Economics & Management Series EMS-2022-03

An Electric Vehicle Migration Framework

El Mehdi Er Raqabi
Alumnus 2019
International University of Japan

Wenkai Li
International University of Japan

April 2022

IUJ Research Institute
International University of Japan

An Electric Vehicle Migration Framework

El Mehdi Er Raqabi[1, 2, 3], Wenkai Li[1,*]

1. *Graduate School of International Management, International University of Japan, Niigata 949-7277, Japan*
2. *Operational Researcher, Fostergy Technologies Inc., Montreal, Canada*
3. *Department of Mathematical and Industrial Engineering, Polytechnique Montreal, H3T 1J4, Canada*

Abstract

Electric vehicles (EVs), with lighter environmental footprint than traditional gasoline vehicles, are growing rapidly worldwide. Some countries such as Norway and Canada have successfully established EV networks and achieved a significant progress towards EV deployment. While the EV technology is becoming popular in developed countries, emerging countries are lacking behind mainly because of the huge investment hurdle to establishing EV networks. This paper developed an efficient Electric Vehicle Migration Framework (EVMF) aiming to minimize the total costs involved in establishing an EV network, using real world data from three major cities of Morocco: Rabat, Casablanca, and Fes. A given set of public institutions having a fleet of EVs are first grouped into zones based on clustering algorithms. MILP (Mixed Integer Linear Programming) models are developed to optimally select EV charging station locations within these organizations, with an objective to minimize the total cost. This paper can help to minimize the investment needed to establish EV networks. The transition towards EV networks can first take place in cities, especially at public institutions, followed by locations among cities. With the framework developed in this paper, policy makers can make better decisions on EV network migration.

Keywords: Electric vehicle, range anxiety, public transport, optimization, MILP, data mining, remote sensing, clustering.

[*] Corresponding author. E-mail: lwk@iuj.ac.jp, wenkaili2002@yahoo.com.

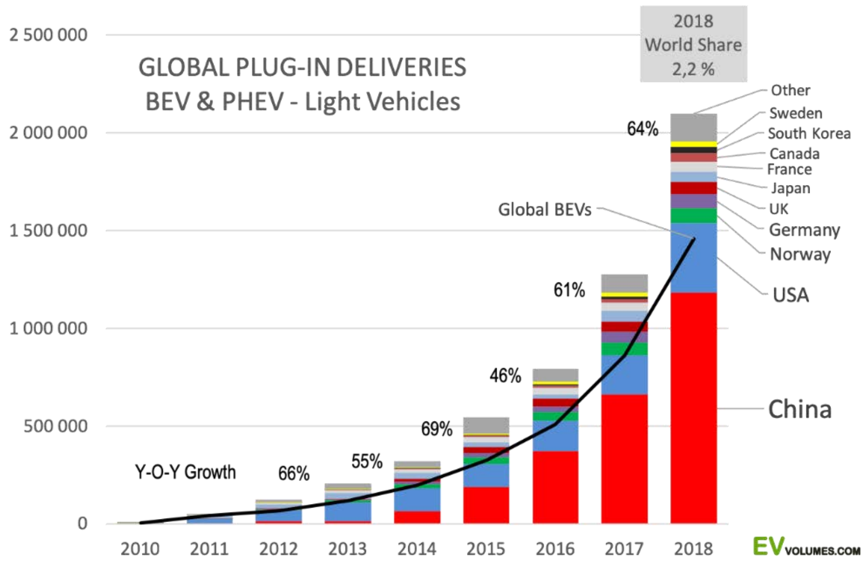
1. Introduction

1.1 Background

EV sales have been growing rapidly over the last decade. The number of EVs is estimated to reach 6.4 million units in 2021 despite Covid-19 restrictions and component shortages (GREENCARS, 2021). The number was only 2.1 million units in 2018 (Irle, 2018). The rapid growth is expected to continue. Between 2017 and 2018, sales grew up by 78% in China, 34% in Europe, 79% in USA, and 86% worldwide (Irle, 2018). This indicates a prospective shift within the transportation sector worldwide as shown in Figure 1. Norway, the country known for spreading electrification, has achieved a high level of EVs domination and significant carbon emissions reduction. As of December 2021, among all new car sales, over 80% were EVs (GREENCARS, 2021). Norway's government is targeting electrification of all new cars within the country by 2025 (Lambert, 2018). Japan laid out a "green growth strategy" to reach net zero carbon emissions and generate nearly $2 trillion a year in green growth by 2050 (Reuters, 2020). Japan aims to eliminate sales of new gasoline-powered vehicles by the mid-2030s, shifting to electric vehicles (Reuters, 2020). Huge efforts on both the design of EVs and the charging infrastructure were made from 2000 in countries such as Norway, Canada, and China, leading to the development of necessary EV infrastructure.

While some countries have achieved significant progress towards the adoption of EVs, many others lag behind. (Linke, 2017) pointed out three major barriers to adopting EVs: limited variety of EV car models, infrastructure, and mindset. With limited EV infrastructure, EV drivers have to research the location of charging stations before driving (Linke, 2017). For transition to EVs in BRICS countries, the prominent barriers are infrastructure, institutional (lack of supporting regulation), demand, and other specific barriers in a specific country (Pratiwi, 2016).

Figure 1. Global EV Deliveries (Adopted from Irle 2018)



(Pratiwi, 2016) suggested that building additional public charging stations and government support are among the most important strategies to overcome EV migration barriers. Given that EV deployment has now mostly been driven by government policies, initiations by government institutions have significant social impact on EV migration. Government institutions, operating public institutions fleets, can set examples to demonstrate benefits, including economic ones, of EV migration. As pointed out by (Ortt, et al., 2013), to commercialize new high-tech products such as EVs, a key niche strategy is to “Demo, experiment, and develop”, that is, to demonstrate the new product in public in a controlled way. Such a strategy can help to change the risk averseness attitude of still-hesitating governments and the public, especially from developing countries. As an example of public institutions fleets, transit buses between towns and cities, may be the key to the electric vehicle revolution (Earthjustice, 2020). Los Angeles Metro has decided to invest in a full fleet of zero-emissions electric buses (Nelson & Reyes, 2017). By 2040, all public transit buses in California will be fleets of EVs (CARB, 2018). The Government of Canada has made clear commitments to reduce emissions from government fleets (Akendi, 2018). In

Canada, besides the central government, many provinces and territories have also adopted greening policies and procedures for their fleets (Akendi, 2018). It is realized that, though governments are directly responsible for a relatively small share of emissions, they have an opportunity to lead by example (Akendi, 2018). Canada, the U.S., and Mexico have agreed to collaborate to deploy greater amounts of EVs in government fleets (Akendi, 2018). Seven countries (Canada, China, France, Japan, Norway, Sweden, the U.K., and the U.S.) have signed on the Government Fleet Declaration, committing to deploy greater numbers of EVs in government fleets (Akendi, 2018).

Public institutions can take the lead towards EV migration through electrification of their fleets. While these institutions will definitely have more EVs over the next years, a cost-efficient charging infrastructure for EV fleets is essential. In this paper, optimization of EV charging stations is presented as a prospective and efficient migration framework. Each government institution is assumed to have a specific fleet of vehicles that is managed by a specific fleet management division. In some developed countries such as Canada and Netherlands, provinces have taken on greening, and especially EVs, policies and procedures for their fleets, and in some cases, they are sharing experiences to support municipal governments to implement their own measures (Akendi, 2018). While the deployment of EVs is advanced in these countries, it is done independently leading to a separate fleet management, which is not optimal. Thus, it is important to manage EV fleets of these institutions as a whole under one framework. Since these EVs will be mainly used for work purposes, their charging stations can be deployed within the workplace. Besides within cities where institutions are located, charging stations are also needed on the highways. This paper proposes a framework to tackle the charging facility location problem with the following questions in mind: How many charging stations are required and into which institutions they should be located?

