Optimal Placement of Fast Charging Infrastructure for Electric Vehicles : an Optimal Routing and Spatial Clustering Approach

Ibtihel Ben Gharbia, Giovanni de Nunzio, Antonio Sciarretta

Optimal Placement of Fast Charging Infrastructure for Electric Vehicles: an Optimal Routing and Spatial Clustering Approach

Ibtihel Ben Gharbia, Giovanni De Nunzio, Antonio Sciarretta

***Abstract*— The rapid growth of electric vehicles (EVs) has brought about the need for an efficient and effective charging infrastructure network. Optimal placement of charging infrastructure plays a crucial role in ensuring the widespread adoption and seamless integration of EVs into the existing transportation system. In this work, a new placement method is proposed with the goal of optimizing trip time for all the long-distance nation-wide journeys. The first step of the strategy consists in identifying the ideal location of charging stations based on an optimal routing strategy with charging constraints. Then, a clustering-based heuristic, which also accounts for real travel demand, is proposed to select the best charging stations among these candidate locations. We apply the method to the French national charging infrastructure and we show that important gains in terms of overall trip time and energy consumption are attainable with respect to the current infrastructure. Finally, the proposed method is used to give a recommendation on where to install the future charging stations in order to maximize their positive impact.**

***Index Terms*— Electric vehicles, charging stations, driving range, constrained shortest path, eco-routing, spatial clustering, bi-level optimization problem, optimal placement.**

I. Introduction

As the number of electric vehicles (EVs) continues to grow, the need for a reliable and efficient charging infrastructure becomes increasingly important. One of the critical challenges in deploying charging infrastructure is determining the optimal placement of charging stations. The optimal placement of charging stations for EVs is a complex problem that involves multiple decision-makers, objectives, and constraints. Charging station operators need to install and operate charging stations at a reasonable cost, while electric vehicle owners need reliable and accessible charging infrastructure. Local communities need to balance the benefits of charging infrastructure with the potential impact on traffic flow, parking availability, geographical and environmental constraints, electrical grid capacity, and cost-effectiveness.

Optimal placement of charging infrastructure is crucial to enhance EV adoption [1], [2], alleviate range anxiety, enable long-distance travel, and ensure cost-efficient utilization and convenient access to fast charging facilities[3]. In recent years, various approaches have emerged for optimal EV charging station placement [4], [5], including data-driven [6], GIS-based [7], and optimization modeling methods [8]. Data-driven methods leverage historical data and machine learning algorithms to identify patterns and correlations, informing optimal locations for stations [9]. GIS-based approaches use spatial analysis to account for accessibility, population density, and environmental factors. Optimization modeling addresses multiple factors and objectives, such as travel demand patterns, station capacity, infrastructure costs, and grid limitations, tailored to urban and long-distance scenarios. Urban settings apply techniques like mixed-integer linear programming and multi-objective optimization, focusing on land use, accessibility, and charging demand [10], [11]. In contrast, long-distance scenarios [12] employ methods like queuing theory, location-allocation models, and spatial optimization to tackle highway networks, intercity travel patterns, and charging speed [13] .

In densely populated urban areas and for daily mobility, studies have shown that EV users tend to rely more on home/work chargers for their charging needs, due to easier access and lower costs [14]. Public charging infrastructure is perceived more as a backup solution in case of emergency. However, for long-distance trips, the paradigm changes and the associated range anxiety due to the lack of diffused and reliable charging infrastructure along the route still hinders the uptake of electric vehicles [15]. For these reasons, in this work, we focus on optimally placing EV charging infrastructure at nation-wide level, with the objective of facilitating long-distance trips, for which at least one charging event is necessary to reach the destination. Our goal is to minimize the experienced travel and charging time of EV drivers by considering realistic travel demand and energy needs. To this aim, we propose a bi-level optimization framework.

Bi-level optimization, a mathematical technique for nested optimization problems, is suitable for balancing infrastructure providers' objectives and EV drivers' needs [16]. In the proposed framework, the upper-level problem minimizes installation and operational costs by selecting locations based on factors like population density, traffic patterns, and electric grid capacity. The lower-level problem models EV drivers' responses, considering route selection and charging behavior based on station availability. To solve this bi-level problem, the nested method iteratively solves both levels until convergence. However, these methods can be computationally expensive, particularly in long-distance scenarios with numerous locations and constraints. As a result, alternative solutions like clustering and heuristics have been proposed to provide more efficient approaches, trading optimality for reduced computational complexity [17], [18].

