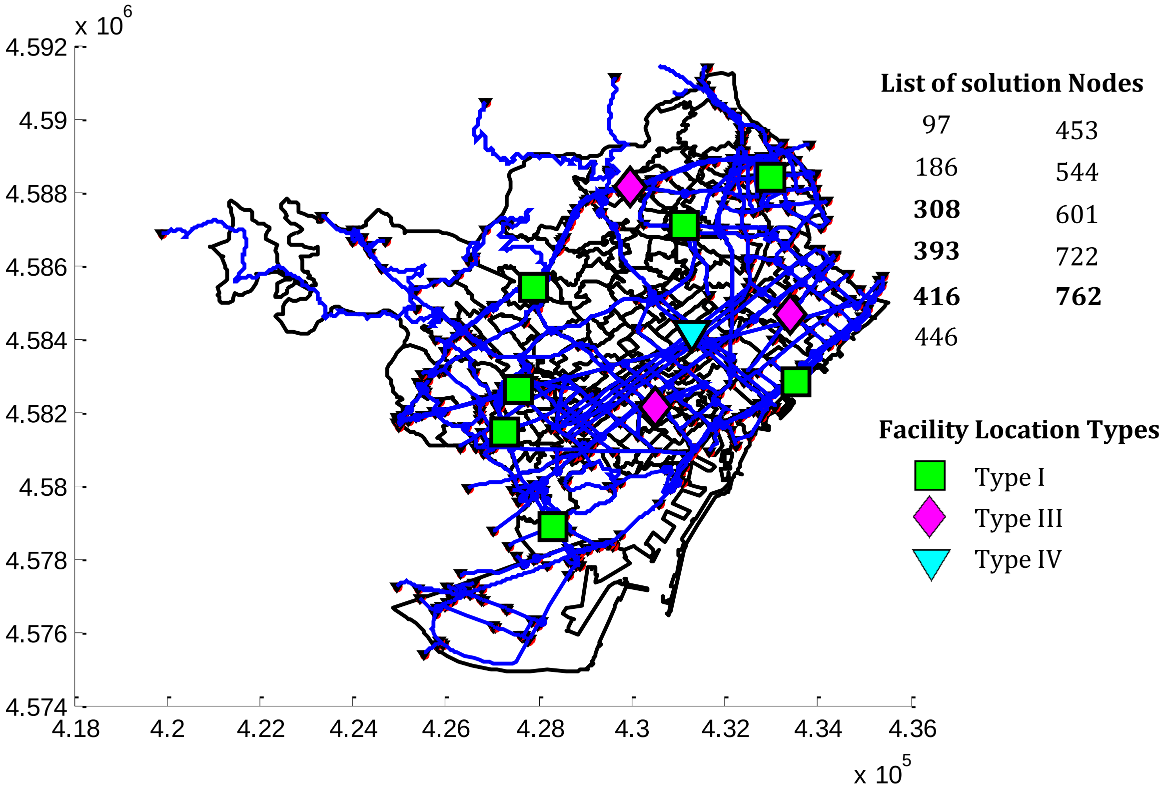
At the other end of the spectrum, Figures 9 and 10 show the solutions found when $\omega_1 = 0$ and $\omega_1 = 0.0001$, respectively.



Total Set up Costs: € 653,484 **Average Deviation Distance**: 1288.02 m

FIGURE 9: Optimal location of Fast Charging Stations when $\omega_1 = 0$, $\omega_2 = 1$