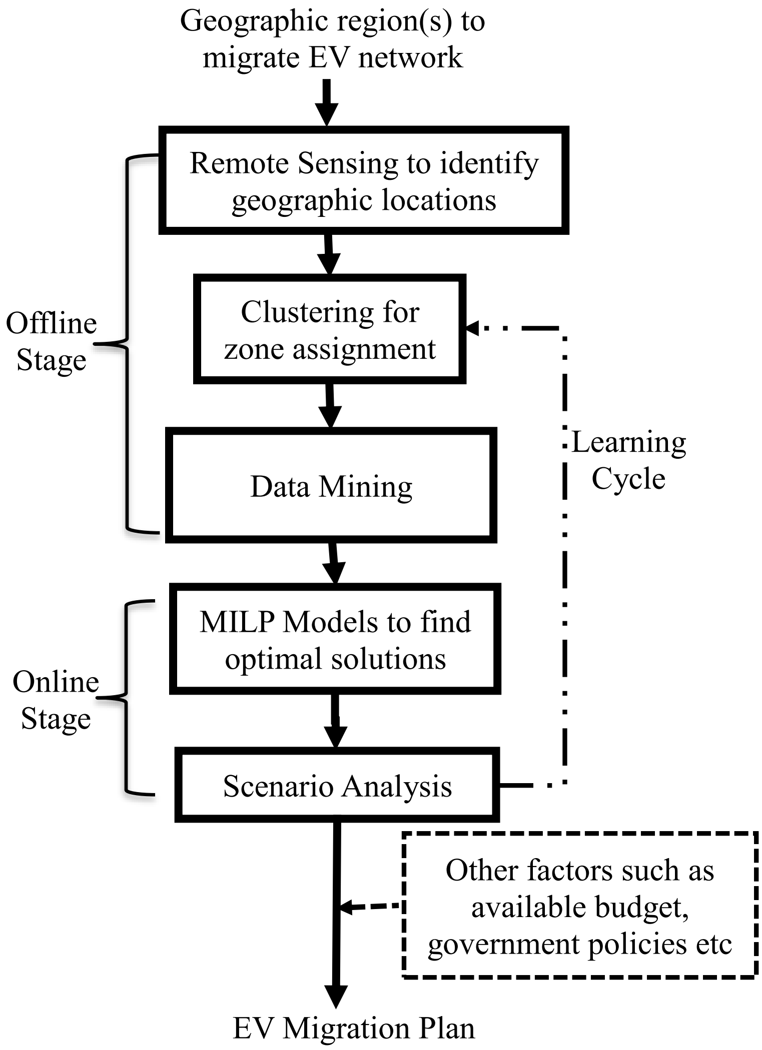
EVs are charged using Electric Vehicle Supply Equipment (EVSE), which are differentiated based on the level (power output range of the EVSE outlet), type (the socket and connector used for charging), and mode (the communication protocol between the vehicle and the charger). This paper adopts the three-level definition of EVSEs as detailed in (CEA, 2013): Level 1 costs less than $1000 and can add about 40 miles of range in an eight-hour overnight charge. Level 2 costs between $3500 and $6000 and can add about 45 miles of range in a two-hour charge. Level 1 and level 2 charging stations are also called slow charging stations. Level 3 costs between $60,000 and $100,000 and can add 50 to 90 miles in half an hour, which is also called fast charging station. Among the three levels, level 2 chargers are the most common public chargers used within the institutions. For charging stations located in public institutions, level 1 and level 2 are suitable. On highways where time is an important constraint, level 3 charging stations is suitable.

This paper focuses on the design of a network of EV charging stations to serve a network of public institutions. It is cost prohibitive to install charging stations at all institutions. To reduce cost, different levels of EV charging stations are differentiated for different purposes: Level 1 charging stations are used for overnight charging while Level 2 charging stations are used during working hours. Level 3 charging stations are used on highways or between two busy and distant city zones. This paper seeks to find the optimal locations of EV charging stations among all city institutions and on highways.

The EVMF proposed in this paper consists of two stages, Offline and Online, as shown in Figure 2.

The input to EVMF is the geographic region(s) wishing to establish an EV network. At the Offline Stage, EVMF first applies remote sensing techniques to identify geographic locations (in this paper, locations of public institutions) to be served by EVs. The output is a location map. Next, locations are grouped into zones applying clustering algorithms and heuristics. Detailed location/zone data are processed at the data mining step. The processed data will be passed to the Online Stage to set values of parameters.

Figure 2. The Electric Vehicle Migration Framework (EVMF)



At the Online Stage, an optimization model is called to read the processed data from the data mining step and set values to its parameters. The optimization model is then solved to find the optimal EV network. Scenario analysis is conducted based on different parameter settings. A learning cycle is used to understand insights on various optimal EV networks found by the optimization model, which involves both Offline and Online Stages. At the scenario analysis step, various settings of several key parameters (e.g., HWD) are tested. Clustering algorithm and heuristics are applied again to obtain updated zone assignment, followed by the data mining to process updated data. The optimal EV network corresponding to the new settings is obtained by calling the optimization model. The learning cycle varies settings of key parameters and requires several iterations. The outputs from the learning cycles provide decision makers essential insights on future EV network of the geographic region(s).

1.2 Literature Review

The facility location problem related to EV charging stations have been studied in several papers. Most papers (e.g.: (Hanabusa & Horiguchi, 2011); (Lee, et al., 2014)) in the literature presented models related to fast (level 3) charging stations, which are usually required for long-distance trips on highways. In such situation, the EV charging demand is computed based on the number of EVs on the road as well as drivers' behavior. Some papers tackle the problem from the demand's point of view, while others tackle it based on the drivers' choices and decisions. The goal is generally similar which consists of allotting demand to charging stations in a balanced way. As a common tool, traffic assignment is used for modeling of EV drivers' route choice (Chen, et al., 2014). Some studies (e.g.: (Liu, 2012)) considered gas stations' locations as a point of origin to determine the location of EV charging stations. However, such approach, similarly to previous ones, does not consider the range anxiety issue, which is the main challenge of EVs.

Some other studies focused on slow (level 2 and level 1) charging stations ((Frade, et al., 2011); (Xi, et al., 2013); (Chen, et al., 2013); (Cavadas, et al., 2015)). Slow charging stations are usually used in residential areas or in the workplace. The models presented in these studies typically used regression analysis to estimate demand within cities. The factors considered included employment, residence, and traffic data. The goal was to therefore maximize the coverage of all EVs given the available charging stations. Regarding the coverage problem, the distinction between full coverage and partial coverage was usually missing.

Only a few studies ((Huang, et al., 2016); (Sun, et al., 2020), (Liu, 2012); (Liu, et al., 2015); (Jordán, et al., 2018)) considered both fast and slow charging stations. (Huang, et al., 2016) considered both fast charging stations for short time needs (i.e. on highways) and slow charging stations for long time needs (i.e. within cities). The paper also used the traffic assignment method. For fast charging stations, the paper used a model with geometric segmentation and considers EVs moving within network links. The main parameter defined is the remaining battery capacity (driving distance). The driver should be able to find a fast charging station before complete battery depletion. For slow charging stations, the demand for charging is based on zones. The parameter defined is the human walking distance (HWD). Hence, a specific point within a zone is covered if and only if the Euclidean distance between this point and the charging station is less than the maximum HWD. The models are designed to tackle range anxiety by minimizing the total cost while guaranteeing a given level of demand coverage. (Sun, et al., 2020) also considered slow and fast charging stations and tackled the limited resources' constraint for both parking vehicles and vehicles on long journeys. The paper used sensitivity analysis to identify specific factors having an impact on the number and location of charging stations. Two papers ((Huang, et al., 2016) and (Sun, et al., 2020)) found out that travelling distance as well as location's capacity are the main factors influencing the number and location of charging stations. Some other papers ((Liu, 2012); (Liu, et al., 2015)) presented a mixed model, which first determines the number of level 1 and level 2 stations within parking and residential areas based on economic data and considers gas station locations as a prospective location for level 3 stations. (Jordán, et al., 2018) used a multi-agent system to characterize potential charging stations areas. Given the large configurations space, (Jordán, et al., 2018) applied metaheuristics (genetic algorithm) to optimize a set of metrics. The metaheuristics provides the most suitable areas of the city for the deployment of EV charging stations.

Among the highlighted literature, only (Huang, et al., 2016) address the range anxiety issue explicitly by ensuring a certain level of demand coverage when minimizing the total cost. Still, they do not consider the interaction between EV drivers' travel behavior and the location of fast charging stations. For instance, an EV driver may consider a route that does not have any charging station leading to battery depletion.

Table 1 provides a summary of major existing work tackling EV network design from different perspectives. It can be seen from Table 1 that most papers tackled fast charging stations only while only a few considered both fast and slow charging stations. In general, the EV network design is tackled as an optimization problem. The objective is usually to minimize cost/usage/time or maximize utilization/benefits/coverage. Exhaustive reviews can also be found in (Amjad, et al., 2018) and (Shareef, et al., 2016).

Fast charging stations are crucial for solving range anxiety issue. However, in most emerging countries, costs incurred to acquire and manage these stations are high, which raises the threshold of an electric grid. As a result, slow charging stations in cities remain an efficient starting point for emerging countries. Then, fast charging stations can be added on highways to ensure the capability to manage fleets among cities.

To design an EV charging network in emerging countries, this paper starts by adding slow charging stations in cities. Then fast charging stations are considered to design EV network among cities. Such an approach is convenient for policy makers to migrate towards EV networks. In our case, EV users' travel behavior is controlled since EVs will be mainly used for work purposes either within the city or among cities. Furthermore, through grouping institutions into zones and ensuring the usage of highways when travelling between cities, the proposed EVMF handles range anxiety effectively.

Table 1. A summary of major existing work on EV network design

Author(s)	Charging	Model	Objective	Model Structure
(Sun, et al., 2020)	Fast & Slow	Exact	Max EV flows coverage	Nodes
(Jordán, et al., 2018)	Fast & Slow	Metaheuristic	Max Configuration	Encoding
(Huang, et al., 2016)	Fast & Slow	Exact	Min total charging cost	Polygons and Links
(Chung & Kwon, 2015)	Fast	Exact	Max flow captured	Graph
(Liu, et al., 2015)	Fast & Slow	Heuristic	Min cost/energy loss	Network
(Chen, et al., 2014)	Fast	Ad hoc	Min total travel time	Graph
(Lee, et al., 2014)	Fast	Exact	Min network cost	Graph
(Lam, et al., 2014)	Fast	Heuristic	Min cost	Graph
(Capar, et al., 2013)	Fast	Heuristic	Max flow captured	Graph
(Chen, et al., 2013)	Slow	Heuristic	Min total access cost	Point
(Liu, 2012)	Fast & Slow	Ad hoc	Min # of charging stations	Polygons and Links
(Hanabusa & Horiguchi, 2011)	Fast	Exact	Min total travel time	Graph
(Ge, et al., 2011)	Fast	Metaheuristic	Min flow captured	Graph
(Kuby & & Lim, 2005)	Fast	Exact	Max flow captured	Graph

1.3 Contributions

The contributions from this paper are summarized as follows.

