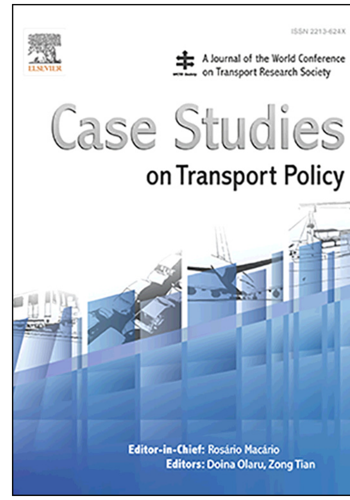

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PII: S2213-624X(18)30340-7
DOI: https://doi.org/10.1016/j.cstp.2019.06.003
Reference: CSTP 365

To appear in: *Case Studies on Transport Policy*

Received Date: 4 October 2018
Revised Date: 17 March 2019
Accepted Date: 4 June 2019

Please cite this article as: S. Bouguerra, S. Bharlayeb, Determining Optimal Deployment of Electric Vehicles Charging Stations: Case of Tunis City, Tunisia, *Case Studies on Transport Policy* (2019), doi: https://doi.org/10.1016/j.cstp.2019.06.003

Determining Optimal Deployment of Electric Vehicles Charging Stations: Case of Tunis City, Tunisia

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Abstract

Due to their reduced fossil fuel consumption and transportation-related emissions, Electric Vehicles (EV) are increasingly emerging. Nevertheless, one of the most important decisions for EV adoption is the planning of EV charging infrastructure. In this work, we address the real case of the centre of Tunis City, Tunisia, where potential charging stations could be located in parking and gas stations. The objective is to place and size EV charging stations in such a way that EV drivers can have access to chargers, within an acceptable driving range, while real world life constraints are respected. We also consider investment costs, as well as EV users' convenience. Toward this end, five Integer Linear Programs based on weighted set covering models are proposed and solved to optimality. Computational experimentation provides optimal infrastructure schemes that public makers could adopt within the emerging

environmental policy.

Keywords: Electric Vehicles; Charging Stations Location; Network Design Strategies; Integer Linear Programming; Tunisia.

1. Introduction

Reliance on fossil fuels has negative effects on the ecological and economic environment. Public awareness is rising concerning environmental and ecological issues. One major way to reduce fossil fuel consumption is using Electric Vehicles (EV). Besides, the fact that EV market is increasing (OECD/IEA 2016) is in line with consumers tending to switch to electric vehicles, if some adoption obstacles are leveraged (e.g. Chachdi et al. 2017 and Juan et al. 2016). In addition to the high price barrier, electric vehicles still have a relatively short driving range. Therefore, the deployment of a charging network to improve users' charging access is crucial to encouraging the adoption of this ecological solution. Recently, some studies on deployment of Electric Vehicles Charging Stations (EVCS) were carried out in cities such as Seattle (Chen et al. 2013), Beijing (Zhu et al. 2016), Ankara (Erbaş et al. 2018), Istanbul (Genevois and Kocaman 2018), and Singapore (Wang et al. 2019). This exploratory work contributes to this emerging field by determining the optimal size, as well as the location, of EVCS within the city center of Tunis, Tunisia. It is worth mentioning that this a pioneer study in Tunisia, and probably in African countries, to the best of our knowledge.

1.1. Related Work

Nowadays, EV charging devices are still under development and not yet fully standardised (Shareef et al.2016). Nevertheless, and prompted by the rapid development of the charging technology, it is usually assumed that there are three types of charging terminals (also called chargers). The power of the so-called chargers Level 1, 2 and 3 ranges from 1.4kw, 7.7kw, and 13.3kw to 1.9kw, 25.6kw, and 96kw, respectively. Moreover, the average charging times of chargers Level 1, 2, and 3are respectively 11.5h, 2h and 0.5h. Thus, Level 1 charging is more suitable for home charging, while chargers of Level 2 and 3 are more suitable for public or private facilities. In line with many recent works (e.g. Çatay and Keskin 2017 and Dascioglu and Tuzkaya, 2019), only Level 3chargers are considered in this study. For an excellent survey on EV charging facilities, the reader is referred to (Baouche et al. 2014) and (Ghamami et al. 2016).

During the last decade, EVCS planning problems have been extensively investigated and are still catching the interest of both practitioners and researchers (e.g. Kumar et al. 2018). The interested reader is referred to the recent review papers (Islam et al. 2015), (Shareef et al.2016), (Jing et al.2016), and (Pagany et al.2018). At this stage, it is worth noting that the problem of EVCS planning could be considered in relation to the city itself (Csiszár et al.2019).On the one hand, because of the EV short range, there are the so-called *inter-city* EVCS location problems that usually focus on locating the stations on highway corridors (e.g. Sathaye and Kelley2013). On the other hand, the variant of *intra-city* or urban EVCS location problems is receiving increasing attention due to the fact that EV users are more often urban drivers (Giménez-Gaydou et al. 2016). In this case, the potential EVCS are usually available parking lots located within the urban area (e.g. Chen et al.2013).

The existing literature about the EVCS planning covers a number of aspects. However, most relevant papers published so far focus on selecting sites for the EVCS. To solve this challenging problem, several modelling tools and solving approaches have been considered. Zhu et al. (2016) have proposed a genetic algorithm that minimises heuristically the sum of installation cost and EV users' travel costs of locating EVCS within a small metropolitan area in the city of Beijing. Similarly, Efthymiou et al. (2017) have developed a genetic algorithm, within the framework of an open-source user-friendly tool, devoted to finding appropriate EVCS deployment. Several mathematical models have also been investigated. Firstly, Frade et al. (2011) proposed a maximal covering location model for determining the optimal location of slow EVCS in Lisbon. Such a covering strategy was recently used by Mete et al. (2018) for finding optimal locations of bike-sharing stations within a university campus. Chen et al. (2013) have presented a Mixed Integer Linear Programming (MILP) formulation to find optimal assignment of EVCS to public parking locations within Seattle's downtown. The authors have also provided a predictive model to charging demand, based on parking demand data. Baouche et al. (2014) have addressed a fixed charge location Integer Linear Programming (ILP) model coupled with realistic p-dispersion constraints that minimizes the sum of the fixed EVCS installation cost and the EV user travel cost. Using a commercial solver, the model yields optimal locations for the EVCS within the city of Lyon, France. Recently, Li et al. (2018) reported a bi-level programming model that integrated decisions of both public makers and private owners of an EV fleet. A framework combining a variable neighbourhood descent based approach and a scatter search procedure is introduced to determine recharging infrastructures deployment. The performance of the proposed hybrid heuristic is assessed only on a dataset of benchmarks, without a real case study application.