The contributions of this work can be summarized as follows. Firstly, the long-distance travel demand used in the optimal placement of charging infrastructure is estimated

I. Ben Gharbia, G. De Nunzio and A. Sciarretta, IFP Energies nouvelles, 1 et 4 avenue de Bois-Préau, 92852 Rueil-Malmaison, France, {ibtihel.ben-gharbia, giovanni.de-nunzio, antonio.sciarretta}@ifpen.fr

based on robust and statistically unbiased national statistics, providing both the likely origin-destination pairs on the territory and the average daily traffic volumes between each pair. Secondly, a new bi-level strategy for the optimal placement of charging infrastructure is proposed. The physics of the long-distance trips are directly considered in the lower level, accounting for vehicle-specific energy needs, traffic-aware trip time, and model-based charging time. The chosen heuristic approximating the upper-level of the optimization is based on a spatial clustering technique, weighted according to the travel demand statistics.

The paper is structured as follows. Section II describes the bi-level optimization problem used for the optimal placement of charging infrastructure. The spatial clustering solution method we propose is detailed in Section III. Simulation and comparison results are presented in Section IV.

II. Bi-level optimization problem

A bi-level optimization problem involves two optimization problems, where the solution of one problem depends on the solution of the other. In the context of minimizing travel time for electric vehicles (EVs) and determining the optimal charging station placement, we can formulate the bi-level optimization problem as follows.

A. Lower-level problem

For the lower-level problem, a time and energy optimal routing strategy, already proposed in our previous work [13], is employed taking into account the constraints related to battery charging. For clarity, we briefly resume in the following the key parts of our previous work adapted to the current framework.

Let $\mathcal{G} = (V, A)$ be a directed acyclic graph, where V is the set of vertices (i.e. the ends of each road segment i), and A is the set of arcs (i.e. road segments i connecting the nodes of the graph). The additional decision variables of the route planning strategy for electric vehicles with charging capabilities (i.e. route, cruise speed on arcs and charging level) are encoded directly in the graph definition. The graph $\mathcal{G}$ is therefore expanded into a directed multigraph $\mathcal{G}' = (V, A')$. This is done by creating additional arcs where charging stations or cruise speed options are available. Then, in order to better model the additional energy expenditure due to acceleration events (i.e. transition from $\bar{V}_i$ and $\bar{V}_{i+1}$), the multidigraph $\mathcal{G}'$ can be conveniently transformed into a line graph $\mathcal{L}(\mathcal{G}) = (A', A^*)$ [19], where each arc in $\mathcal{G}'$ becomes a node, and each arc represents a pair of adjacent arcs in $\mathcal{G}'$. The models for estimating the time and energy required to travel along each arc (i.e. the graph weighting functions) are detailed in [13].

The route planning problem is formulated as a bi-objective optimization aiming to find the best trade-off between trip time and energy consumption. Let us denote with ζ the arcs of the routing graph $\mathcal{L}(\mathcal{G})$, with i^+ the set of arcs ζ entering $i \in A'$, and with i^- the set of arcs ζ leaving $i \in A'$. Let also i^o be the origin arc and i^d the destination arc. Finally, let us denote with $\mathcal{P}_i$ the sub-path composed by all the arcs ζ connecting the origin i^o to i. The route optimization problem can be formulated as follows:

$$\begin{cases} \min\limits_{x_\zeta} \quad \sum\limits_{\zeta \in A^*} (\lambda \omega_{i,t} + (1-\lambda)\omega_{i,e}) \cdot x_\zeta & \text{(1a)} \\ \text{s.t.} \quad \sum\limits_{\zeta \in i^+} x_\zeta - \sum\limits_{\zeta \in i^-} x_\zeta = \begin{cases} 1, & \text{if } i = i^o \\ -1, & \text{if } i = i^d \\ 0, & \text{otherwise} \end{cases} & \text{(1b)} \\ C_{\min} \leq \sum\limits_{\zeta \in \mathcal{P}_i} \omega_{i,e} \leq C, \ \forall i \in A' & \text{(1c)} \\ x_\zeta \in \{0, 1\}, & \text{(1d)} \end{cases}$$

where the objective function (1a) is written as a weighted sum of the time $\omega_{i,t}$ and energy costs $\omega_{i,e}$ on each arc of the routing graph, with λ being the trade-off weight. In this work, in the lower-level, we optimize trip time, therefore we set $\lambda = 1$. The decision variable x_ζ takes on binary values as imposed by (1d) depending on whether the arc ζ belongs to the optimal path or not. Constraints (1b) are classical flow conservation constraints. Constraint (1c) enforces every possible sub-path to verify the physical bounds of battery capacity. In this work, as in [13], the constrained problem is relaxed by incorporating constraints directly in the graph via the lexicographic product of the routing graph and a fully-disconnected graph that represents the feasible battery levels for consideration during optimization. The unconstrained problem is then solved via the Bellman-Ford (BF) shortest-path algorithm.

The lower problem's solution, determining optimal charging decisions for each EV, is integrated into the upper problem to identify optimal charging station placement. This approach determines the best locations for stations while considering the charging needs of all EVs in the network.