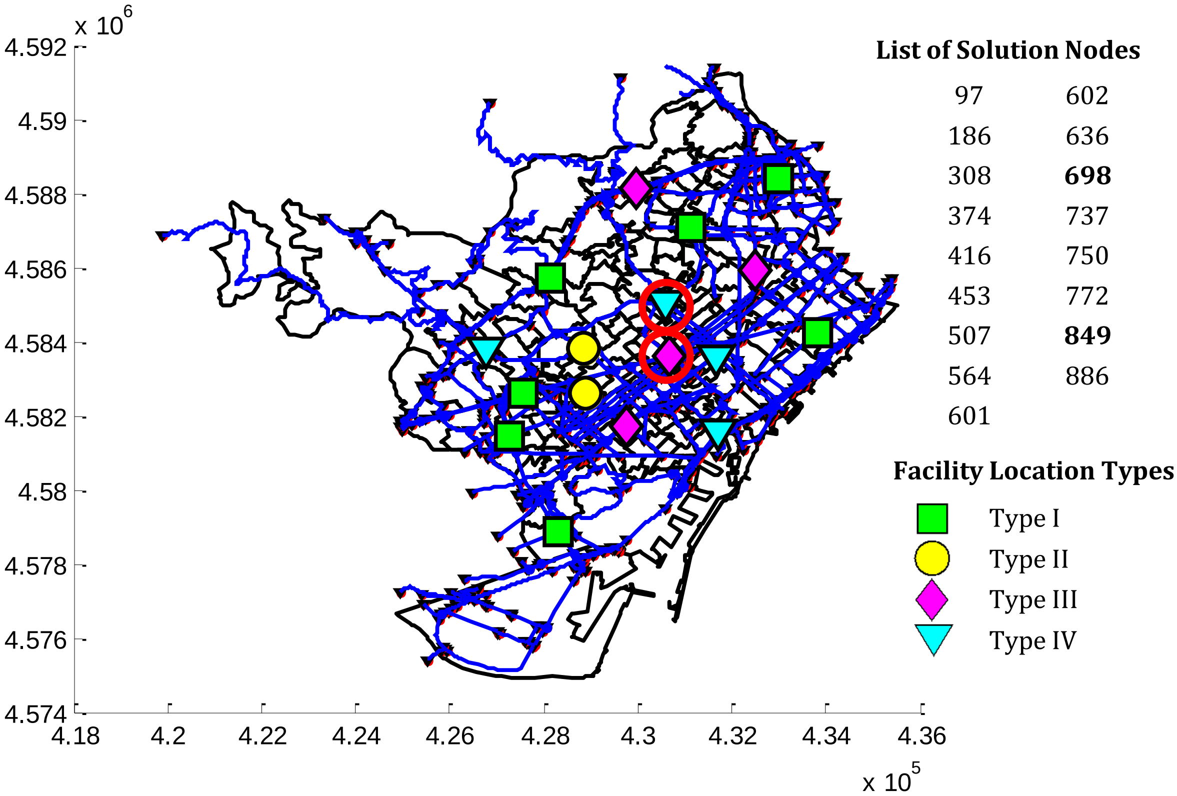
A list of nodes *j* for which $Y_j = 1$ is given for each of these solutions; nodes that do not coincide for the two solutions are written in bold text. We can see here that by including deviation distance in the objective function even with a relatively very small weight, the average deviation distance drops from 1288.02 to 549.19 metres, whilst the total set up costs remain unchanged. As we can see from the list of solution nodes, this is achieved by changing the location of four fast charging stations; the rest of the locations are the same for both solutions. These two solutions highlight the fact that making seemingly subtle changes in the EV fast charging stations infrastructure can have a sizeable effect on the deviations the average consumer would have to travel.