In contrast to studies on EVCS location, the literature on both locating and sizing EVCS is relatively scant. For an urban zone of Tehran, Sadeghi-Barzani et al. (2014) constructed a Mixed Integer Non-Linear

Programming (MINLP) model that aims to minimize the installation cost of EVCS, including land, investment and electrification costs, as well as the electric grid loss and the EV energy loss in transmission. A genetic algorithm is provided to find adequate fast charging station placing and sizing. Experimentation showed that the cost of installing the EVCS represents one of the main parts of the total costs. In the same vein, a realistic multi-objective optimisation problem is formulated by Mozafar et al. (2017) taking into consideration several minimisation objective functions, such as voltage fluctuations index, power losses, depreciation of EV battery value and EVCS installation costs. A genetic algorithm, coupled with a particle swarm optimization based procedure, is established to find the appropriate allocation of the EVCS, as well as the renewable energy sources. In an inter-city context, Wang et al. (2018) have recently proposed a hybrid genetic algorithm within a two-stage procedure to first sit and then size EVCS in a highway network. The EV drivers' charging strategy is formulated with utility theory principles, taking into account the congestion of the site of each charging station. It is worth mentioning that the proposed procedure contains optimization, mainly in the first stage of the EVCS site selection procedure.

With regard to theoretical works or real case studies, there are almost no research papers that focus on developing or African countries, to the best of our knowledge. Besides, the large majority of the studies above provide heuristic approaches and more precisely enhanced genetic algorithms. This exploratory work contributes to the emerging field of EVCS sitting and sizing by addressing an appropriately weighted set covering based models under real life constraints. Solved to optimality, the proposed models provide an optimal scheme for the EVCS location and sizing, within the city centre of Tunis, Tunisia.

1.2. Context and Contributions

Being a signatory of the Paris Agreement, within the United Nations Framework Convention on Climate Change (UNFCCC, 2016), Tunisia has to take adequate measures to decrease greenhouse gas emissions, including the promotion of EV adoption. In this context, we are looking for optimal location, as well as sizing, EVCSs in one of the most densely-populated urban area of Tunisia: the centre of Tunis. To this end, we investigated several models regarding investment costs and users' convenience. To the best of our knowledge, this approach has only been addressed in a recent paper by Bouguerra and Layeb (2018), where the authors used two basic ILP models yielding only decisions about the location of the potential EV charging stations.

In this paper, we mainly make the following contributions:

1. We propose five ILP models to solve an urban parking EVCS location and sizing problem. These models are grouped into two families: (i) ILP models for location decisions only; and, (ii) ILP models for location and sizing decisions. Each of these families is characterised by specific decision variables, corresponding objective function, and appropriate real world constraints.

2. We present a real case study on the city centre of Tunis, Tunisia. For this pioneer work, a site investigation was conducted to collect and prepare data. The proposed infrastructure deployments would help Tunisian authorities to decide on locating future EVCS.

1.3. Paper Structure

The remainder of this paper is organised as follows. Section 2describes the case study and the proposed Integer Linear Programming models. Section 3 reports the numerical experimentation and the proposed infrastructure installation schemes. Finally, Section 4 draws conclusions and provides avenues for future research.

2. Problem Modelling

2.1. Assumptions

For the sake of convenience, we have made the following key assumptions:

- only day time charging is considered for the EV users. This seems convenient for a workplace urban area, such as our case study;

- only fast chargers (Level 3) are considered, and each installed charger could serve more than one EV;

-the access of EV drivers to a charging station within a tolerable travelled distance is a requirement;

- each EV can only be charged at one station.

2.2. Network Preparation

An important phase of this study is identifying potential locations for future EVCS. As considered in previous works such as Chen et al. (2013) and Zhu et al. (2016), candidate locations for the EV charging stations are existing gas and parking stations in the area included in the study. Geographic data is collected from Google Maps@. Parking lot data is also gathered from the Tunis municipality website (http://www.commune-tunis.gov.tn). A field study was also conducted to consolidate all these data. Details on potential locations are given in Annex 1. As shown in Figure 1, we identified *31* parking lots (marked in red) and *8* gas stations (marked in blue) within a *4.5* by *2.5km* service area.

Figure1:The identified potential EVCSlocations

Once the 39 candidate locations candidates had been identified, a graph of adjacency was derived as shown in Figure 2. In term of graph theory, it is a weighted undirected graph $G= (V, E).V$ is a set of n nodes presenting the potential charging stations ($n=39$) and E is a set of m edges presenting the possible neighbourhood based connections between the potential charging stations ($m=105$). The Cartesian distance on the neighbourhood of each station is then derived and annotated as $d_{i,j}(i, j\in V)$ representing the distance between locations i and j. The matrix of distances is given in Annex 2.