B. Upper-level problem

The upper-level problem seeks to minimize the overall travel time for all EVs in the network by strategically placing charging stations. This involves considering factors like detour time, waiting times, and travel efficiency related to station placement and its impact on EV users. We define N as the number of candidate locations for charging stations and M as the set of potential EV users. Assuming we have a set of candidate locations $X = (x_1, x_2, \dots, x_N)$, where each location x_k is a potential charging station site. Let s_k be a binary decision variable, where $s_k = 1$ if a charging station is placed at location k, and $s_k = 0$ otherwise. This leader problem can be formulated as follows

$$\begin{cases} \min\limits_{s_k} \quad \sum\limits_{j=1}^{M} T_j(s_k) & \text{(2a)} \\ \text{s.t.} \quad \sum\limits_{k=1}^{N} s_k \leq K, & \text{(2b)} \\ s_k \in \{0, 1\}, & \text{(2c)} \end{cases}$$

where the objective function (2a) is a the travel time of each vehicle

$$T_j(s_k) = \sum_{\mathcal{P}_*^j} \omega_{i,t},$$

where $\mathcal{P}_*^j$ represents the optimal path for EV j determined as a solution to the lower-level problem that takes into account the selected charging stops X. The decision variable s_k takes on binary values as imposed by (2c) depending on whether a station exists at a specific location or not. Constraints (2b) ensures that the total number of charging stations to be placed does not exceed the given budget (i.e. maximum number of charging stations to be placed) K, with $K \leq N$. The resolution of this problem involves addressing the challenges and complexities that arise when solving two interconnected optimization problems. Due to their hierarchical structure, it is computationally demanding, particularly due to the complexity and large-scale nature of the lower-level problem (1a)-(1d).

Therefore, a novel heuristic approach is proposed to effectively tackle the complexities of this intensive bi-level optimization problem. The approach is designed to yield feasible and optimal solutions for strategically positioning direct-current (DC) fast-charging stations in France.

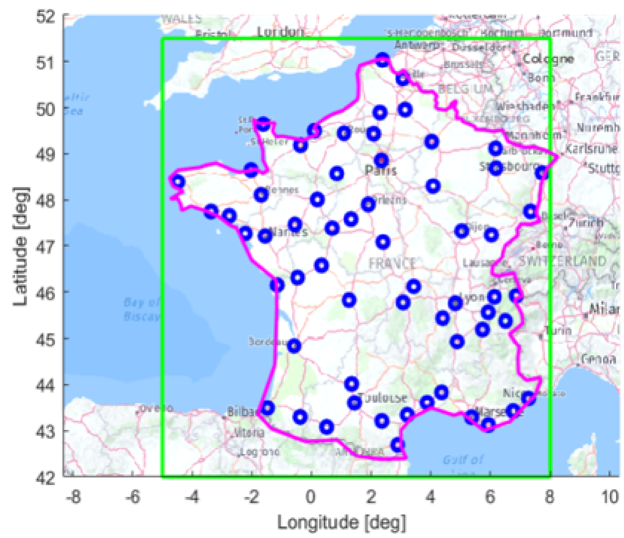

Fig. 1: The 61 selected French cities for our study.

III. Methodology

To identify the location of fast-charging stations that is most appropriate for the charging needs related to the long-distance trips, it is crucial to analyze the various routes connecting different cities. By examining all possible routes, we can ensure that the charging infrastructure is optimally distributed to cater to the needs of electric vehicle users traveling between cities.

Using data from studies conducted by the French national institute of statistics and economics (Insee)[1], we have filtered a list of cities based on two criteria: population and hotel capacity, as well as their proximity to one another. Specifically, we have selected the top hundred most populated cities in France with the highest hotel capacity and then narrowed down the list by keeping only the cities that are more than 40 km apart. As a result, we have ended up with a final list of 61 cities, illustrated in Figure 1, that meet these criteria. This approach makes sense since we are trying to identify a set of cities where there is a high likelihood of demand for charging stations due to the number of people and hotels in the area, while also ensuring that the cities are spaced out enough to increase the spatial coverage of the analysis. In this study, we calculate via the lower-level of the optimization the fastest route for each of the 3,600 origin-destination (O-D) pairs, assuming the availability of all stations and the absence of any queuing at the charging stations. This implies that for the lower-level optimization problem presented in section II-A, the wait time is considered to be equal to zero and the trade-off weight λ is set equal to one. This is an ideal scenario that would make it easier and more convenient for EV drivers to charge their vehicles, and would also help to reduce range anxiety, which is a common concern among EV drivers.

The location and the available power of the charging stations within the considered network are key parameters to schedule the optimal sequence of charging events. The proposed heuristic strategy consists of two steps. The first step involves identifying a set of optimal candidate stations, while the subsequent step focuses on determining the optimal placement of the required stations, which could be a subset of the candidate ones.

A. Phase 1: Identification of candidate charging stations

The first step of the methodology assumes the presence of a virtual charging station at each node of the graph. This setup establishes an ideal scenario, serving as the foundation for determining the necessary charging stations required for the network. By adopting this approach, we gain valuable insights into the optimal conditions for electric vehicle users, enabling us to make informed decisions regarding the placement of charging infrastructure.