Total Set up Costs: € 653,484 **Average Deviation Distance**: 549.19 m

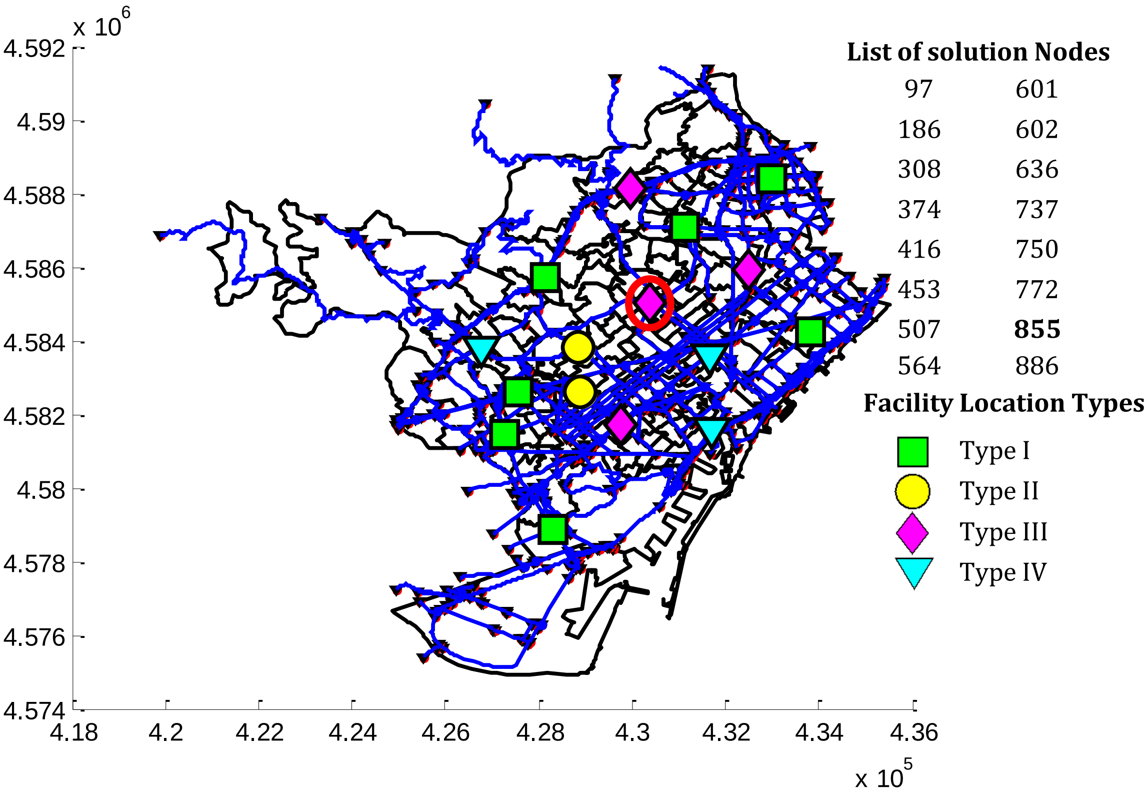
FIGURE 10: Optimal location of Fast Charging Stations when $\omega_1 = 0.0001$, $\omega_2 = 0.9999$

Figures 11 and 12 show two optimal solutions found in the middle section of the trade-off curve, using weights $\omega_2 = 0.94$ and 0.95, respectively. Moving from $\omega_2 = 0.94$ to $\omega_2 = 0.95$ implies opening one fast charging station less, associated with a cost reduction of €103,484 and an increase in Average Deviation Distance of 27 metres. These differences are associated with the removal of facilities at nodes 698 and 849 (circled in Figure 11), and introducing a facility at node 855 (circled in Figure 12). The assessment of which of these two solutions is better is not immediate—if choosing between these two solutions, a DM would have to make a judgement of whether they felt the reduction of costs was worth the implied extra deviation distance.



Total Set up Costs: €1,183,936 **Average Deviation Distance**: 134.53m

FIGURE 11: Optimal location of Fast Charging Stations when $\omega_1 = 0.06$, $\omega_2 = 0.94$



Total Set up Costs: €1,080,452 **Average Deviation Distance:** 161.31 m

FIGURE 12: Optimal location of Fast Charging Stations when $\omega_1 = 0.05$, $\omega_2 = 0.95$

At more extreme ends of the trade-off curve this type of judgement may be easier to make, since the sacrifices one has to make for one objective to achieve improvements for the other get relatively larger. For example, moving from $\omega_2 = 0.97$ to $\omega_2 = 0.98$ implies a cost saving of €220,452 (approximately twice that of the previous case), and an increase in average deviation distance of 128 metres (five times the increase for $\omega_2 = 0.94$ and 0.95).

In addition, a DM may also wish to account for other factors that have not been considered for optimisation. For example, looking at the maps in Figures 11 and 12, somebody familiar with the city of Barcelona would notice that the former places an additional fast charging station on, or very near to, Avinguda Diagonal, one of the city's broadest and most important avenues; this fact could affect a planner's preference between these two solutions. Unaccounted for considerations such as these provide yet further justification for using a multi-objective approach that provides DM's with a set of potential locations rather than a single solution with no alternative, based of preferences stated or assumed *a priori.*

6.2 Distribution of Deviations

In addition to the average deviation distance, and the maximum possible deviation distance enforced through the definition of matrix N_q, a DM may also be interested in knowing how the total deviation distance is distributed between consumers. The path-facility allocation decision variables x_{qj} are used in conjunction with d_{qj} to calculate how far consumers on different paths must travel to reach their nearest fast charging facility. To demonstrate how this information can be used, Figure 13 shows the distribution of the necessary consumer deviations for the solution where $\omega_1 = 0.06$, $\omega_2 = 0.94$.