1) Proposes an integrated, fast, scalable, and flexible framework, EVMF, to facilitate decision-making for future EV network migration.

This paper proposes a two-stage framework for EV network design. In EVMF, the usage of all EVs are considered as an integrated model, and global optimal solutions at various scenarios are found. Such an integrated model can find overall better optimal solutions than those decentralized models which consider EV usage regionally. To the best of the authors' knowledge, such governmental integration or centralization of EV usage has not been proposed in the literature.

Through scenario analysis, EVMF can find optimal solutions at different settings quickly. The execution time of each scenario is very short (in seconds). Such a learning cycle provides essential insights for policy makers to plan the migration towards EVs by considering budget constraints, available EVs, and other factors.

EVMF is scalable and flexible. The models in this paper were firstly designed within a city then were scaled up to a network of three cities linked with two highways. The extension can be done easily and efficiently to a network of institutions within a specific country or even between countries. This paper presents models for EV network of public institutions. The models can be readily applied to other organizations such as transportation companies, travel agencies, city buses, etc., having a fleet of EVs.

2) Range anxiety issue imbedded into EVMF

This paper proposes a new way to tackle range anxiety. In the literature, range anxiety problem is either avoided or tackled partially. Taking into account HWD when defining a zone's size, this paper assigns each institution to one zone. Within each zone, a charging station is designed (either fast or slow charging stations) where EVs users can charge EVs within HWD. Since fleets of EVs are managed among all public institutions by government, EVs can also be charged in other zones or even between zones. Furthermore, the centralized management ensures the flexible distribution of EVs based on demand within each zone. For instance, when one EV is being charged, other EVs can be used to maintain the operability of an EV network. On highways, a network of fast charging stations is designed while talking into account the distance between two neighboring charging stations. Such factors are imbedded into EVMF and the mathematical models developed in this paper. In such a way, range anxiety problem is efficiently solved.

3) Remote sensing, clustering, and data mining were integrated into EV network problem

This paper firstly used remote sensing to identify geographic locations of public institutions. Applying clustering algorithms and heuristics, based on results from remote sensing, zones are defined and clusters of organizations are identified. Data mining is then used to define parameters for mathematical models. Clustering contributed significantly in reducing the execution time and making the mathematical models powerful. While remote sensing has been used before (e.g.: (Huang, et al., 2016)), To the best of the authors' knowledge, this paper is the first to combine it with clustering algorithm and data mining in EV literature.

4) Introduction of Importance Factors

The concept of "Importance Factor" proposed in this paper reflects the importance and customer demand of an institution. An "Importance Factor" is computed based on readily available information of an institution including the number of employees, the number of vehicles, inflows, outflows, as well as the location of an institution within a zone. Importance factor is used as a metric to determine the optimal location of EV charging station within a zone. This paper further defined Importance Factors for zones and between two zones, which are used to compute the costs to open different levels of EV charging stations and to find the optimal EV network design.

2. The Electric Vehicle Migration Framework (EVMF)

EVMF includes two stages: Offline and Online, as briefly described in Figure 2. We present details of EVMF in this section.

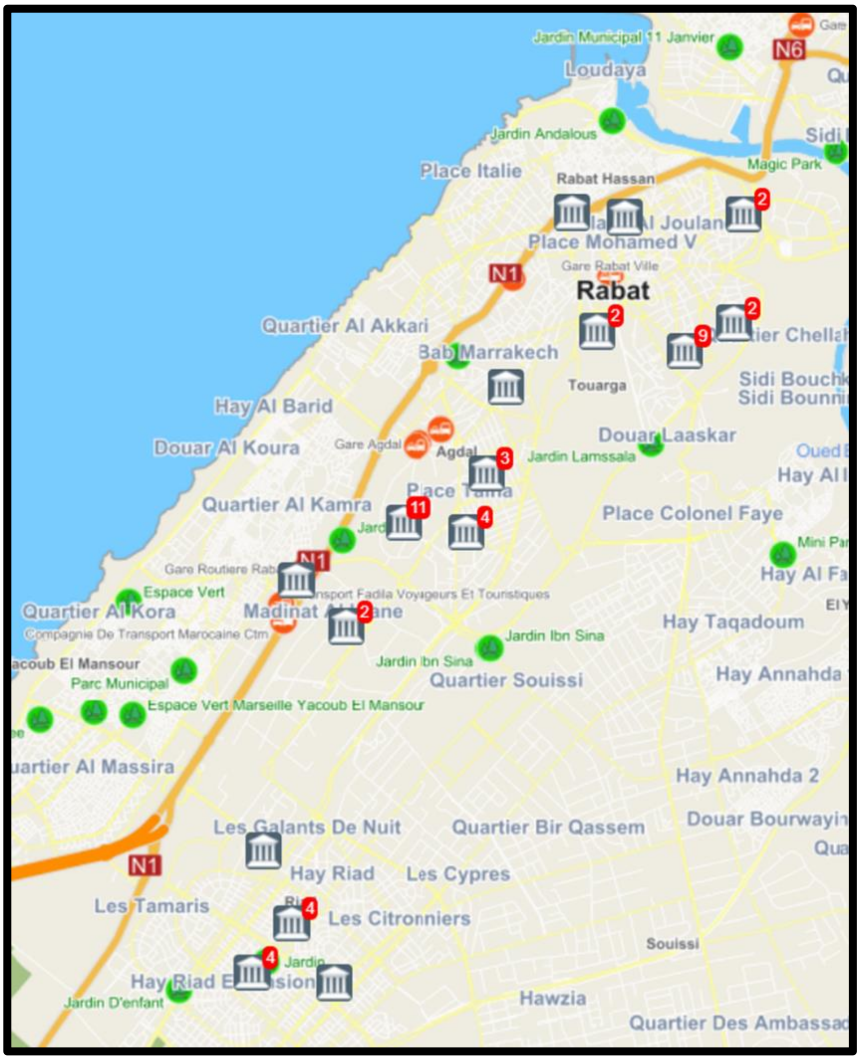
2.1 The Offline Stage

The Offline Stage involves three steps: identifying geographic locations, clustering, and data mining. The Offline Stage generates inputs for the Online Stage. The first offline step is to identify geographic locations of institutions in a geographic area studied. Clustering algorithms and heuristics are then applied to assign institutions into zones. Finally, at the data mining step, all offline data are added into an Excel file, which will be read directly by mathematical models at the Online Stage. To reduce the execution time of the mathematical models in the Online Stage, it is important to shift as much as possible preparation work from online to offline.

2.1.1 Step 1: Identifying geographic locations

To optimize the EV network among institutions, the geographic locations of the set of points studied (public institutions in this paper) should be identified. Working with satellite pictures such as Google Maps and other geographic captures is nowadays an efficient way to conduct research on transportation. ArcGIS or QGIS are usually used to prepare a remote sensing map. This paper generates remote sensing maps from (Service-public, 2022), an official Moroccan government website which provides detailed information of Moroccan public institutions. Figure 3 shows the remote sensing map for Rabat, the capital city of Morocco, generated from (Service-public, 2022). The map provides the locations of public institutions (only ministries are considered) in Rabat. The red index at the top right corner of each blue house-shaped icon represents the number of institutions located within that area. By zooming in on the map, more details will be provided and all the institutions can be identified. The information provided by the map as well as the institutions locations are inputs to the next clustering step.

Figure 3. The remote sensing map for Rabat

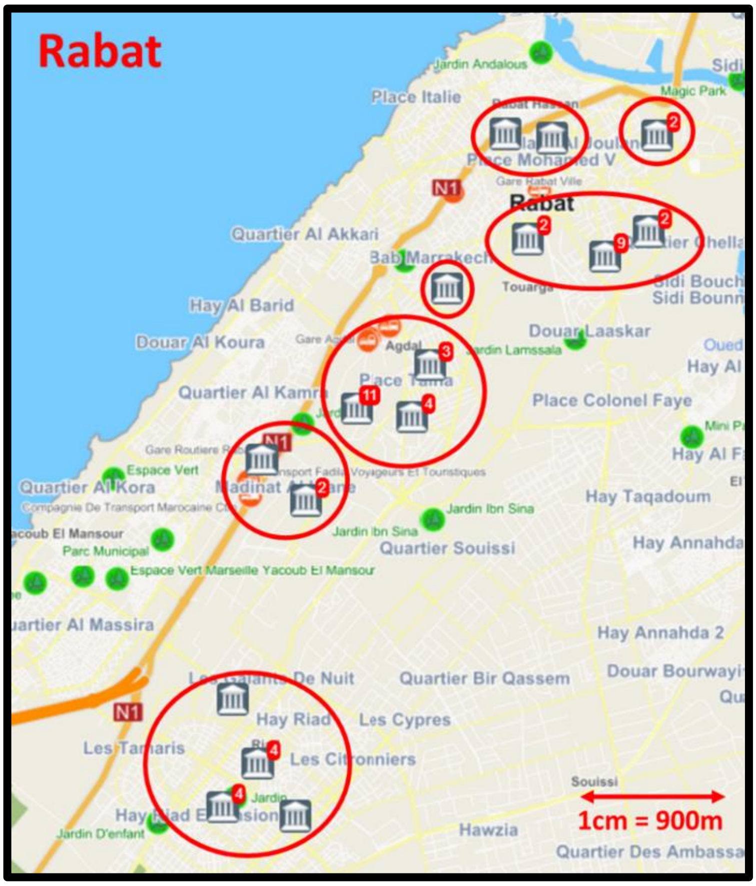


2.1.2. Step 2: Clustering

In this step, centroid-based clustering (Hartigan & Wong, 1979), also called k-means clustering, which is based on the idea of grouping objects based on proximity, is applied in this paper. Since this paper seeks to group institutions based on normal HWD ranges between 300m and 600m, the centroid-based clustering approach is suitable and efficient.