For each O/D pair, the lower-level optimization problem is solved using the unconstrained shortest-path algorithm BF on the expanded graph, as in (1a)-(1d), to integrate the battery constraints [13]. Adding virtual charging stations at each node can be advantageous for identifying optimal candidate charging locations and analyzing various scenarios. However, this approach presents some computational challenges. Specifically, as the number of nodes (and thus virtual stations) increases (about 6.000 virtual stations per each considered O/D), the memory required to store the information in the expansion graph (about 7 billion arcs per each considered O/D) also increases drastically. The large number of nodes and arcs can put a significant strain on memory resources and computational time. The positive aspect is that this calculation is performed only once, and the resulting solutions, comprising the selected search stations retained by the optimization process, are saved and treated as the set of optimal candidate stations for the upper-level optimization problem.

In this set of optimal candidates, equal charging station needs were assumed for all roads. However, this does not

[1]Source: statistiques-locales.insee.fr

accurately reflect real-life situations since road usage varies. By incorporating travel flows and weights, charging station placement and capacity can be optimized for high-demand areas, improving infrastructure efficiency and sustainability.

The weighting process utilized the national origin-destination (O-D) matrix of vehicle flows from the French government's official open data platform[2], estimating daily average vehicle travel between departments in 2011. This approach mitigates biases in real-world data (e.g., data collection methods or regional differences), providing a more accurate and realistic representation of travel flows. In this study, the O-D matrix data was processed to convert interdepartmental flows into inter-city flows for the selected cities (see Figure 1). Subsequently, a vehicle flow f_k is assigned to each candidate station x_k.

B. Phase 2: Optimal charging station selection

In the second part, the main goal is to address the upper-level problem as described by equations (2a)-(2c). However, given the computational time challenges associated with this problem, a practical alternative solution is proposed by employing the following weighted K-means clustering approach [20].

The candidate locations for charging stations are treated as data points, represented by the set $X = (x_1, x_2, \ldots, x_N)$, with each x_k corresponding to a potential site. Vehicle flows at each location serve as weights and are denoted by $F = (f_1, f_2, \ldots, f_N)$, where f_k signifies the vehicle flow at location x_k. The objective of this approach is to identify K optimal charging station locations $C = (c_1, c_2, ..., c_K)$, minimizing the objective function $J(C)$, which is defined as

$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in C_k} f_i |x_i - c_k|^2.$$

The objective function seeks to minimize the sum of squared distances between candidate locations x_i and their assigned centroids c_k, accounting for the location-specific importance f_i. To solve this optimization problem, the algorithm initializes K centroids, assigns each data point to the nearest centroid based on a distance metric (e.g., euclidean distance), recalculates the centroids as the weighted mean of the data points assigned to each cluster, and iterates these steps until convergence. The resulting centroids represent the K optimal locations for the charging stations, considering both proximity and importance. This ensures that charging stations are strategically placed in areas with higher traffic volumes, effectively addressing the charging demands of electric vehicles and enhancing the overall charging infrastructure.

With respect to minimizing the collective travel time of all EVs in the network as presented in (2a), this metric will be evaluated a posteriori, after the weighted K-means clustering algorithm has been applied to determine the optimal charging station locations. By assessing the time efficiency of the charging station placements, it is possible to ensure that users experience reduced waiting times and efficient access to charging facilities. This post-hoc analysis can also help identify areas for improvement and adjustments to the initial clustering algorithm or additional constraints that may be incorporated, ultimately leading to better charging station placements that cater to both spatial and temporal demands.

[2]Source: data.gouv.fr

IV. Simulation Results

For each examined infrastructure configuration, the lower-level optimization problem is solved for the 3,600 considered O/D pairs, as outlined in Section II-A, identifying fast routes and sequencing battery charging events. We then assess various metrics to evaluate system performance, such as average daily travel time per EV, average daily energy consumption per EV, and feasibility rate. The feasibility rate represents the percentage of routes that can be successfully completed by EVs without battery depletion, considering the presence of installed charging stations. A higher feasibility rate implies that the proposed approach effectively increases the number of viable routes for EV users, ensuring they can reach their destinations without exhausting their charge. This metric serves as an indicator of the approach's effectiveness in enhancing EV transportation's overall feasibility and usability.

The routing algorithm was implemented in MATLAB on a computer with an Intel(R) Core(TM) i7-8850H CPU at 2.6 GHz and 16 GB of RAM. Traffic data for the road network was sourced from HERE Maps for March 15, 2022, specifically during off-peak hours. We assume each O/D pair is served by an electric vehicle equipped with a 30 kWh battery. To provide a conservative and robust analysis of charging infrastructure requirements, a low-capacity battery was intentionally chosen to prevent reliance on high-capacity batteries for long-distance travel, thus ensuring users aren't forced to purchase EVs with larger batteries. This approach delivers practical and feasible solutions for charging infrastructure without imposing excessive demands on EV technology. In this study, we assume a charging power of 50 kW. As for the K-means clustering, the algorithm was executed in Python using the scikit-learn library.