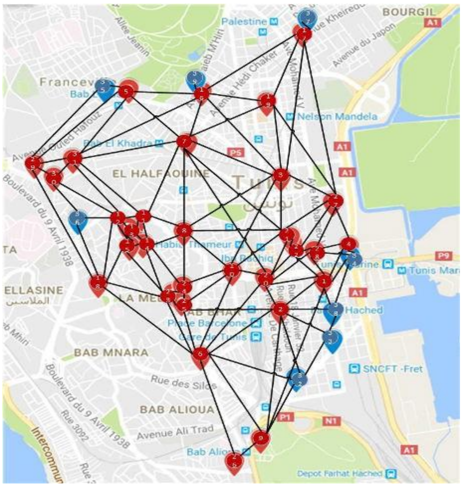

Figure 2: The constructed graph of adjacency

2.3. Linear Programming Models

In this section, we investigate two classes of ILP models based on the type of decision to be made.

2.3.1. ILP models for location decisions only

We begin by describing the first class of Integer Linear Programming (ILP) models based on the NP-hard set covering problem (Conforti et al. 2014). To that end, we define for each location $i \in V$, a binary variable x_i that takes the value *1* if a charging station is installed in location i and *0* otherwise. We denote by R a pre-fixed coverage radius representing the tolerable distance for EV users to travel in order to find an available charging station.

An intermediate constant is then used. Thus, let $\alpha_{i,j}$ $(i, j \in V)$ be a binary constant that takes value *1* if $d_{i,j} \leq R$, and *0*otherwise, where $d_{i,j}$ is the distance between locations i and j as established in Section 2.2. Accordingly, the first model could be derived as follows:

$$\textbf{M}_1\text{: } Minimize \sum_{i \in V} x_i \tag{1}$$

subject to:

$$\sum_{i \in V} \alpha_{i,j} x_i \geq 1, \forall j \in V, \tag{2}$$

$$x_i \in \{0,1\}, \quad \forall i \in V. \tag{3}$$

This first model minimizes the objective function (1) representing the total number of installed stations. Constraint (2) asserts the coverage radius for EV users' accessibility. Constraint (3) expresses binary restrictions imposed on *x* variables.

Model **M_1** is useful when only the number of installed stations gives cause for concern, especially when the installation cost is invariant from a station to another (e.g. for a standard service station network, the cost of the charger is negligible in terms of the opening cost etc.).

To take into account the infrastructure opening costs, we introduce f_i ($i \in V$) a size-independent cost of opening a station in each potential location *i*. It corresponds to the cost of converting a parking lot or a gas station into a plug-in EV compatible lot, more precisely equipment costs and administration costs (Ghamami et al. 2016).When the accommodation capacity is pre-fixed for all locations, the size dependent costs become invariant and the optimization model should minimize only the opening costs. Thus, the second model is stated as follows

M_2: $$\left\{ Minimize \sum_{i \in V} f_i x_i : (2)-(3) \right\}.$$

2.3.2. *ILP models for location and sizing decisions*

To go beyond finding the charging stations locations, we now turn our attention to a second family of ILP models in order to produce the appropriate stations sizes. First, we associate with each potential location $i \in V$: (i) a capacity c_i representing the maximal number of chargers that could be installed and in relation to the location's parking capacity; (ii) a per unit price of installing one charger denoted u_i, and (iii) a demand m_i representing the number of electric vehicles potentially using location *i*. Then, we introduce φ as the maximal number of parked electric vehicles served by a charger and calculated as

$$\varphi = \lambda * S^t, \qquad (4)$$

where λ is the service rate and more precisely the number of electric vehicles that could be charged per hour (Shareef et al. 2016), and S^t is the total charger service time. As our study is focusing on the centre of Tunis, which is not surprisingly an overcrowded workplace, considering charger efficiency is a noteworthy feature. Besides, each location $i \in V$ could be interestingly considered as the centroid of EV drivers' region as well as a candidate construction point for charging stations. This introduces two new decision variables. We define for each location $i \in V$ a non-negative integer variable n_i that represents the number of chargers to be installed in location *i*. We also define a binary variable $y_{i,j}$ that takes the value *1* if the electric vehicles of location *i* are charged in location *j*. Thereby, the third proposed ILP model reads as

$$\mathbf{M_3}: \quad Minimize \sum_{i \in V} (f_i x_i + u_i n_i) \tag{5}$$

subject to:

$$\sum_{j \in V} y_{i,j} = 1, \forall i \in V, \tag{6}$$

$$y_{i,j} \le x_j, \quad \forall i, j \in V, \tag{7}$$

$$x_i \le n_i \le c_i x_i, \quad \forall i \in V, \tag{8}$$

$$\sum_{i \in V} m_i y_{i,j} \le n_j \varphi, \forall j \in V, \tag{9}$$

$$d_{i,j} y_{i,j} \le R, \quad \forall i, j \in V, \tag{10}$$

$$x_i \in \{0,1\}, \quad \forall i \in V, \tag{11}$$

$$y_{i,j} \in \{0,1\}, \quad \forall i, j \in V, \tag{12}$$

$$n_i \in IN, \quad \forall i \in V. \tag{13}$$

Model **M3** aims to minimize the infrastructure opening costs and the charger installation costs as expressed in the objective function (5). Constraint (6) ensures the assignment of all electric vehicles to a charging station. Constraint (7) requires that electric vehicles could be charged in location $j \in V$, only if this location is selected to accommodate a charging station. Constraint (8) requires that if a station is selected then at least one charger is installed, while the number of chargers does not exceed its accommodation capacity. Obviously, if a station is not selected then no chargers are installed within it. Constraint (9) denotes that the total number of EV owners that choose to charge their vehicles in a location should not exceed its available service chargers. Constraint (10) requires that the EV assignment from location $i \in V$ to location $j \in V$ is possible only when the distance between them is less that the tolerance radius. Finally, (11)-(12) are the integrality constraints and Constraint (13) defines the non-negativity of integer variables *n*.