Institutions located within a specified HWD are grouped in the same zone. Heuristics are used to handle special institutions or outliers. The heuristic enumerates all special institutions and their Importance Factors (details in Section 2.1.4). The special institutions are defined either as a new zone or added into the closest zone. In general, a special institution with high Importance Factor is defined as a new zone. A special institution located around 1km and with low Importance Factor are added to the closest zone. Applying the connectivity-based clustering and heuristics, the clustering results for Rabat are shown in Figure 4. When the HWD is assumed to be 500m, the 49 institutions considered within the geographic area of Rabat can be grouped into 7 zones (the red circles in Figure 4). Each zone is given a zone ID. Note that, by varying the HWD from 300m to 600m, the number of zones and the institutions' zone assignment may also change accordingly. In this paper, the term "zone" and "cluster" have the same meaning and will be used interchangably.

Figure 4. The clustering results for Rabat



2.1.3. Step 3: Data Mining

The data mining step is to prepare inputs for mathematical models using outputs from the above steps 1 and 2. An Excel workbook which contains seven worksheets (Data Blocks) for the MIPC model and six worksheets for the MIPCH model is used for step 3. The Excel worksheets (Data Blocks) are described as follows:

1) Worksheet (Block) 1: Institutions

This worksheet contains a summary of institutions data which includes: institution name, institution ID, zone assigned, Institution Factor, location of institution, Importance Factor of an institution, and cost of building an EV charging station. "institution names" are obtained from the step 1 of Offline Stage. "institution IDs" are assigned based on proximity, i.e. closer institutions have closer "institution IDs". "Zone assigned" is decided at the step 2 of Offline Stage. The "Institution Factor", "location of institution" are obtained from the step 1 of Offline Stage. The Importance Factor of an institution, $impi_i$, is explained in detail in Section 2.1.4.

If an institution is located in the city, the cost of level 2 charging station, $c2_i$, is computed. Otherwise, if a pseudo-institution is located on a highway, the cost of level 3 charging station, $c3h_i$, is computed. Details are given in Section 2.1.4.

2) Worksheet (Block) 2: Clusters

This worksheet is a matrix mapping each institution to a zone, which is obtained at the "Clustering" step of the Offline Stage. If an institution "i" is assigned to zone "z," the corresponding cell of the matrix takes value of 1, Otherwise, 0. This matrix is used as direct input to mathematical models (sets values to parameter $cl_{i,z}$).

3) Worksheet (Block) 3: Importance of Institutions

This worksheet lists the Importance Factor of each institution, either in a city or on a highway. This table is used as direct input to mathematical models (sets values to parameter $impi_i$).

4) Worksheet (Block) 4: Cost of Level 1 Charging Stations

This worksheet computes and lists the cost to install a level 1 charging station at a zone based on the average Importance Factor of all the institutions assigned to the zone. This table is used as direct input to mathematical models (sets value to parameter $c1_z$).

5) Worksheet (Block) 5: Cost of Level 2 Charging Stations

This worksheet lists the cost to install a level 2 charging station at an institution if the institution is located inside a city. This table is used as direct input to mathematical models (sets value to parameter $c2_i$**)**.

6) Worksheet (Block) 6: Cost of Level 3 Charging Stations

For institutions located in a city, this worksheet computes the cost to install a level 3 charging station between two zones in a city. The computation details are explained in Section 2.1.4. The resulting matrix is used as direct input to mathematical models (sets values to parameter $c3c_{z,z'}$). For pseudo-institutions located on a highway, this worksheet lists the cost of level 3 charging station at each institution, which is used as direct input to mathematical models (sets values to parameter $c3h_i$).

7) Worksheet (Block) 7: Importance between two zones (Only for model MIPC).

This worksheet computes the average Importance Factor between two zones (i.e., $\overline{imp}_{z,z'}$). The value of $imp_{z,z'}$ is then computed based on $\overline{imp}_{z,z'}$ and the distance between two zones and used as direct input to mathematical models (sets values to parameter $imp_{z,z'}$).

2.1.4. Determination of key parameters

Based on authors' experiences on the EV industry, the determination of the following key parameters is explained in detail. The values of these parameters are computed at the Offline Stage and used as direct inputs to Online Stage.

$\boldsymbol{impi_i}$= the Importance Factor of institution i. The parameter $impi_i$ is computed based on institution i's location within its zone and other factors (i.e.,the total number of employees, fleet size, traffic inflows, and traffic outflows). The computation of $impi_i$ is illustrated using the example of a public institution, the Ministry of Economy and Finance of Morocco (MEFM) located in Rabat, as follows.

Table 2. Data on MEFM

Institution ID	Zone ID	Institution Factor	Location	Institution Importance Factor
$i14$	$z3$	90	M	100

As shown in Table 2, MEFM is assigned an ID of "$i14$". It is assigned to zone "$z3$" after "Clustering". MEFM has an "Institution Factor" of 90 which is determined by four traits: number of employees, number of vehicles, magnitude of inflows, and magnitude of outflows. The four traits, representing the movement around the institution and consequently the usage of its EV fleet, can be obtained from public sources (e.g., the data on MEFM were obtained from Moroccan Department of Administration Reform (MDAR, 2022). Each trait of an institution is given a score from zero to a maximum score as listed in Table 3, based on the institution's information. The total score of the four traits accounts for the "Institution Factor" of an institution.

Table 3. Maximum score on each trait of an institution

Factor	Number of Employees	Number of Vehicles	Magnitude of Inflows	Magnitude of Outflows	Location
Maximum Score	25	25	20	20	10

Another factor considered separately is the location of an institution inside a zone. If an institution is located close to or at the center of the zone, a score of 10 is given to its "Location" factor. The sum of the "Institution factor" and the "Location" factor gives the "Importance Factor" of an institution. The maximum value of "Importance Factor" is therefore 100. In our example, MEFM is scored 25 on the factor "Number of Employees" given its high number of employees, 25 on the factor "Number of Vehicles" given the high number of vehicles MEFM uses to transport its employees, and scored 20 on both the "Magnitude of Inflows" and "Magnitude of Outflows" given the high traffic inflows and outflows of MEFM's vehicles. Thus, the "Institution Factor" of MEFM is 90 (25+25+20+20). "M" in Table 2 means that MEFM is located in the middle of zone "*z3*" based on the clustering algorithm. Hence, MEFM has a score of 10 for its "Location" factor. MEFM's "Importance Factor" is thus 100 (90+10), as listed in the last column of Table 2. The same approach is applied to obtain the Importance Factors of all other public institutions considered in this paper.

$\boldsymbol{impfz_z}$ = the Importance Factor of zone *z*. The parameter $impfz_z$ is computed by taking the average of the Importance Factors of all institutions assigned to zone *z* as follows:

$$impfz_z = \frac{\sum_{i \in \boldsymbol{ZIC}_{z,i}} impi_i}{|ZIC_{z,i}|}$$

Where $ZIC_{z,i}$is the set of institutions assigned to zone *z*; $|ZIC_{z,i}|$ is the cardinal number of set $ZIC_{z,i}$.

$\boldsymbol{imp_{z,z'}}$ = the Importance Factor between zones z and z'. The parameter $imp_{z,z'}$ reflects the magnitude of traffic flow between two zones. We first compute the average of two zone Importance Factors:

$$\overline{imp}_{z,z'} = \frac{impfz_z + impfz_{z'}}{2}$$

Then, $imp_{z,z'}$, is obtained as follows:

$$imp_{z,z'} = \begin{cases} 0, & if\ |DIST_{z,z'}| < EVDIST \\ \overline{imp}_{z,z'}, & if\ |DIST_{z,z'}| \geq EVDIST \end{cases}$$

Where $|DIST_{z,z'}|$ is the distance between zones z and z'. *EVDIST* is a distance threshold. In general, it is not necessary to open a level 3 fast charging station within a city because EVs have longer time for charging (with backup EVs available) and zones in a city are usually not very far from each other. EVs can move between zones without requiring a stop for charging. An EV can be charged at a level 2 charging station of the source zone and if necessary at a level 2 charging station of the destination zone. Thus, when the distance between zones z and z', $|DIST_{z,z'}|$, is less than a distance threshold, *EVDIST*, it is not necessary to open a level 3 charging station because EVs can move between the two zones without requiring a stop for charging. $imp_{z,z'}$ is thus set to 0. *EVDIST* is set to 30Km in this paper. For zones which are far from each other ($|DIST_{z,z'}| \geq EVDIST$), $imp_{z,z'}$ is set to $\overline{imp}_{z,z'}$, which captures the traffic flows between two zones. When two zones in a city are both important (the parameter $\overline{imp}_{z,z'}$ has high value), the traffic flows between them are usually high. In situations where two zones are far and $imp_{z,z'}$ is also high, it becomes necessary to set up a level 3 fast charging station between two zones so that EVs can be charged rapidly in between.