The proposed method can be employed to strategically position charging stations on a road network currently lacking such infrastructure, while simultaneously improving the overall system by considering the existing stations.

A. Ideal scenario with no pre-existing charging infrastructure

The first simulation results seek to exhibit the effectiveness of the proposed method in strategically situating fast charging stations across France, assuming no pre-existing stations in the country. Our objective is to determine the optimal number of stations that achieve the highest route feasibility rate while simultaneously complying with the optimization criteria.

The computationally intensive initial phase, described in Section III-A, yielded a substantial set of 1,767 optimal candidate stations. During the optimal station placement phase, the upper-level problem ($M = 3,600$ and $N = 1,767$) was addressed using the weighted K-means algorithm with

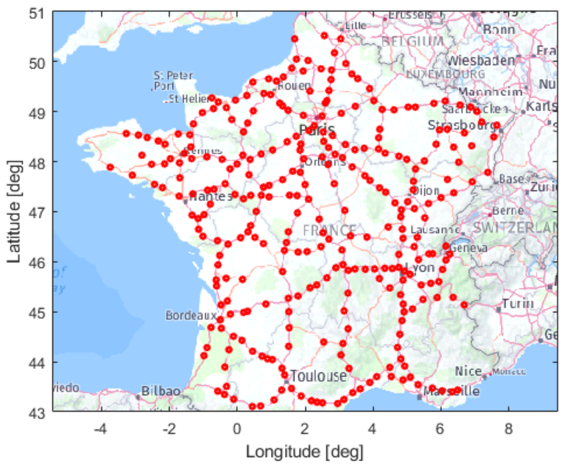

Fig. 2: Locations of 300 fast charging stations in France determined by weighted K-Means (displayed in Red)

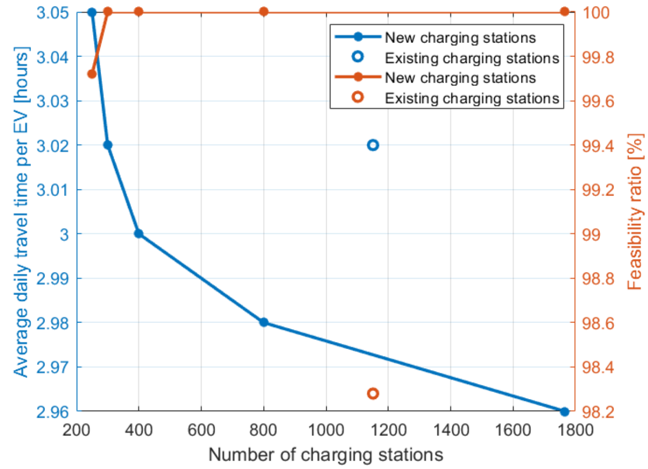

Fig. 3: Mean travel time vs. number of charging stations

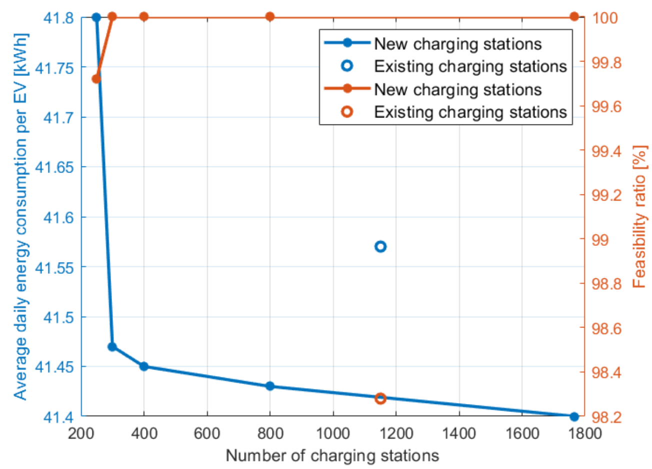

Fig. 4: Average energy consumption vs. number of charging stations

multiple values of K (K = 250, 300, 400, 800). This approach allowed for the analysis and understanding of the number of stations' influence on the overall solution. By examining different values of K, we aimed to gain insights into the impact of varying station quantities on the results and determine the optimal configuration for station placement.

To evaluate the performance of our approach, we compared various investment scenarios with the existing charging station network. For this purpose, we utilized the REST API of OpenChargeMap, a non-commercial, crowdsourced service known for its comprehensive and accurate information. This API facilitated the retrieval of precise charging station locations within the analyzed network. In September 2022, a data extraction was conducted, resulting in 1,150 existing fast charging stations in France.