So far, we are focusing only on minimising the infrastructure installation costs. In what follows, we will also consider the access costs. More precisely, as EV owners could travel from a location to another in order to charge their vehicles, we found it more insightful to integrate the users' travel costs. This consideration was first introduced by Zhu et al. (2016) for their study on a 60km^2 metropolitan region of Beijing, where the potential charging stations are far away from the workplace. They consider that the EV drivers could walk, take a bus or a taxi for their travel from a location to another within the area studied. As we are interesting in an overcrowded 4.5 by 2.5 km workplace area, we consider only walking as the means of travel. Indeed, it is highly unlikely that Tunisian EV owners would take a bus or a taxi from charging stations to their destinations. We denote by ϕ the walking cost corresponding to the estimated cost of each walked kilometre and calculated as

$$\phi = \frac{W^h}{W^s}, \qquad (4)$$

where W^h is the average hourly wage of an electric vehicle owner and W^s is the average walking speed. Consequently, Model **M4** is derived as:

M4: $$\left\{ Minimize\, \omega_1 \sum_{i \in V} u_i n_i + \omega_2 \phi \sum_{i \in V} m_i \sum_{j \in V} d_{i,j} y_{i,j} : (6)-(13) \right\},$$

where ω_1 and ω_2 are non-negative weights. The objective function minimizes the total weighted costs. The weights reflect individual preferences regarding station installation and users' access costs. Naturally, we propose enhancing the foregoing model by considering the total station construction costs. To that end, we introduce the following ILP model:

M5: $$\left\{ Minimize\, \omega_1 \sum_{i \in V} (f_i x_i + u_i n_i) + \omega_2 \phi \sum_{i \in V} m_i \sum_{j \in V} d_{i,j} y_{i,j} : (6)-(13) \right\}.$$

Obviously, Model **M3** corresponds to Model **M5** in the special case where $\omega_1 = 1$ and $\omega_2 = 0$.

3. Numerical Experimentation

This section presents experimental analysis and empirical results of the proposed ILP models. The platform for carrying on the experiments is a Dual Core 2.16 GHz and x64-based processor64-bit OS laptop with 2 Go of RAM. The five ILP models were coded using the Optimization Programming Language (OPL) and solved using the general MIP solver (IBM Cplex, version 12.7). It is noteworthy that all of the models found optimal locations in an average CPU time of less than 1 minute.

3.1. Parameter Setting

In the forthcoming experimentation, the installed charger's cost is considered pre-fixed and independent of the location where it is to be installed. As in Ghamami et al.(2016) and Baouche et al.(2014), u_i ($i \in V$) is set to $*56,000*. Moreover, as our study area is the centre of Tunis which is an overcrowded workplace, we assume that charging demand is equally distributed between locations stations. Thus, m_i ($i \in V$) is fixed at *13* which represents a reasonable expectation for the emerging electric vehicle market in Tunisia, based on the work of Zhu et al.(2016). We assume that a coverage distance of *1km* seems practicable and appropriate for EV users. In Equation (4), the charger service rate λ is set to *3* EV per hour and the charger service time is set to *12* hours per day. The average hourly wage W^h is equal to $*17 per hour*, since it is computed as the average monthly wage of an EV owner *$3,000* divided by the number of worked hours per month. As in Carey (2005) and Ghamami et al. (2016), the average walking speed W^s is assumed as *5 km/h*. For Models **M4** and **M5**, we attach the same importance to stations' costs and to the users' access costs and we set $\omega_1 = \omega_2 = 0.5$.

3.2. Sensitivity Analysis

3.2.1. Impact of the coverage radius

First, we are focusing on the coverage radius *R*. Thus, we examine the effect of its variation on the optimal infrastructure deployment as the output of each ILP model. More precisely, the tolerable distance *R* ranges from *0km* to *2km*. Table1 summarises the results of Models **M1** and **M2** that output location decisions only. *Ns* and $Cost_i$ denote the number of selected stations and the corresponding cost upon model **Mi**.

Table 1: Impact of the coverage radius on Models **M1** and **M2** outputs

	Model **M1**		Model **M2**	
R in *km*	*Ns*	$Cost_1$	$Cost_2$	*Ns*
0	39	$77 878	$77 878	39
0.2	27	$54 579	$53 903	27
0.4	17	$34 763	$33 553	17
0.6	11	$22 059	$21 311	11
0.8	10	$20 082	$19 419	10
1	8	$16 303	$15 958	8
1.2	8	$16 303	$15 958	8
1.4	8	$16 042	$15 958	8
1.6	8	$16 229	$15 958	8
1.8	8	$16 229	$15 958	8
2	8	$16 229	$15 958	8

Obviously, *R= 0km* corresponds to installing an EV charging station in each available location, leading to *Ns=39*. Furthermore, increasing the *R* value decreases the opening costs, as well as the number of selected locations. Interestingly, the models outputs remain unchanged from *R=1km* and correspond to *8* stations to install. As shown in Figures 3 and 4, it is not the same *8* selected locations from models **M1** and $\mathbf{M_2}$. Reducing the number of selected locations is not equivalent to reducing the station opening costs.

Next, the results of ILP models for locating and sizing decisions are displayed in Table 2. *Nc* denotes the number installed chargers. Pushing the envelope further, we report for Model $\mathbf{M_5}$ the corresponding total installation costs (station opening and chargers costs) denoted by $ICost_5$.