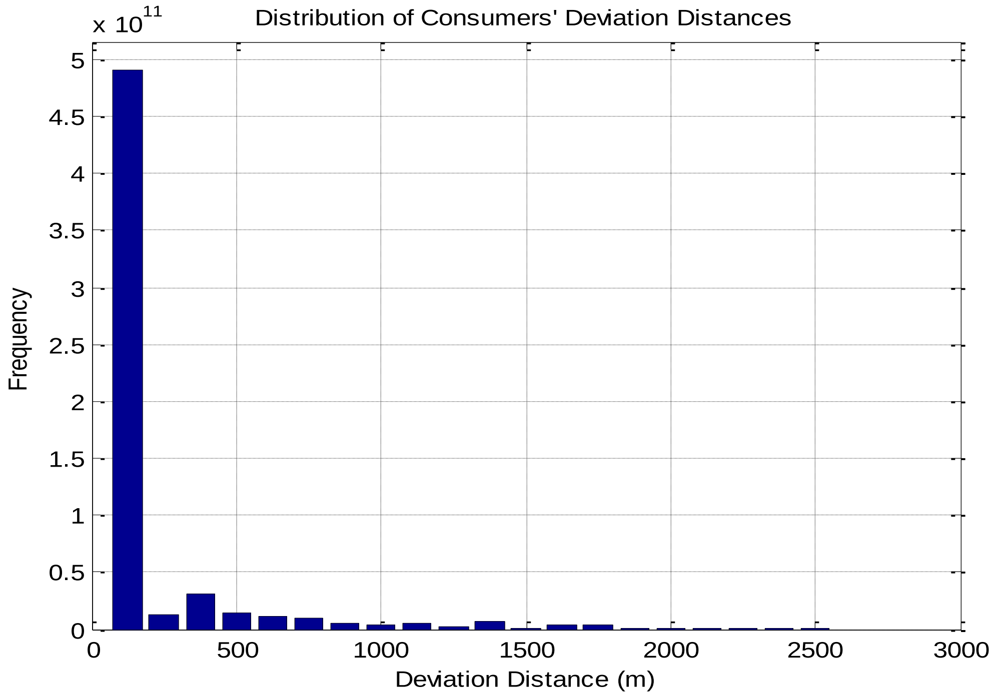


FIGURE 13: Distribution of consumers' deviations when $\omega_1 = 0.06$, $\omega_2 = 0.94$

It can be seen that for this solution, the vast majority of consumers would have to deviate less than 125 metres, which is consistent with the average deviation distance of 134.53m. In fact, in this solution, 71 percent of consumers have a deviation distance of zero. Figure 14 shows the same distribution, but removing consumers who do no not have to deviate at all, in order to get a better picture of the distribution for the remaining 29 percent. It is found that over 95 percent of consumers have a deviation distance of less than one kilometre, and more than 99 percent have a deviation distance of less than two kilometres. Interestingly, although the definition of N_q used allows consumer deviation distances to reach up to 3 kilometres, all deviation distances for this solution are found to be within 2.5 kilometres.