$\boldsymbol{c1_z}$=the cost to open a level 1 charging station in zone *z*. The parameter $c1_z$ is computed as follows:

$$\mathbf{c1}_z = \begin{cases} \dfrac{impfz_z}{ImpBase} \times FixedCostLvl1\,, & if\ impfz_z \geq ImpBase \\ FixedCostLvl1, & otherwise \end{cases}$$

Where *FixedCostLvl1* is the average fixed cost of a level 1 charging station, *ImpBase* is the base Importance Factor of an institution. When $impfz_z$ is greater than or equal to *ImpBase*, the cost $c1_z$ is proportional to $impfz_z$. The higher the Importance Factor of a zone, the higher the cost $c1_z$. The Higher Importance Factor of a zone means the zone is busier; a larger charging station that can host more EVs is then needed. Such proportional relationship is based on authors' field experiences, which holds for all levels of charging stations. *ImpBase* represents the Importance Factor of an average institution operating at basic capacity. Since $impfz_z$ is the average of the Importance Factors of all institutions assigned to zone *z*, the value of $impfz_z$ of an average zone with average institutions operating at basic capacities is also *ImpBase*. Thus, *ImpBase* is also the base Importance Factor of a zone. If $impfz_z$ is less than *ImpBase*, the cost $c1_z$ is fixed to a minimum cost, *FixedCostLvl1*, which represents the cost necessary to set up an average level 1 charging station and operate at basic capacity. To set up such a station, the cost is between \$300 and \$600 while the parts cost varies between \$0 and \$1700 based in authors' experience. We assume in this paper that the level 1 station fixed cost (*FixedCostLvl1*) is \$500 (\$300 for the station and \$200 for the labor). The cost $c1_z$ is incurred if and only if a level 1 charging station is decided to be opened in zone z.

$\boldsymbol{c2_i}$= the cost of opening a level 2 charging station at institution *i*. The parameter $c2_i$ is computed as follows:

$$c2_i = \begin{cases} \frac{impi_i}{ImpBase} \times FixedCostLvl2\,, & if\ impi_i \geq ImpBase \\ FixedCostLvl2, & otherwise \end{cases}$$

Where *FixedCostLvl2* is the average fixed cost of a level 2 charging station. When the Importance Factor of an institution, $impi_i$, is greater than or equal to *ImpBase*, the cost $c2_i$ is proportional to $impi_i$. If $impi_i$ is less than *ImpBase*, the cost $c2_i$ is fixed to a minimum cost, *FixedCostLvl2*, which represents the cost necessary to set up an average level 2 station operating at basic capacity. To set up such a station, the cost is between $500 and $2,200 while the parts cost varies between $1,200 and $3,300 based in authors' experience. Parameter *FixedCostLvl2* is assumed to be $5,000 ($2,000 for the setup and $3,000 for the labor) in this paper.

$\boldsymbol{c3c_{z,z'}}$ = the cost of opening a level 3 charging station between zones z and z' in a city. The cost $c3c_{z,z'}$ is computed as follows:

$$c3c_{z,z'} = \begin{cases} \frac{imp_{z,z'}}{ImpBase} \times FixedCostLvl3\,, & if\ imp_{z,z'} \geq ImpBase \\ FixedCostLvl3, & otherwise \end{cases}$$

Where *FixedCostLvl3* is the average fixed cost of a level 3 charging station. When $imp_{z,z'}$ is greater than or equal to *ImpBase*, the cost $c3c_{z,z'}$ is proportional $imp_{z,z'}$. The parameter *FixedCostLvl3* represents the fixed cost necessary to set up a level 3 station operating at basic capacity. To set up such a station, the station cost is between $20,000 and $50,000 while the parts cost is above $10,000 based on authors' experience. Parameter *FixedCostLvl3* is assumed to be $30,000 ($20000 for the station and $10000 for the labor).

$\boldsymbol{c3h_i}$ = the cost of opening a level 3 station on a highway pseudo-institution *i*. Each potential charging stations on a high way is defined as a pseudo-institution. The cost $c3h_i$ represents the cost necessary to build a level 3 station at a pseudo-institution *i*:

$$c3h_i = \begin{cases} \dfrac{impi_i}{ImpBase} \times FixedCostLvl3\,, & if\ impi_i \geq ImpBase \\ FixedCostLvl3, & otherwise \end{cases}$$

2.2. The Online Stage

The Online Stage includes executing mathematical models and conducting scenario analysis. We now present two Mixed Integer Linear Programming (MILP) models for EV charging network design. The first model is to design an EV charging network for institutions within a geographic area, usually in a major city (MIPC). The second model extends MIPC to a network of several cities linked through highways (MIPCH).

2.2.1. The MIPC model

The MIPC model is to design an EV charging network for institutions within a geographic area or a city. The Appendix contains the sets, parameters, and variables used in MIPC. Key parameters are explained in Section 2.1.4.

Objective Function

The objective is to minimize the total cost of opening all levels of EV charging stations within a network of institutions.

$$\text{Minimize} \quad TC = \sum_{z \in Z} c1_z l1_z + \sum_{i \in I} c2_i l2_i + \sum \sum_{z,z' \in Z \cap z \neq z'} c3c_{z,z'} \, l3c_{z,z'} \qquad (1)$$

If a level 1 ($l1_z$), level 2 ($l2_i$), or level 3 ($l3c_{z,z'}$) EV charging station is opened, its respective costs is incurred and added to the total cost, *TC*. This paper seeks to find the minimum *TC* as an important input for decision makers to migrate EV network in a geographic area.

Constraints

We now present the following constraints applicable to MIPC.

1) Within each zone, only one level 2 charging station is opened.

$$\sum_{i \in ZIC_{z,i}} cl_{i,z} l2_i = 1, \quad \forall z \in Z \tag{2}$$

Each institution is assigned to a specific geographic zone. Among all institutions within a zone, one institution is selected to set up a level 2 charging station, which in turn contains several level 2 electric terminals. Opening a level 2 charging station is the most suitable choice for a zone within a city because a leve1 1 charging station takes hours to charge an EV, which is non-operable for institutions operating fleets of EVs, while opening level 3 charging stations is not economical given significantly higher installation and equipment costs. Since the geographic size of each zone is within HWD, opening one level 2 charging station is enough and EVs operating in a zone can be charged easily.

2) Within each zone, the most important institution is selected to open a level 2 charging station.

$$\sum_{i \in ZIC_{z,i}} cl_{i,z} impi_i l2_i \geq \max_{i \in ZIC_{z,i}} cl_{i,z} impi_i \,, \forall z \in Z \tag{3}$$

Since we seek the centralization of EV charging within each zone, selecting the most important institution, i.e., the one which has high traffic magnitude while being close to the center of the zone, is more convenient and operational. Indeed, such institution is within the HWD from other institutions within the same zone and has higher flows within the zone. Hence, locating a level 2 charging station at the most important institution ensures an efficient handling of transportation within the zone as well as with other zones.

3) Within each zone, a level 1 charging station is opened when the zone Importance Factor is high.

$$impz + BM1 \times l1_z \geq impfz_z, \forall z \in Z \tag{4}$$

Within a zone, one institution is selected to host a level 2 charging station, which can be used throughout a day to charge EVs. If a zone is particularly important (consists of institutions with high Importance Factors and hence operating more EVs), the zone is further supported by a level 1 charging station where EVs of public institutions can be charged overnight and be ready the next day. In constraint (4), a level 1 charging station is opened when the important factor of the zone is higher than a specific importance threshold, *impz*. *BM1* is a large number whose value is set to (100-impz), the smallest possible value of *BM1*.

4) A level 3 charging station is opened when the Importance Factor between two zones is high.

$$impbz + BM2 \times l3c_{z,z'} \geq imp_{z,z'}, \; \forall z, z' \in Z, z \neq z' \tag{5}$$

The Importance Factor between two zones z and z', $imp_{z,z'}$, reflects the magnitude of traffic flows between two zones. When $imp_{z,z'}$, is higher than a specific threshold, *impbz*, a level 3 charging station is opened. Within a city, it is usually not necessary to open a level 3 charging station given short distances among zones. This paper takes into account special cases that may occur within a city when the traffic flow between two zones are very high and it becomes necessary to add a fast charging station (i.e., level 3) to avoid traffic flow interruptions. In constraint (5), *BM2* is a large number whose value is set to (100- *impbz*), the smallest possible value of *BM2*.

Assumptions

The following assumptions are used for MIPC:

- In most cities of the world, traditional public buses are operated by city governments. The buses shuttle among zones of a city and are scheduled as a whole by the city. In this paper, we assume a city government replaces traditional public buses with fleets of EVs serving public institutions in a city. To manage EV fleets, opening one central EV charging station serving all EVs may not be feasible given limited driving range of EVs. This paper assumes that EV charging stations are distributed among public institutions. The MIPC model seeks to find the optimal locations of EV charging stations.

- This paper assumes that EVs shuttle within a zone and/or between zones. EVs are shared by all zones and can be moved to high demand zones. EVs can be charged at any zone and parked overnight at any zone.
- An EV user (an EV passenger or an EV driver) may face three scenarios: (i) The user can use available EVs within his/her institution; (ii) The user needs to walk to the institution where the charging station is installed if there is no EV available at his/her institution; (iii) The user waits for the prospective arrival of an EV at his institution. To cope with the above scenarios, each zone consists of institutions that are within the walking range of a normal human, i.e., between 300m to 600m. EV users can thus walk among institutions located in the same zone.
- One EV charging station contains several electric terminals of the same type. An EV charging station can thus serve several EVs simultaneously. The number of electric terminals within one charging station can be determined based on the average number of EVs, traffic flows and other factors, which is out of the scope of this paper.