Table 2: Impact of the coverage radius on Models $\mathbf{M_3}$, $\mathbf{M_4}$ and $\mathbf{M_5}$ outputs

	Model $\mathbf{M_3}$			Model $\mathbf{M_4}$			Model $\mathbf{M_5}$			
R in km	$Cost_3$	*Ns*	*Nc*	$Cost_4$	*Ns*	*Nc*	$Cost_5$	$ICost_5$	*Ns*	*Nc*
0	$2 261 878	39	39	$1 092 000	39	39	$44 106 621	$2 261 878	39	39
0.2	$1 733 903	27	30	$840 023	29	30	$33 812 294	$1 733 903	27	30
0.4	$1 265 553	17	22	$616 092	20	22	$24 682 659	$1 265 553	17	22
0.6	$1 029 311	11	18	$504 156	14	18	$20 078 842	$1 029 311	11	18
0.8	$971 475	10	17	$476 183	12	17	$18 953 301	$971 475	10	17
1	$912 042	8	16	$448 258	9	16	$17 798 115	$912 042	8	16
1.2	$912 042	8	16	$448 251	9	16	$17 798 115	$912 042	8	16
1.4	$912 042	8	16	$448 251	9	16	$17 798 115	$912 042	8	16
1.6	$911 958	8	16	$448 251	9	16	$17 798 115	$912 042	8	16
1.8	$911 958	8	16	$448 251	9	16	$17 798 115	$912 042	8	16
2	$911 958	8	16	$448 251	9	16	$17 798 115	$912 042	8	16

As in Table1, for *R* above *1km* the optimal output infrastructure remain unchanged for all models. In this case, according to Models **M3** and **M5**, *8* EV charging stations should be installed with an average of *2* chargers in each station. But, from Model $\mathbf{M_4}$ that does not consider the stations' opening costs, *9* stations should be selected with almost half costs compared to those indicated by Model $\mathbf{M_3}$. Furthermore, note that the high costs of Model $\mathbf{M_5}$ are due to considering the users access costs. However, columns $ICost_5$ and $Cost_3$ are of the same magnitude.

3.2.2. *Impact of the charging time*

As the EV charging technology is developing very rapidly, we wanted to investigate the effect of the evolution of the charging time on the proposed EVCS deployment. Table 3 reports the models outputs regarding the evolution of the charging time and the charger service rate λ .

Table 3: Impact of the Charging Time on Models $\mathbf{M_3}$, $\mathbf{M_4}$ and $\mathbf{M_5}$ outputs

		Model $\mathbf{M_3}$			Model $\mathbf{M_4}$			Model $\mathbf{M_5}$			
Charging Time in minutes	λ	*Cost₃*	*Ns*	*Nc*	*Cost₄*	*Ns*	*Nc*	*Cost₅*	*ICost₅*	*Ns*	*Nc*
5	12	$463 958	8	8	$224 295	8	8	$9 059 231	$463 958	8	8
10	6	$520 042	8	9	$252 242	9	9	$10 154 573	$520 042	8	9
15	4	$687 958	8	12	$336 276	9	12	$13 427 861	$687 958	8	12
20	3	$912 042	8	16	$448 258	9	16	$17 798 115	$912 042	8	16
30	2	$1 359 958	8	24	$672 253	9	24	$26 531 659	$1 359 958	8	24

It is worth noticing that the longer the EV charging time increases, the more the number of chargers to be installed *Nc* increases and consequently the installation costs, which depends on the number of chargers, too. On the other hand, the number of EVCS to be installed stabilizes at *9* for Model $\mathbf{M_4}$ and *8* for Models $\mathbf{M_3}$ and $\mathbf{M_5}$. This shows that the proposed models still exhibit the same EVCS deployment. Thus, even if the technology advances and the charging times decrease, the found EV charging networks remain valid.

3.2.3. *Impact of the EV charger cost*

Now, let's turn to evaluating how the models outputs vary by increasing the EV charger' unitary cost in the range [$*42000*, $*70000*] with a step of *5%*. The numerical results are displayed in Table 4. Not surprisingly, increasing the per unit price of EV charger yields to increasing the objective costs of the proposed models. In line with Table3, Table 4 shows that the outputs of each model, in term of number of stations as well as number of chargers to install, stand unaffected.

Table 4: Impact of the EV Charger Cost on Models $\mathbf{M_3}$, $\mathbf{M_4}$ and $\mathbf{M_5}$ outputs

	Model $\mathbf{M_3}$			Model $\mathbf{M_4}$			Model $\mathbf{M_5}$			
EV Charger Cost (u_i)	*Cost₃*	*Ns*	*Nc*	*Cost₄*	*Ns*	*Nc*	*Cost₅*	*ICost₅*	*Ns*	*Nc*
$42 000	$688 042	8	16	$336258	9	16	$13 430 115	$688 042	8	16
$44 800	$732 842	8	16	$358658	9	16	$14 303 715	$732 842	8	16
$47 600	$777 642	8	16	$381058	9	16	$15 177 315	$777 642	8	16
$50 400	$822 442	8	16	$403458	9	16	$16 050 915	$822 442	8	16
$53 200	$867 242	8	16	$425858	9	16	$16 924 515	$867 242	8	16
$56 000	$912 042	8	16	$448 258	9	16	$17 798 115	$912 042	8	16
$58 800	$956 842	8	16	$4706578	9	16	$18 671 715	$956 842	8	16
$61 600	$1 001 642	8	16	$493058	9	16	$19 545 315	$1 001 642	8	16
$64 400	$1 046 442	8	16	$515458	9	16	$20 418 915	$1 046 442	8	16
$67 200	$1 091 242	8	16	$537858	9	16	$21 292 515	$1 091 242	8	16
$70 000	$1 136 042	8	16	$560258	9	16	$22 166 115	$1 136 042	8	16

3.3. The Proposed EV Charging Networks

We now attempt to propose the appropriate EV charging deployment infrastructure. To this end, the proposed installation schemes according to each ILP model are presented in Figures 3-7.