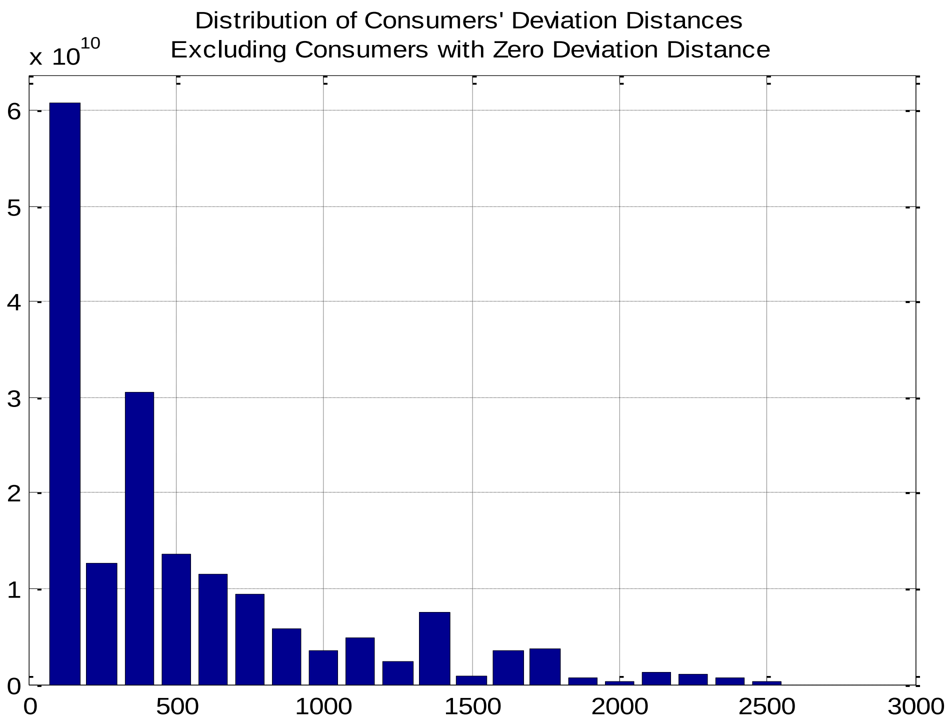


FIGURE 14: Distribution of consumers' non-zero deviations when $\omega_1 = 0.06$, $\omega_2 = 0.94$

Should it be required, it would also be possible to observe this data in a more disaggregated format. For example, one could examine the deviation distribution depending on the district of origin for the different paths.

6.3 Changing N_q

In order to assess the effect of the definition of the candidate location matrix N_q , a second smaller set of results were found, changing N_q's deviation distance limit from 3km to 2km. 21 different weights combination implemented for this version of N_q; the results are shown in Table 3. As can be seen from the first and final rows, imposing a stricter limit on N_q reduces the range of solution values for the two objectives; i.e. $(d^{max} - d^o)$ and $(c^{max} - c^o)$ are both smaller than for the previous case. This is shown in Figure 14, in which the average deviation distances are plotted against the total set up costs for both definitions of N_q.

TABLE 3
Solution Values for N_q limit fixed at 2km

ω_2	Total Set up Costs (EUR)	Total Deviations (m)	Average Deviation Distance (m)	Number of Facilities Opened
0	86,103,132	0	0.00	852
0.1	3,894,972	4.10E+07	0.16	40
0.2	3,778,004	8.66E+07	0.34	39
0.3	3,570,584	3.35E+08	1.32	38
0.4	3,287,100	7.08E+08	2.79	35
0.5	3,455,584	8.64E+08	3.41	37
0.6	2,796,196	2.25E+09	8.89	31
0.7	2,669,228	3.05E+09	12.02	31
0.8	2,232,260	6.61E+09	26.08	27
0.85	2,192,260	7.19E+09	28.38	26
0.9	1,741,808	1.55E+10	61.23	22
0.93	1,561,356	2.04E+10	80.45	21
0.94	1,432,872	2.52E+10	99.43	20
0.95	1,302,420	3.08E+10	121.55	19
0.96	1,145,452	4.01E+10	158.33	17
0.97	1,145,452	4.02E+10	158.40	17
0.98	1,145,452	4.02E+10	158.45	17
0.985	1,095,452	4.72E+10	186.34	17
0.99	1,013,936	6.63E+10	261.42	14
0.999	1,013,936	7.18E+10	283.25	14
1	1,013,936	2.25E+11	887.30	14

On the left hand side of Figure 15, the solutions found for the two definitions of N_q appear to be on the same, Pareto curve, but divert as we move to the right with an increasing ω_2 . This can be explained by the fact that when more weight is given to the value of average deviations, the same optimising solutions can be found using either definition of N_q. However, as more weight is given to costs, the stricter limit on deviations inhibits solutions with a cost smaller than €1,013,936 (marked by the red dotted line), since they are no longer feasible. Figure 15 highlights one of the important features of using a limited N_q rather than setting all nodes as candidates to service all paths: not only does limiting N_q limit the deviation distances, but it also creates a lower bound for the set up costs. Thus, imposing a stricter limit on N_q reduces the size of the attainable set. If there is no notion of cost constraints known in advance, it is therefore advisable to limit N_q as little as possible, whilst taking into account that greater N_q sets make the optimisation problem more computationally demanding