Figures 3 and 4 showcase the comparison results. As demonstrated, increasing the density of charging stations leads to reduced average travel times and decreased energy consumption, owing to enhanced route planning efficiency. Installing a large number of stations may offer extensive coverage and convenience for EV users. However, it can also result in higher costs for station acquisition and installation, as well as increased operational and maintenance expenses.

Through strategic determination of ideal charging station locations, Figures 3 and 4 illustrate that it is feasible to minimize the required number of stations while still achieving a 100% feasibility rate. These figures emphasize the effectiveness of thoughtful placement in optimizing charging infrastructure, ensuring maximum coverage and accessibility for EV users while minimizing infrastructure costs. Using our approach, we can strategically position 300 charging stations (depicted in Figure 2) to achieve substantially improved performance across the network compared to the existing infrastructure. The observed gains per day and per EV are relatively modest due to the application of an optimal recharging strategy, which is also applied to the existing stations. Nevertheless, we observe an average reduction of 150 Wh in daily energy consumption per EV in France, mainly thanks to reduced detours to reach farther charging points. This leads to an overall decrease of 162 MWh per day nationwide, considering the over one million of daily trips contained in the national O-D matrix. This notable reduction underlines the effectiveness of our approach in enhancing energy efficiency and lowering the overall energy demand of electric vehicles in the country.

B. Realistic scenario incorporating existing charging infrastructure

Since September 2022, the existing charging infrastructure has experienced considerable enhancements. During our study, we performed two additional data extractions using the REST API. The first extraction in January 2023 recorded an increase of 82 charging stations, and the second one in April 2023 detected 273 newly installed stations throughout France.

Our method was applied to enhance the existing charging station infrastructure starting from September 2022. To take into account the existing stations and identify optimal areas for infrastructure improvement, a 10 km x 10 km mesh covering the area within the square that includes France (refer to the green square in Figure 1). We then calculated the optimal candidate stations density and the density of actual stations as of September 2022 within each mesh cell, considering traffic volume weighting. Figure 5 and Figure 6 illustrate the heat map of charging station density for the actual infrastructure and for the set of optimal charging stations. In the second step, we identify intersections of grid cells in the heat maps containing at least one charging station. This analysis reveals areas lacking charging infrastructure, enabling us to focus on regions requiring additional stations. By targeting non-intersecting squares, we enhance the charging infrastructure and derive station locations from the centers of these squares, yielding a new set of candidate sites with $N = 740$.

The second set of simulation results evaluates the effectiveness of our infrastructure development strategy by comparing it to the real-world charging station locations observed in January 2023 and April 2023. To achieve this, we employed the spatial clustering weighted K-means approach on this new set of candidate charging station locations, using $K = 82$ and $K = 273$ as the desired number of clusters. In each scenario, the new stations will be incorporated with the 1,150 existing stations as of September 2022. Figures 7 and 8 depict the impact of charging station expansion on travel time and daily energy savings per EV. These figures offer a comparison between the current infrastructure and our proposed infrastructure development strategy, beginning with the infrastructure status in September 2022 and tracing back its evolution. As observed, our approach yields a greater gain in comparison to the existing stations. Furthermore, with the incorporation of 273 additional stations, we achieve a 100% feasibility rate, surpassing the performance of existing infrastructure in April 2023, which does not currently attain such a rate. This improvement is especially notable when addressing the challenge of long-distance route planning for electric vehicles, considering battery charging constraints for all 3600 O/D pairs in our study. We also observe that, with our strategy, we could save approximately 160 MWh per day in France. This amount is approximately equivalent to the electricity generated by 15 onshore wind turbines, each with a power of 2 MW, a typical size for this type of turbines. Furthermore, this energy savings is comparable to the average daily electricity consumption of a small town of about 20,000 people in France. In addition, these figures show that the proposed strategy for placing charging stations achieves the performance of April 2023 with only 82 new stations, as opposed to the 273 existing stations. This means that our strategic placement could have saved nearly 200 stations. Given the average purchase and installation cost of a rapid charging station, ranging from 30,000 € to 60,000 €, the potential savings in infrastructure investment are substantial. For instance, with each station costing 45,000 € (mid-range), the savings could be approximately 9M €. This indeed emphasizes the effectiveness of our strategy in optimizing the deployment of EV charging

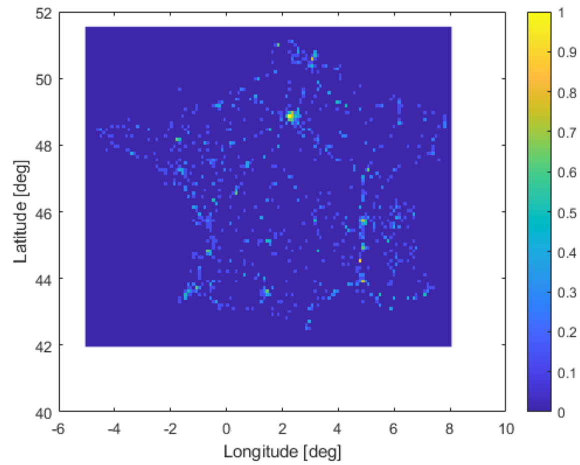

Fig. 5: Heat map of existing charging stations in France per 10 km square area.