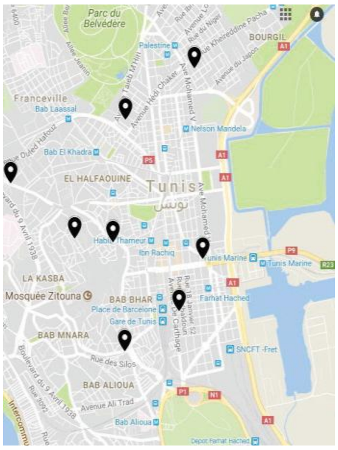

Figure 3: EV charging station locations (Model $\mathbf{M}_1$)

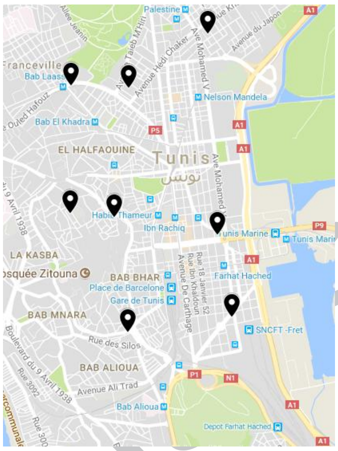

Figure 4: EV charging station locations (Model $\mathbf{M}_2$)

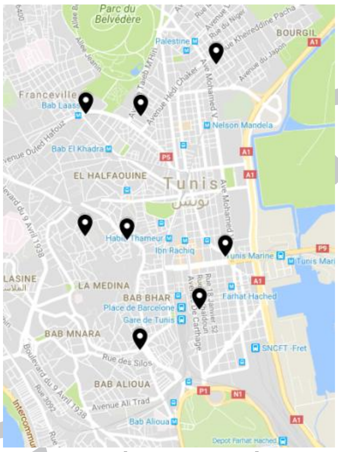

Figure 5: EV charging station locations (Model $\mathbf{M}_3$)

Figure 6: EV charging station locations (Model $\mathbf{M}_4$)

The first network, shown in Figure 3, should be constructed when only minimizing the number of stations is considered. The network deployed in Figure4 should be constructed when only opening costs that are not related to size are considered. Furthermore, the network displayed in Figure 5 should be installed when only investor’s convenience is considered. Then, the network presented in Figure 6 should be implemented when investors and users’ convenience are equally important but stations’ opening costs are not considered, as in the work of Zhu et al. (2016).

Figure 7 shows the most appropriate EVCS deployment that takes into consideration realistic stations’ installation costs, as well as the EV users’ access costs. Thus, the investors and the EV owners’ convenience are equally taken into account. Without wasting public/private resources, while keeping an appropriate service level for EV users, we strongly recommend these locations for charging stations deployment in the centre of Tunis.

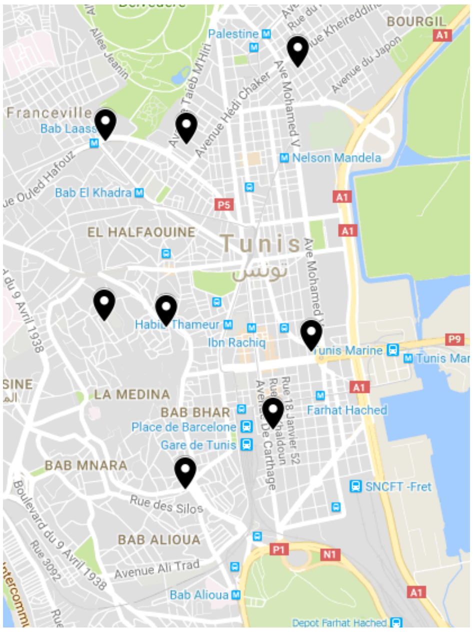

Figure 7: EV charging station locations (Model $\mathbf{M}_5$)

4. Conclusions and Future Work

Electric vehicles seem to be the future means of transport. This trend is steeply rising worldwide and is proving to offer sustainable solutions to many issues such as air pollution, CO_2 emissions, urban noise, etc. However, the unavailability of sufficient electric power storage creates a short range handicap for electric vehicles. Therefore, a public electric charging network must be installed to incentivise adoption of this promising technology. This pioneer work investigates determining appropriate locations for electric vehicle charging stations in the city of Tunis, Tunisia. More precisely, we are concerned with respecting a tolerable coverage radius of the deployed infrastructure. In fact, electric vehicle drivers are unlikely to accept walking long distances from charging stations to their destinations. To that aim, we propose five integer linear programming formulations based on weighted set covering models. Despite their deceptive simplicity, the proposed models can help public makers decide on locations and sizes of potential charging stations, while minimizing investment costs and respecting users' convenience.

It is notable that there are some limitations in this pioneer study which can be improved in future research. For instance, we can offer the following research directions:

1- Considering the preference of EV users from their original location to other charging locations as fractional; i.e. considering the *y* decision variables in the proposed models as continuous within [0,1].

2- Sharpening the distance matrix by estimating appropriate paths between all pairs of potential locations (e.g. average paths) instead of the Cartesian distance used above.

3- Conducting a comprehensive study on the demand estimates of EV, using market anticipation and consumers' behaviour, while combining that with energy consumption in Tunisia (Moon et al. 2018).

Acknowledgement

The authors would like to express their gratitude to anonymous referees for their valuable suggestions. Special thanks are addressed to Paul Randall and James Bleach of the ōbex project for providing language editing support.

Compliance with Ethical Standards

Conflict of interest: The authors declare that they have no conflict of interest.

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Annexe 1: Characteristics of Potential Locations for EV Charging Stations