Results of MIPC and Scenario Analysis

The MIPC model, which includes objective function (1) and constraints (2)-(5), is applied to the capital of Morocco, Rabat, as shown in Figure 4. There are 49 major public institutions in Rabat which are considered in the model. To save space, Table 4 provides the detailed data only for the first 6 institutions. The clustering step of Offline Stage of EVMF provided the zone assignment of each institution shown in the second column. The

Institution Factor/Location/ Importance Factor of each institution is shown in columns 3, 4, 5, respectively. The last column provides the computed costs for opening a level 2 charging station within each institution.

Table 4. Partial Data for MIPC model

ID	Zones	Institution Factor	Location	Importance Factor	Cost Level 2 ($)
i1	z1	70	M	80	5714
i2	z1	70	M	80	5714
i3	z2	70	M	80	5714
i4	z2	80	M	90	6429
i5	z3	90	-	90	6429
i6	z3	70	-	70	5000

The parameter HWD can significantly affect the model size and results. Table 5 lists the MIPC model size at different HWDs. With the increase of HWD, the number of zones assigned in city Rabat decreases, and hence the decrease of the MIPC model size.

Table 5. MIPC Model Size at Different HWD

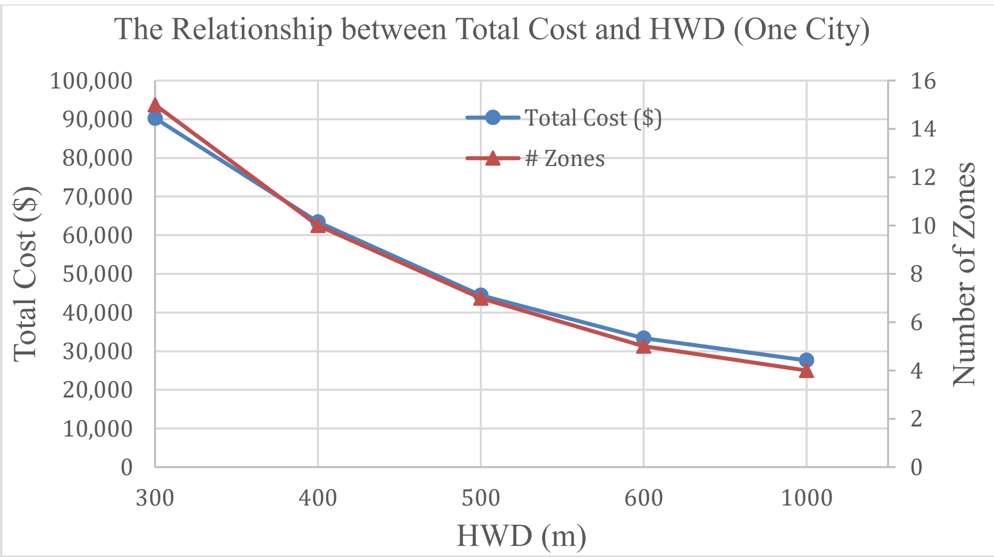
HWD (m)	# Single Equations	# Single Variables	# Discrete Variables
300	271	290	289
400	131	160	159
500	71	106	105
600	41	80	79

ILOG CPLEX 12.7 is used to solve all the models in this paper on a HP computer with Intel Core i7 7th Gen. All CPLEX settings follow directly from the system default. Table 6 summarizes the results from the MIPC model for city Rabat. In Table 6, "# Level 1/# Level 2/# Level 3" shows the total number of level 1/level 2/level 3 charging station opened, respectively. We can see that the total costs are negatively correlated with the HWD. A shorter HWD (e.g., 300 m) leads to more zones assigned and more EV charging stations opened and hence higher costs. This trend can also be observed in Figure 5. It can be also observed that, with the increase of HWD, "# Zones" and the "Total Cost" decrease at similar trend. The model execution is very efficient with solution time less than 0.1 second. With such short MIPC execution times, policy makers can easily simulate various scenarios for EV migration. The Offline Stage of EVMF has prepared necessary parameters and reduced the computational load of the model MIPC.

Table 6. MIPC Model Results

HWD (m)	Sol. Time (s)	# Zones	# Level 2	# Level 1	# Level 3	Total Cost ($)
300	0.09	15	15	5	0	90,283.7
400	0.08	10	10	3	0	63,427.8
500	0.06	7	7	2	0	44,434.1
600	0.06	5	5	2	0	33,324.9
1000	0.05	4	4	2	0	27,606.1

Figure 6. The Relationship between Total Cost and HWD (One City)



This papers also tests scenarios when HWD is 700/800/900/1000 m. Further increase of HWD beyond 1000 m becomes impractical for human walking. When HWD is 700/800/900 m, the number of zones obtained by clustering is the same as when HWD is 600 m according to the clustering algorithm. In Figure 7, we can see that, when HWD increases beyond 600, the total cost reduces at slower speed. Such kind of analysis can provide importance insights for decision making.

2.2.2. The MIPCH Model

The MIPCH model extends MPIC model to include a network of cities connected through highways. The Appendix contains the sets, parameters, and variables used in MIPCH. Key parameters are explained in Section 2.1.4.

Objective Function

The objective is to minimize the total cost of opening three levels of charging stations within cities and on highways connecting cities.

$$\text{Minimize} \quad \text{TC} = \sum_{z \in ZC} c1_z l1_z + \sum_{i \in IC} c2_i l2_i + \sum_{i \in IH} c3h_i l3h_i \tag{6}$$

Similar to model MIPC, level 2 charging stations may be opened within a city ($l2_i = 1$) and level 1 charging stations may be opened when a zone's Importance Factor is high ($l1_z = 1$). On highways, only level 3 charging stations are opened due to the requirement of short EV charging time ($l3h_i = 1$). An EV can complete charging at a level 3 charging station in half an hour while it takes a few hours for level 1 or level 2 charging stations.

Constraints

We now present the following constraints applicable to MIPCH.

1) Within each zone in cities, only one level 2 charging station is opened.

$$\sum_{i \in ZIC_{z,i}} cl_{i,z} l2_i = 1, \;\; \forall z \in ZC \tag{7}$$

Without loss of generality, institutions at different cities are indexed consecutively. Zones assigned to institutions at different cities are also indexed consecutively.

2) Within each zone in cities, the most important institution is selected to open a level 2 charging station.

$$\sum_{i \in ZIC_{z,i}} cl_{i,z} impi_i l2_i \geq \max_{i \in ZIC_{z,i}} cl_{i,z} impi_i, \;\; \forall z \in ZC \tag{8}$$

3) Within each zone in cities, a level 1 charging station is opened when the zone Importance Factor is high.

$$impz + BM1 \times l1_z \geq impfz_z, \forall z \in ZC \tag{9}$$

4) Within each zone on highways, only one level 3 charging station is opened.

$$\sum_{i \in IH \cap ZIC_{z,i}} cl_{i,z} l3h_i = 1, \forall z \in ZH \tag{10}$$

In this paper, each highway between two cities is segmented into several zones (set *ZH*) depending on highway length. Each highway zone contains several pseudo-institutions (set *IH*), each representing a potential level 3 charging station. Among these pseudo-institutions within a highway zone, one is selected to be the location of a level 3 charging station, which contains several level 3 electric terminals. EVs traveling between cities can be charged rapidly on highways at level 3 charging stations.

5) Within each highway zone, the most important pseudo-institution is selected to open a level 3 charging station.

$$\sum_{i \in IH \cap ZIC_{z,i}} cl_{i,z} impi_i l3h_i \geq \max_{i \in IH \cap ZIC_{z,i}} cl_{i,z} impi_i, \;\; \forall z \in ZH \tag{11}$$

Assumptions

Besides the assumptions used in model MIPC, the following additional assumptions are used for MIPCH:

- This paper assumes that EVs shuttle within a zone, between zones, and on highways. EVs are shared by all zones of all cities. EVs can be moved to high demand zones and can be charged in any zone. This is ensured by government fleet management centralization.
- A highway is segmented into zones based on a specific distance (30km is used in this paper). It means that an EV can be charged every 30 Km. This paper assumes that a 30km of highway segmentation distance (HSD) is sufficient enough to tackle the range anxiety with a highway. The impact of different HSDs is simulated and discussed below.
- Pseudo-institutions are either existing gas stations or newly opened terminals located along highways which can be potentially used as EV charging locations. The Importance Factor of a pseudo-institution is obtained based on factors such as the size of its parking lot, ease of access from highway, and availability of services such as restaurants, shops, and toilets etc. The more important a pseudo-institution, the more suitable it is for EV charging.
- For simplicity, in the MIPCH model, it is assumed that level 3 charging stations are needed only on highways. They are not needed within cities. This assumption can be released by adding a constraint similar to constraint (5) of model MIPC.

Results of MIPCH and Scenario Analysis

To illustrate the MIPCH model, three major cities of Morocco, the capital Rabat, Casablanca, and Fes linked through two highways are used as an example. Figure 6 shows the map of the three cities.