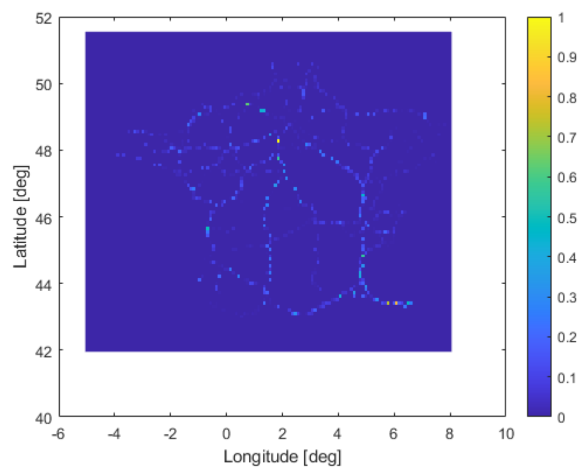

Fig. 6: Density of candidate charging stations, weighted by traffic volume per 10 km square area.

infrastructure, yielding considerable cost savings as well as energy reduction. The proposed approach not only results in significant financial savings but also contributes to a more sustainable and energy-efficient transportation system.

V. Conclusion

This work addresses the problem of optimal placement of fast charging infrastructure at nation-wide scale. A new bi-level optimization strategy is proposed accounting for the physics of long-distance trips. This includes vehicle-specific energy requirements, traffic-aware trip time, and model-based charging time. The chosen heuristic method, which approximates the upper-level of the optimization, allows the strategy to yield fast and practical results. These results can be utilized as a decision support tool for stakeholders in the charging infrastructure domain. The demand for long-distance travel is calculated using reliable and statistically unbiased national data, which determines the

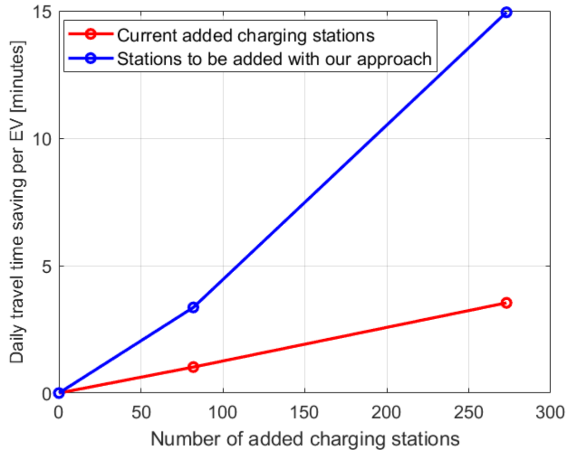

Fig. 7: Impact of charging infrastructure expansion on travel time savings per day and per EV

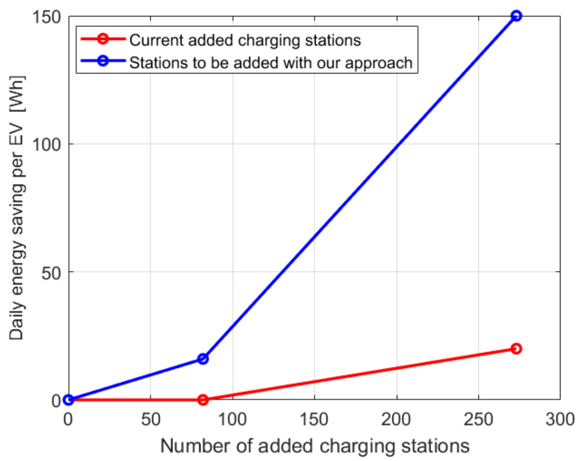

Fig. 8: Impact of charging infrastructure expansion on energy savings per day and per EV

probable origin-destination pairs within the territory and the corresponding average daily traffic volumes between each pair. Our approach has been compared with the current infrastructure, and the results demonstrate its superior efficiency in terms of travel time, energy consumption and feasibility rate.

Acknowledgments

This research was funded by ADEME (French Environment and Energy Management Agency); MOUVEMENT project, APRED 2020/2021, grant number 2266D0005.

References

[1] M. Z. Zeb, K. Imran, A. Khattak, A. K. Janjua, A. Pal, M. Nadeem, J. Zhang, and S. Khan, "Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network," *IEEE Access*, vol. 8, pp. 68 124–68 134, 2020. [Online]. Available: http://dx.doi.org/10.1109/ACCESS.2020.2984127

[2] M. F. Anjos, B. Gendron, and M. Joyce-Moniz, "Increasing electric vehicle adoption through the optimal deployment of fast-charging stations for local and long-distance travel," *European Journal of Operational Research*, vol. 285, no. 1, pp. 263–278, 2020.