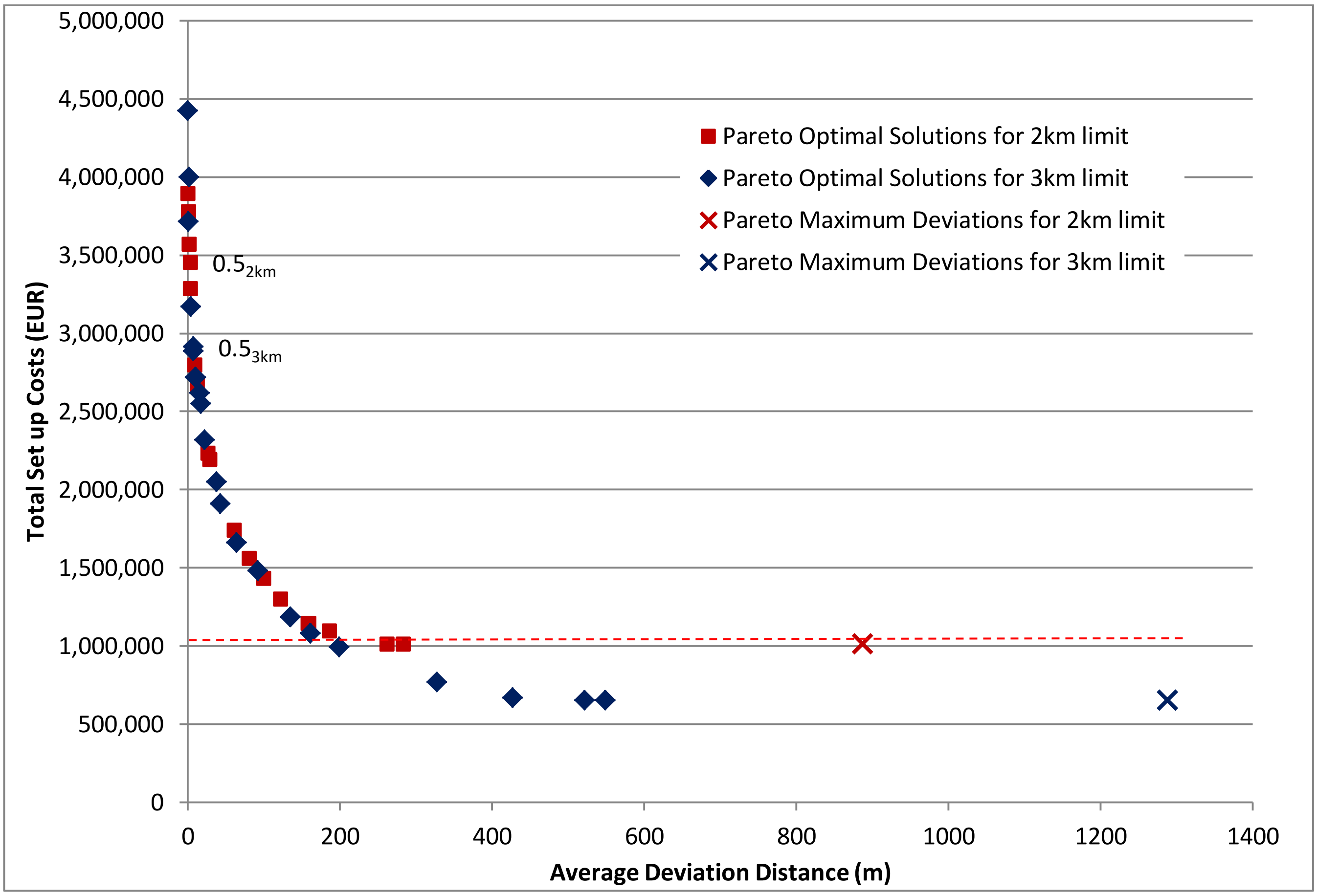


FIGURE 15: Trade-off curve for Set up Costs and Average Deviations

Notice that although many weights combinations are used for both N_q limits, when using the same weights the solution found for one definition does not correspond with that of the other. In order to demonstrate this solutions found for $\omega_1, \omega_2 = 0.5$ for the two N_q's have been labelled.