There are 49/127/39 major public institutions in Rabat/Casablanca/Fes considered in the model. The data of the institutions in Rabat are the same as those used in model MIPC. From data mining step, parameters are defined the same way as in model MIPC. Three highway zones and 17 pseudo-institutions are considered on the highway between Rabat and Casablanca. To save space, Table 7 lists 9 out of the 17 pseudo-institutions considered on the highway between Rabat and Casablanca. Seven highway zones and 27 pseudo-institutions are considered on the highway between Rabat and Fes.

Figure 6. The Three Cities and Two Highways used in model MIPCH

Table 7. Partial Data of Pseudo-Institutions on the Highway Between Rabat and Casablanca

Institution ID	Assigned Zone ID	Importance Factor	Cost of Opening a Level 3 Charging Station, $
i216	z50	67	28,714
i217	z50	81	34,714
i218	z50	72	30,857
i219	z50	63	27,000
i220	z51	65	27,857
i221	z51	65	27,857
i222	z51	84	36,000
i223	z51	74	31,714
i224	z51	64	27,429

Two parameters, HWD and HSD, can significantly affect the model size and results. To understand the impacts at different scenarios, a learning cycle is formed which involves both Offline and Online Stages. The results for different sets of HWDs and HSDs are presented in Table 8 and Table 9. Table 8 and Figure 7 show results at different HWDs with HSD fixed to 30 Km. Similar to results from MIPC, shorter HWD leads to more zones assigned and more EV charging stations to be opened and hence higher costs. Table 9 and Figure 8 show results at different HSDs with HWD fixed to 500m. We can see that, with the increase of HSDs, less zones and EV charging stations, in particular, level 3 charging stations, are required. The total cost is hence reduced.

Table 8. Results With HSD=30km

HWD (m)	Sol. Time (s)	# Zones	# Level 2	# Level 1	# Level 3	Total Cost ($)
300	0.03	80	70	21	10	795,134.1
400	0.03	66	56	16	10	714,094.4
500	0.06	59	49	10	10	668,078 .1
600	0.06	45	35	9	10	587,332.6

Figure 7. The Relationship between Total Cost and HWD (With HSD=30km)

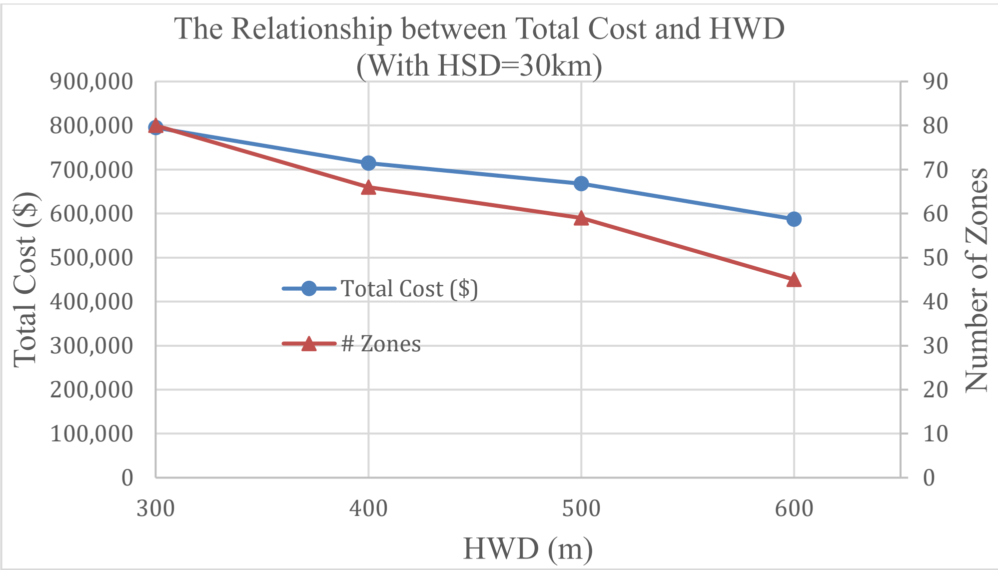
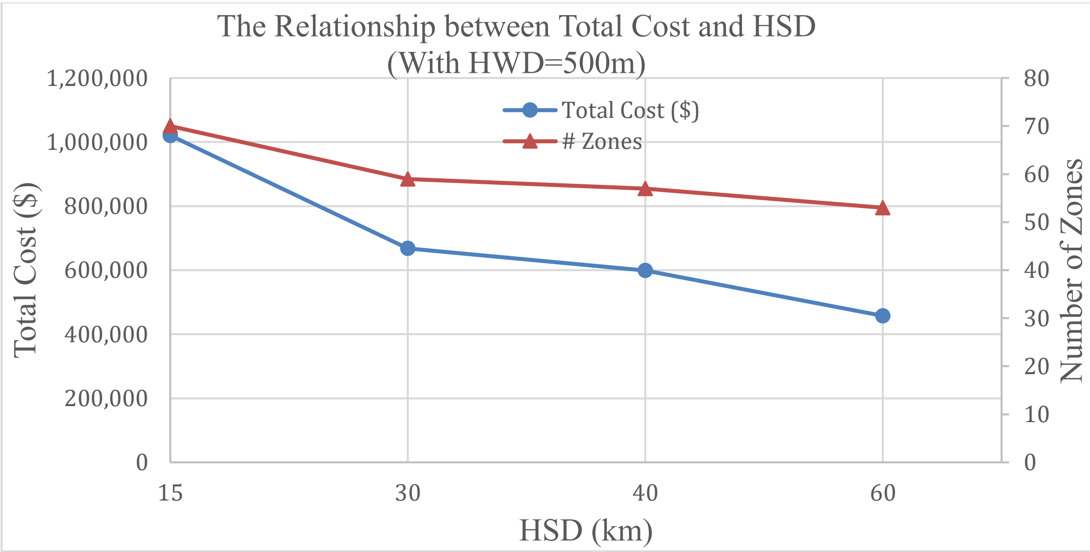


Table 9. Results With HWD=500m

HSD (km)	Sol. Time(s)	# Zones	# Level 2	# Level 1	# Level 3	Total Cost ($)
15	0.03	70	49	10	21	1,020,792.4
30	0.06	59	49	10	10	668,078 .1
40	0.10	57	49	10	8	598,847.8
60	0.11	53	49	10	4	457,419.2

Figure 8. The Relationship between Total Cost and HSD (With HWD=500m)



The MIPCH model size in different settings is presented in Table 10 and Table 11. The model execution time is less than 1s. The results show the scalability of the MIPCH model. The model can be extended to optimize an EV network of several cities and highways. Results from the learning cycle provide essential insights on EV migration in a region or a country.

Table 10. Model Size With HSD=30km

HWD (m)	# Single Equations	# Single Variables
300	231	330
400	189	316
500	168	309
600	126	295

Table 11. Model Size With HWD=500m

HSD (km)	# Single Equations	# Single Variables
15	190	309
30	168	309
40	164	309
60	156	309

3. Conclusions

This paper has developed an efficient two-stage framework, EVMF, to assist decision makers for EV migration. The Offline Stage involves three steps: identifying geographic locations, clustering, and data mining. The Online Stage includes two mathematical models (MIPC and MIPCH) and scenario analysis. EVMF considers all the institutions and fleets of EVs as a whole, and develops integrated models to find optimal solutions. EVMF is applied to the capital of Morocco (Rabat) and also to three major Moroccan cities (Rabat, Casablanca, and Fes) linked with two highways. Optimal results for various scenarios are obtained with rapid solution time (less than 1 second). The MIPC model tested scenarios with human walking distance ranges from 300 to 1000 m. The MIPCH model tested scenarios with human walking distance ranges from 300 to 600 m and with Highway Segmentation Distance ranges from 15 to 60 km. The total cost at different scenarios provide important insights for decision making. The results demonstrated the celerity, scalability, and flexibility of the framework. EVMF is particularly useful for developing countries lacking tools in making efficient decisions for EV migration.

This research opens the window towards another important topic: EV routing and scheduling. Once an EV network is determined following EVMF, future work can include routing and scheduling to minimize traveling time and costs of EVs, leading to better management and utilization of existing charging stations and better traffic flow balance among all zones either in cities or on highways. Even though the EV charging stations designed in this paper are used to serve EV fleets for public institutions, it is possible to share such charging stations with private EVs. With demand data from private EVs within a region or among several regions, future research can extend models in this paper to design EV networks which can serve both public and private EV fleets. EVMF can also be readily extended to include city residential areas by adding zones from residential areas.

Acknowledgments

The authors are grateful for technical support from Fostergy Technologies Inc., a company specializing in EV simulation and EV migration.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix Definitions of indices, sets, parameters, and variables

a) Indices

i = institutions, public institutions in regions or pseudo-institutions on highways, i= 1,2, …, I.

z, z' = zones, a cluster of neighboring institutions, z, z' =1,2,…, Z.

b) Sets

I = set of all institutions in cities or pseudo-institutions on highways.

IC = set of institutions in cities.

IH= set of pseudo-institutions on highways.

Z= set of zones assigned to institutions in cities or pseudo-institutions on highways.

ZC= set of zones assigned to institutions in cities.

ZH= set of zones assigned to pseudo-institutions on highways.

$ZIC_{z,i}$ = set of institutions assigned to zone z.

c) Parameters

$c1_z$= The cost to open a level 1 charging station in zone z. This cost is incurred only if a zone is very important.

$c2_i$= The cost of opening a level 2 charging station at institution i.

$c3c_{z,z'}$ = The cost of opening a level 3 charging station between zones z and z' in a region or a city.