[3] T. Franke and J. Krems, "Understanding charging behaviour of electric vehicle users," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 21, p. 75–89, 11 2013.

[4] A. A. Galadima, T. Aja Zarma, and M. A. Aminu, "Review on Optimal Siting of Electric Vehicle Charging Infrastructure," *Journal of Scientific Research and Reports*, pp. 1–10, oct 15 2019. [Online]. Available: http://dx.doi.org/10.9734/jsrr/2019/v25i1-230175

[5] M. Suhail, I. Akhtar, and S. Kirmani, "Objective Functions and Infrastructure for Optimal Placement of Electrical Vehicle Charging Station: A Comprehensive Survey," *IETE Journal of Research*, pp. 1–11, aug 31 2021. [Online]. Available: http://dx.doi.org/10.1080/03772063.2021.1959425

[6] Y. Yang, Y. Zhang, and X. Meng, "A data-driven approach for optimizing the ev charging stations network," *IEEE Access*, vol. 8, pp. 118 572–118 592, 2020.

[7] B. Vansola, M. Chandra, and R. Shukla, *GIS-Based Model for Optimum Location of Electric Vehicle Charging Stations*, 11 2022, pp. 113–126.

[8] W. Ejaz, M. Naeem, M. R. Ramzan, F. Iqbal, and A. Anpalagan, "Charging infrastructure placement for electric vehicles: An optimization prospective," in *2017 27th International Telecommunication Networks and Applications Conference (ITNAC)*. IEEE, 11 2017. [Online]. Available: http://dx.doi.org/10.1109/ATNAC.2017.8215427

[9] Z. Chen, F. He, and Y. Yin, "Optimal deployment of charging lanes for electric vehicles in transportation networks," *Transportation Research Part B: Methodological*, vol. 91, pp. 344–365, 9 2016. [Online]. Available: http://dx.doi.org/10.1016/J.TRB.2016.05.018

[10] A. Hess, F. Malandrino, M. B. Reinhardt, C. Casetti, K. A. Hummel, and J. M. Barceló-Ordinas, "Optimal deployment of charging stations for electric vehicular networks," in *Proceedings of the first workshop on Urban networking*. ACM, dec 10 2012. [Online]. Available: http://dx.doi.org/10.1145/2413236.2413238

[11] Z. Yi and P. H. Bauer, "Optimization models for placement of an energy-aware electric vehicle charging infrastructure," *Transportation Research Part E: Logistics and Transportation Review*, vol. 91, pp. 227–244, 7 2016. [Online]. Available: http://dx.doi.org/10.1016/J.TRE.2016.04.013

[12] W. Kong, Y. Luo, G. Feng, K. Li, and H. Peng, "Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid," *Energy*, vol. 186, p. 115826, 11 2019. [Online]. Available: http://dx.doi.org/10.1016/J.ENERGY.2019.07.156

[13] G. De Nunzio, I. Ben Gharbia, and A. Sciarretta, "A time- and energy-optimal routing strategy for electric vehicles with charging constraints," in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, 2020, pp. 1–8.

[14] F. Jabeen, D. Olaru, B. Smith, T. Braunl, and S. Speidel, "Electric vehicle battery charging behaviour: findings from a driver survey," in *Australasian Transport Research Forum 2013 proceedings*. Australasian Transport Research Forum, 2013, australasian Transport Research Forum 2013 ; Conference date: 02-10-2013 Through 04-10-2013.

[15] Q. Yuan, W. Hao, H. Su, G. Bing, X. Gui, and A. Safikhani, "Investigation on Range Anxiety and Safety Buffer of Battery Electric Vehicle Drivers," *Journal of Advanced Transportation*, vol. 2018, no. 8301209, 2018.

[16] B. Zeng, H. Dong, R. Sioshansi, F. Xu, and M. Zeng, "Bilevel robust optimization of electric vehicle charging stations with distributed energy resources," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5836–5847, 2020.

[17] L. Yan, "Optimal layout and scale of charging stations for electric vehicles," in *2016 China International Conference on Electricity Distribution (CICED)*. IEEE, 8 2016. [Online]. Available: http://dx.doi.org/10.1109/CICED.2016.7575934

[18] B. Ferguson, V. Nagaraj, E. C. Kara, and M. Alizadeh, "Optimal Planning of Workplace Electric Vehicle Charging Infrastructure with Smart Charging Opportunities," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 11 2018. [Online]. Available: http://dx.doi.org/10.1109/ITSC.2018.8569299

[19] G. De Nunzio and L. Thibault, "Energy-Optimal Driving Range Prediction for Electric Vehicles," in *IEEE Intelligent Vehicles Symposium*, 2017, pp. 1608–1613.

[20] I. S. Dhillon and D. S. Modha, "Concept decompositions for large sparse text data using clustering," *Machine Learning*, vol. 42, pp. 143–175, 2004.