6.4 Deviations in Monetary Terms

Using the results above, it would also be possible to estimate the cost of deviations in monetary terms; some central planners may prefer to assess the economic cost of different solutions. This can be achieved by estimating the monetary cost implied for the average consumer to travel an extra metre in order to recharge their electric vehicle. Since the monetary cost is considered to be dependent on time, one must first calculate the cost in time of deviating. For a simple estimation, one can use the average speed travelled in Barcelona. The Barcelona City Council (Ajuntament de Barcelona, 2012), estimated the average speed travelled by private vehicles within the city of Barcelona in 2012 was 20.9 km (20,900 metres) per hour; using this one can convert the deviation distances into time. For example, a deviation distance of 500 metres would equate to approximately 0.02 hours (1.45 minutes) of travel time on average. A common approach to valuing time in monetary terms is to use a population's average income, since this represents the *opportunity cost* of people's time; i.e. how much they could be earning if they were engaging in economic activity rather than travelling to a charging point. This was the approach used by Gutiérrez-Domènech (2008) in a study for "la Caixa" investigating the cost of travelling to work. The most recent average hourly income in Catalonia published by the Catalan Institute of Statistics (IDESCAT, 2011), was €15.55 per hour.

For the solution presented in Figure 12, the average cost per consumer of deviating to the nearest fast charging station could be estimated as $\frac{161.31}{20900} * 15.55 = €0.12$, associated with a deviation distance of 161.31 metres, which takes an average of approximately 28 seconds to travel. Using the total deviation distance $F_1(\boldsymbol{x}^*)$ for the same solution, one can also calculate the total monetary cost associated with the all respondents of the mobility survey deviating once to their nearest charging point. For this example, for this solution the cost would be $\frac{40{,}900{,}000{,}000}{20{,}900} * 15.55 = €30{,}430{,}383$.

Should it be in the interest of the decision maker, these monetary costs could be calculated in a more sophisticated way, for example adjusting average speeds depending on road types; the crude estimation used here has been made for demonstration purposes.

It could be suggested that since deviations can be converted into monetary costs, one could combine the set up costs with deviation costs as a single objective, without having to split the objectives and applying different weights to them as has been done here. However, since the set up costs are a one-off fixed cost and deviation costs are ongoing in time, they are not considered to be equivalent. Furthermore, since the costs are felt by different agents (set up costs by local authorities and potentially firms, and deviation costs by EV users), and these may be given different levels of importance by the DM, the multi-objective approach is deemed more appropriate.

7. Discussion and Limitations

As with any study of this kind there are a number of limitations that one must acknowledge, in particular with respect to the input data and methodologies used. Some of the limitations deemed noteworthy are outlined here.

The journey distances and deviations used for the study are calculated using Dijkstra's shortest path algorithm, applied to distances between nodes in Barcelona. While these calculations provide a reasonable estimate of the journey lengths, they do not consider other factors that may considerably affect journey times, and thus chosen paths. Notably among these factors are traffic flows, road types (and thus differing transit speeds) and congestion. In particular, whilst our interpretation assumes each individual represented in the sample survey acts as an independent agent, the reality of congestion causes individuals' route choices to be affected by those of others. In the presence of congestion therefore, factors such as travel time along each path become a factor of demand. In addition, roads used to calculate path distances are assumed to be bi-directional, which is a substantial simplification of the Barcelona road network. For future research, it would be interesting to see whether and to what extent these factors would affect the results, potentially by developing a more complex travel demand model.

Additionally, it is assumed here that the information regarding journeys taken from the mobility survey is representative of the entire population of Barcelona on a normal day. Solutions have therefore been found under the assumption that what is best for this sample will be best for the population it represents. However, it may be the case that the mobility survey does not cover all journeys typically made within the city, particularly for less common routes; paths were not considered for Origin-Destination combinations that were not observed in the survey. As a result, those taking rarer routes might find themselves at a disadvantage if they were not represented in the mobility survey. A potential improvement for this input data would be to adjust the matrix of journeys between zones to account for the fact that it has been taken from a sample, in such a way that increases the likelihood of it accurately representing the whole of Barcelona.