$c3h_i$= The cost of opening a level 3 charging station at pseudo-institution i.

$cl_{i,z}$ = A matrix mapping institutions to zones. $cl_{i,z}$ takes value of 1 if institution i is assigned to zone z and 0 otherwise. The mapping is done offline at the "Clustering" step of the Offline Stage. The values are stored at Worksheet (Block) 2.

$\left|DIST_{z,z'}\right|$ = the distance between zones z and z'.

$EVDIST$ = a distance threshold. $EVDIST$ is set to 30Km in this paper taking into account EV range anxiety.

$impi_i$= The Importance Factor of institution i.

ImpBase = the base Importance Factor of institutions. In this paper, its value is assumed to be 70.

$impfz_z$ = The Importance Factor of zone *z*.

$imp_{z,z'}$ = the Importance Factor between zones *z* and z' .

$\overline{imp}_{z,z'}$ = the average of Importance Factors of zones *z* and z' .

impbz = the threshold of the Importance Factor between two zones to set up a level 3 charging station. *impbz* is set to 95 in this paper. The value of *impbz* can be adjusted according to factors such as available budget, the frequency and urgency of activities, the city role in a country, and other factors.

impz = the threshold for a zone to set up a level 1 charging station. *impz* is set to 80 in this paper. The value of *impz* can be adjusted according to factors such as available budget, facility availability, nature of working, and other factors.

BM1 = a large number whose value is set to (100-*impz*), the smallest possible value of *BM1*.

BM2 = a large number whose value is set to (100- *impbz*), the smallest possible value of *BM2*.

FixedCostLvl1 = the fixed cost necessary to set up an average level 1 charging station operating at basic capacity. It is assumed to be $500 in this paper.

FixedCostLvl2 = the fixed cost necessary to set up an average level 2 charging station operating at basic capacity. It is assumed to be $5,000 in this paper.

FixedCostLvl3 = the fixed cost necessary to set up an average level 3 charging station operating at basic capacity between zones. It is assumed to be $30,000.

d) Variables

TC = The total cost of setting up an EV charging network.

$l1_z$ = Binary variable. It takes values of 1 if a level 1 charging station is to be opened in zone z and 0 otherwise.

$l2_i$ = Binary variable. It takes value of 1 if a level 2 charging station is to be opened at institution i and 0 otherwise.

$l3c_{z,z'}$ = Binary variable. It takes value of 1 if a level 3 charging station is to be opened between zones z and z' in a region or a city and 0 otherwise.

$l3h_i$ = Binary variable. It takes value of 1 if a level 3 charging station is to be opened at pseudo-institute i and 0 otherwise.

References

Akendi (2018). Greening Government Fleets, A helpful guide to understanding best practices. *https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/energy/pdf/transportation/NRCan_GreeningGovFleets_e.pdf* (accessed in Feb. 2022).

Amjad, M., Ahmad, A., Rehmani, M. H., & Umer, T. (2018). A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques. *Transportation Research Part D: Transport and Environment*, *62*, 386-417.

Capar, I., Kuby, M., Leon, V. J., & Tsai, Y. J. (2013). An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. *European Journal of Operational Research*, *227*(1), 142-151.

CARB (The California Air Resources Board) (2018). California transitioning to all-electric public bus fleet by 2040, *https://ww2.arb.ca.gov/news/california-transitioning-all-electric-public-bus-fleet-2040* (accessed in Feb. 2022).

Cavadas, J., de Almeida Correia, G. H., & Gouveia, J. (2015). A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. *Transportation Research Part E: Logistics and Transportation Review*, *75*, 188-201.

Chen, N., Gardner, L. M., Duell, M., & Waller, S. T. (2014). Evaluating Location Alternatives for Electric Vehicle Re-charging Infrastructure Using a Distance Constrained Equilibrium Assignment Model. In *Transportation Research Board 93rd Annual Meeting* (No. 14-1840).

Chen, T. D., Kockelman, K. M., & Khan, M. (2013). Locating electric vehicle charging stations: Parking-based assignment method for Seattle, Washington. *Transportation research record*, *2385*(1), 28-36.

Chung, S. H., & Kwon, C. (2015). Multi-period planning for electric car charging station locations: A case of Korean Expressways. *European Journal of Operational Research*, *242*(2), 677-687.

Community Energy Association. (2013). Planning for Electric Vehicle Charging Infrastructure: A Toolkit, *https://www.communityenergy.ca/wp-content/uploads/dlm_uploads/2014/06/Planning-for-EV-Charging-Infrastructure-A-Toolkit-June-2013.pdf* (accessed in Feb. 2022).

Earthjustice.org (2020). Electric vehicles are not just the wave of the future, they are saving lives today. Ten things to know about electric vehicles — and how you can make the future electric, *https://earthjustice.org/features/electric-vehicles-explainer* (accessed in Feb. 2022).

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. P. (2011). Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal. *Transportation Research Record*, *2252*(1), 91-98.

Ge, S., Feng, L., & Liu, H., The planning of electric vehicle charging station based on Grid partition method, 2011 International Conference on Electrical and Control Engineering, 2011, pp. 2726-2730, doi: 10.1109/ICECENG.2011.6057636.

GREENCARS (2021). How Many Electric Vehicles Sold in 2021? December 23, 2021, *https://www.greencars.com/post/how-many-electric-vehicles-sold-in-2021* (accessed in Feb. 2022).

Hanabusa, H., & Horiguchi, R. (September 2011). A study of the analytical method for the location planning of charging stations for electric vehicles. In *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems* (pp. 596-605). Springer, Berlin, Heidelberg.

Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. *Journal of the royal statistical society. series c (applied statistics)*, *28*(1), 100-108.

Huang, K., Kanaroglou, P., & Zhang, X. (2016). The design of electric vehicle charging network. *Transportation Research Part D: Transport and Environment*, *49*, 1-17.

Irle Roland, Global EV Sales for 2018 – Final Results, http://www.ev-volumes.com/news/global-ev-sales-for-2018 (accessed in Feb. 2022).

Jordán, J., Palanca, J., Del Val, E., Julian, V., & Botti, V. (2018). A multi-agent system for the dynamic emplacement of electric vehicle charging stations. *Applied Sciences*, *8*(2), 313.

Kuby, M., & Lim, S. (2005). The flow-refueling location problem for alternative-fuel vehicles. *Socio-Economic Planning Sciences*, *39*(2), 125-145.

Lam, A. Y., Leung, Y. W., & Chu, X. (2014). Electric vehicle charging station placement: Formulation, complexity, and solutions. *IEEE Transactions on Smart Grid*, *5*(6), 2846-2856.

Lambert, F. (2018). Electric vehicle sales achieve new record in Norway with 45% of new cars being all-electric and 60% plug-in, *https://electrek.co/2018/10/01/electric-vehicle-sales-new-record-norway-tesla* (accessed in Feb. 2022).

Lee, Y. G., Kim, H. S., Kho, S. Y., & Lee, C. (January 2014). UE-based location model of rapid charging stations for EVs with batteries that have different states-of-charge. In *Proceedings of the Transportation Research Board 93rd Annual Meeting, Washington, DC, USA* (pp. 12-16).

Linke, R. (2017). The real barriers to electric vehicle adoption. MIT Sloan. https://mitsloan.mit.edu/ideas-made-to-matter/real-barriers-to-electric-vehicle-adoption (accessed in Feb. 2022).

Liu, J. (2012). Electric vehicle charging infrastructure assignment and power grid impacts assessment in Beijing. *Energy policy*, *51*, 544-557.

Liu, M., Mcnamara, P., Shorten, R., & McLoone, S. (2015). Residential electrical vehicle charging strategies: the good, the bad and the ugly. *Journal of Modern Power Systems and Clean Energy*, *3*(2), 190-202.

MDAR (Moroccan Department of Administration Reform), https://www.mmsp.gov.ma (in French, accessed in Feb. 2022).

Nelson, L. J., & Reyes, E. A. (2017). Metro Agrees to Buy 95 Electric Buses, in the First Step toward an Emissions-Free Fleet. *Los Angeles Times*, *27*.

Ortt, J. R., Langley, D. J., & Pals, N. (2013, June). Ten niche strategies to commercialize new high-tech products. In *2013 International Conference on Engineering, Technology and Innovation (ICE) & IEEE International Technology Management Conference* (pp. 1-12).

Pratiwi, L. (2016). Barriers and Strategies for Transition to Electric Vehicles in BRICS Countries: Case Study of South Africa, India, and Brazil, https://repository.tudelft.nl/islandora/object/uuid:0b25e361-31ec-4cbf-9653-1e8764ce1864/datastream/OBJ/download (accessed in Feb. 2022).

Reuters (2020). Factbox-Japan's green growth strategy to help achieve carbon neutral goal, December 25, 2020, *https://reut.rs/3pnmwmt* (accessed in Feb. 2022).

Service-public.ma (2022), *http://maps.service-public.ma/mfpma/geo/front* (In French, accessed in Feb. 2022).

Shareef, H., Islam, M. M., & Mohamed, A. (2016). A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. *Renewable and Sustainable Energy Reviews*, *64*, 403-420.

Sun, Z., Gao, W., Li, B., & Wang, L. (2020). Locating charging stations for electric vehicles. *Transport Policy*, *98*, 48-54.

Xi, X., Sioshansi, R., & Marano, V. (2013). Simulation–optimization model for location of a public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, *22*, 60-69.