Index (i)	Type	Designation	Longitude, Latitude	Parking capacity (c_i)	Opening cost(f_i)
1	Parking Lot	Parking A Chraibi	10.186147,36.798158	49	2051
2	Parking Lot	Parking A Trad / R Carthage	10.182425,36.795826	50	2110
3	Parking Lot	Parking Av Ghana	10.182515,36.806419	51	2097
4	Parking Lot	Parking Av H B / Highway	10.18824,36.800917	35	2168
5	Parking Lot	Parking Av O Hafouz	10.169628,36.813392	50	1841
6	Parking Lot	Parking Bab Jedid	10.175749,36.792181	35	2145
7	Parking Lot	Parking Bab Khadra	10.174597,36.809133	60	1997
8	Parking Lot	Parking Bab Souika	10.174314,36.802064	50	1828
9	Parking Lot	Parking Cim Jallez	10.180784,36.785551	50	2198
10	Parking Lot	Parking Elalem	10.178445,36.798893	36	1926
11	Parking Lot	Parking Hafsia 1	10.17011,36.802346	36	1802
12	Parking Lot	Parking Hafsia 2	10.169533,36.80244	36	2169
13	Parking Lot	Parking Hafsia 3	10.170197,36.801443	36	1992
14	Parking Lot	Parking Hafsia 4	10.170808,36.801101	36	2073
15	Parking Lot	Parking Hafsia 5	10.169743,36.800886	250	1916
16	Parking Lot	Parking Kartoum	10.175834,36.813233	250	2159
17	Parking Lot	Parking Khaireddine	10.18435,36.817842	1200	1926
18	Parking Lot	Parking La Kasbah	10.167085,36.797935	630	1888
19	Parking Lot	Parking Lafayette	10.181292,36.81239	243	2103
20	Parking Lot	Parking Le Palmarium	10.181109,36.798435	240	2119
21	Parking Lot	Parking M Attia Nord	10.183261,36.801648	750	1935
22	Parking Lot	Parking M Attia Sud	10.183446,36.801142	50	2144
23	Parking Lot	Parking M Halfa	10.173414,36.797171	50	1957
24	Parking Lot	Parking M Halfa 2	10.174193,36.797757	50	1806
25	Parking Lot	Parking M Halfa 3	10.174072,36.796474	50	1897
26	Parking Lot	Parking Manachou	10.17857,36.783813	750	2167
27	Parking Lot	Parking Med V	10.186916,36.804372	50	1923
28	Parking Lot	Parking Place 14 Janvier	10.185341,36.800582	50	1864
29	Parking Lot	Parking R Bab Saadoun	10.161624,36.807441	50	2102
30	Parking Lot	Parking R des Arcs	10.163324,36.806388	70	1818
31	Parking Lot	Parking S Aloui	10.164962,36.807872	90	1966
32	Gas Station	Electro Diesel Tunisia	10.1837874,36.7904707	6	1929
33	Gas Station	Shell Moncef Bey	10.1869011,36.7934777	10	2026
34	Gas Station	Station Agil Av H B / Highway	10.1883602,36.8001445	12	2054
35	Gas Station	Station Agil Franceville	10.1676536,36.8134142	6	2001
36	Gas Station	Station Total Bab Allouj	10.1653281,36.8029346	10	1901
37	Gas Station	Station Total Khereddine Pacha	10.1847832,36.8189667	11	2034
38	Gas Station	Station Total Rue de Turquie	10.1869366,36.7956717	12	1938
39	Gas Station	Station- Total Taieb Mhiri	10.1753300,36.8141100	7	1908

Annexe 2: Table of distances (in *km*)

	Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39
Index	Designation	ParkingAChraibi	ParkingATrad/RCarthage	ParkingAvGhana	ParkingAvHB/Highway	ParkingAvOHafouz	ParkingBabJedid	ParkingBabKhadra	ParkingBabSouika	ParkingCimJallez	ParkingElalem	ParkingHafsia1	ParkingHafsia2	ParkingHafsia3	ParkingHafsia4	ParkingHafsia5	ParkingKartoum	ParkingKhaireddine	ParkingLaKasbah	ParkingLafayette	ParkingLePalmarium	ParkingMAttiaNord	ParkingMAttiaSud	ParkingM Halfa	Parking MHalfa2	Parking MHalfa3	ParkingManachou	Parking MedV	ParkingPlace14Janvier	ParkingRBabSaadoun	ParkingRdesArcs	ParkingSAloui	ElectroDieselTunisia	ShellMoncefBey	StationAgilAvHB/Highway	StationAgilFranceVille	StationTOTALBabAllouj	StationTOTAL KhereddinePacha	StationTOTALRuedeTurquie	StationTOTALTaiebMhiri
1	ParkingAChraibi	0.00	0.42	+∞	0.37	+∞	+∞	+∞	+∞	1.51	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.42	+∞	0.40	+∞	+∞	+∞	+∞	+∞	0.30	+∞	+∞	+∞	+∞	+∞	0.30	+∞	+∞	+∞	0.29	+∞
2	ParkingATrad/R Carthage	0.42	0.00	+∞	+∞	+∞	0.71	+∞	+∞	1.18	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.32	+∞	+∞	+∞	+∞	0.74	+∞	+∞	+∞	+∞	+∞	+∞	0.61	0.47	+∞	+∞	+∞	+∞	0.40	+∞
3	ParkingAvGhana	+∞	+∞	0.00	+∞	+∞	+∞	0.77	0.90	+∞	0.90	+∞	+∞	+∞	+∞	+∞	0.98	1.29	+∞	0.66	+∞	0.55	+∞	+∞	+∞	+∞	+∞	0.45	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
4	ParkingAvHB/ Highway	0.37	+∞	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.38	0.26	+∞	+∞	+∞	+∞	+∞	0.09	+∞	+∞	+∞	+∞	+∞
5	Parking AvO Hafouz	+∞	+∞	+∞	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.36	+∞	0.57	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.94	+∞	0.73	+∞	+∞	+∞	0.17	+∞	+∞	+∞	+∞
6	ParkingBabJedid	+∞	0.71	+∞	+∞	+∞	0.00	+∞	+∞	0.83	0.80	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.99	+∞	0.85	+∞	+∞	0.60	+∞	0.49	0.95	+∞	+∞	+∞	+∞	+∞	0.75	+∞	+∞	+∞	+∞	+∞	+∞	+∞
7	ParkingBabKhadra	+∞	+∞	0.77	+∞	+∞	+∞	0.00	+∞	+∞	+∞	0.85	+∞	+∞	+∞	+∞	0.48	+∞	+∞	0.69	1.32	1.12	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.86	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
8	ParkingBabSouika	+∞	+∞	0.90	+∞	+∞	+∞	+∞	0.00	+∞	0.51	0.38	+∞	+∞	0.33	+∞	+∞	+∞	+∞	+∞	+∞	0.81	+∞	+∞	0.45	+∞	+∞	+∞	+∞	+∞	+∞	1.03	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
9	ParkingCimJallez	1.51	1.18	+∞	+∞	+∞	0.83	+∞	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.24	+∞	+∞	+∞	+∞	+∞	0.64	+∞	+∞	+∞	+∞	+∞	+∞	+∞
10	ParkingElalem	+∞	+∞	0.90	+∞	+∞	0.80	+∞	0.51	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.23	0.51	+∞	+∞	0.40	0.48	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
11	ParkingHafsia1	+∞	+∞	+∞	+∞	+∞	+∞	0.85	0.38	+∞	+∞	0.00	0.08	0.60	0.15	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.77	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
12	ParkingHafsia2	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.08	0.00	0.11	+∞	0.18	+∞	+∞	0.54	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.70	0.73	+∞	+∞	+∞	+∞	0.38	+∞	+∞	+∞
13	ParkingHafsia3	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.60	0.11	0.00	0.07	0.08	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
14	ParkingHafsia4	+∞	+∞	+∞	+∞	1.36	+∞	+∞	0.33	+∞	+∞	0.15	+∞	0.07	0.00	0.10	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.49	0.59	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
15	ParkingHafsia5	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.18	0.08	0.10	0.00	+∞	+∞	0.38	+∞	+∞	+∞	+∞	0.52	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
16	ParkingKartoum	+∞	+∞	0.98	+∞	0.57	+∞	0.48	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.92	+∞	0.49	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.15	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.12
17	ParkingKhaireddine	+∞	+∞	1.29	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	+∞	0.68	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.51	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.14	+∞	+∞
18	ParkingLaKasbah	+∞	+∞	+∞	+∞	+∞	0.99	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.38	+∞	+∞	0.00	+∞	+∞	+∞	+∞	0.57	+∞	+∞	+∞	+∞	+∞	1.16	+∞	+∞	+∞	+∞	+∞	+∞	0.59	+∞	+∞	+∞
19	ParkingLafayette	+∞	+∞	0.66	+∞	+∞	+∞	0.69	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.49	0.68	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.01	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
20	ParkingLe Palmarium	0.42	0.32	+∞	+∞	+∞	0.85	1.32	+∞	+∞	0.23	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	0.35	0.36	+∞	+∞	+∞	+∞	+∞	0.45	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
21	ParkingMAttia Nord	+∞	+∞	0.55	+∞	+∞	+∞	1.12	0.81	+∞	0.51	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.35	0.00	0.06	+∞	+∞	+∞	+∞	0.42	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
22	ParkingMAttia Sud	0.40	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.36	0.06	0.00	+∞	+∞	+∞	+∞	0.45	0.18	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
23	ParkingM Halfa	+∞	+∞	+∞	+∞	+∞	0.60	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.49	0.52	+∞	+∞	0.57	+∞	+∞	+∞	+∞	0.00	0.10	0.40	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
24	Parking MHalfa2	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.45	+∞	0.40	+∞	+∞	+∞	0.59	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.10	0.00	0.15	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
25	Parking MHalfa3	+∞	0.74	+∞	+∞	+∞	0.49	+∞	+∞	+∞	0.48	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.40	0.15	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
26	Parking Manachou	+∞	+∞	+∞	+∞	+∞	0.95	+∞	+∞	0.24	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
27	Parking MedV	+∞	+∞	0.45	0.38	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.51	+∞	1.01	+∞	0.42	0.45	+∞	+∞	+∞	+∞	0.00	0.44	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
28	ParkingPlace14 Janvier	0.30	+∞	+∞	0.26	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.45	+∞	0.18	+∞	+∞	+∞	+∞	0.44	0.00	+∞	+∞	+∞	+∞	+∞	0.28	+∞	+∞	+∞	+∞	+∞
29	Parking RBab Saadoun	+∞	+∞	+∞	+∞	0.94	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	1.16	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	0.22	0.28	+∞	+∞	+∞	0.85	+∞	+∞	+∞	+∞
30	ParkingRdesArcs	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.70	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.22	0.00	0.23	+∞	+∞	+∞	+∞	0.42	+∞	+∞	+∞
31	ParkingSAloui	+∞	+∞	+∞	+∞	0.73	+∞	0.86	1.03	+∞	+∞	0.77	0.73	+∞	+∞	+∞	1.15	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.28	0.23	0.00	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞
32	Electro Diesel Tunisia	+∞	0.61	+∞	+∞	+∞	0.75	+∞	+∞	0.64	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	0.43	+∞	+∞	+∞	+∞	+∞	+∞
33	ShellMoncefBey	+∞	0.47	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.43	0.00	+∞	+∞	+∞	+∞	0.25	+∞
34	StationAgilAvHB /Highway	0.30	+∞	+∞	0.09	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.28	+∞	+∞	+∞	+∞	+∞	0.00	+∞	+∞	+∞	0.52	+∞
35	StationAgil Franceville	+∞	+∞	+∞	+∞	0.17	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.85	+∞	+∞	+∞	+∞	+∞	0.00	+∞	+∞	+∞	+∞
36	StationTOTAL BabAllouj	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.38	+∞	+∞	+∞	+∞	+∞	0.59	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.42	+∞	+∞	+∞	+∞	+∞	0.00	+∞	+∞	+∞
37	StationTOTAL KhereddinePacha	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.14	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00	+∞	+∞
38	StationTOTAL RuedeTurquie	0.29	0.40	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.25	0.52	+∞	+∞	+∞	0.00	+∞
39	StationTOTAL TaiebMhiri	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.12	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	+∞	0.00

Highlights

- Potential EVCS locations in the centre of Tunis are investigated.
- 5 ILP set covering based models are addressed.
- Optimal EVCS infrastructure deployment is found.