The costs data used, as estimated by Cruz-Zambrano et al (2013), account for costs associated with grid reinforcement and consider the average price of land in Barcelona. However, these costs do not account for differences in land and rent prices that may exist between different potential facility locations within the same city. Should this model be implemented for the real life application, a more detailed study of costs would be necessary to correctly assess the appeal of different potential sites. One would also need to consider the potential agreements or arrangements necessary to install charging points in different types of location, for which one would need additional input from the local authorities, in order to determine the exact policies to be implemented. For example, an assumption of zero land costs has been made for existing petrol stations; however it may be that existing service providers in these facilities will not be directly responsible for the installation of fast charging stations, in which case some form of land rent cost would be applicable. In their current form, the costs used allow us to demonstrate how true costs would be included in the model.

As briefly mentioned in chapter two, it would also be desirable to consider the characteristics of potential facility locations that would make them attractive to users. These may include, for example, the different amenities within their vicinity. In order to account for these, one would need an estimation of the utility associated with having different types of amenities at fast charging stations. Indeed, in their approach, Bernardo et al. (2013) take the parameters for such utility values estimated by Houde (2012) for gasoline station consumers in the city of Quebec. However, it is felt that there are likely to be considerable differences between gasoline refuelling and EV charging activities, as well as differences in the consumers, and thus their preferences. With greater resources, one would ideally consider the preferences displayed by the population of Barcelona and, where possible, try to identify specific tastes of EV users in the early stages. Incorporating this in the optimisation model, potentially as a third objective function to consider would provide scope for further study.

Nevertheless, since the majority of these limitations relate to either restrictions on the availability of data or the time needed for implementation, they can be considered independent from the proposed optimisation methodology, and thus the validity of this methodology is maintained. Improvements made to the input data using the suggestions outlined above could therefore be applied to obtain more accurate results for a decision maker, without needing to alter the proposed optimisation model. Only if one wished to include a third objective would the model need to change; in this case, one would add a third component to the objective function in (10), using the same transformation as has been applied to the existing objective functions $\mathrm{F}_1(\mathrm{x})$ and $\mathrm{F}_2(\mathrm{x})$. The general methodology would therefore remain unchanged, although the observation of trade-offs between conflicting objectives would be less straightforward.

8. Conclusions and Further Research

This study addresses the problem of locating fast charging stations for electric vehicles in the early stages of infrastructure implementation for the case study of Barcelona, providing two primary contributions to the existing literature. Firstly, the concept of deviations is introduced to this particular facility location problem; previous studies have considered EV users to be fixed to particular paths, and optimised the capture of flow along these. Allowing consumers to deviate from their original paths provides a more realistic approach, and ensures that everybody is accounted for in the optimisation problem. The second important contribution is the use of the multi-objective weighted sums methodology. Previous studies have either considered only a single objective, or set a fixed constraint for a second objective. In this study, using different weights combinations has enabled the computation of multiple solutions and the depiction of the Pareto front, which could provide valuable information to a central planner, particularly when preferences are not clear. This approach could be applied not only for the city of Barcelona but for other cities facing similar problems.

For the case study addressed, with the function transformation applied, it is found that solutions offering the greatest balance in trade-offs between the conflicting objectives are for values of, ω_1 between 0.02 and 0.3, or equivalently values of ω_2 between 0.7 and 0.98. Furthermore, it is shown that the definition of the candidate node set N_q can have an important effect on the size of the attainable set and the shape of the trade-off curve, and should therefore be considered carefully prior to implementation.

Of the limitations outlined in section 7, two are considered particularly important. In order for solutions to be applicable, a more sophisticated travel demand model should be developed to gain a more accurate estimation of paths taken by EV users, and thus the implied deviations associated with recharging. Furthermore, the estimation of set up costs implied for locating charging stations should consider the policy options under consideration by local authorities, and be made more case specific.

Finally, it is considered that the natural next step for further research would be to consider a third objective related to amenities within the vicinity of candidate facility locations. This is deemed particularly important given the nature of EV charging, in which even with “Fast Charging” provided by DC points, there is a standard associated waiting time considerably longer than the petrol refuelling time most car users are accustomed to. Indeed, without the possibility of engaging in other activities whilst waiting for an EV to charge, one could posit that the cost associated with this lost time should also be taken into account; this also provides scope for further study.

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