Optimising the positioning of charging points for electric vehicles

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Abstract. In this work, we tackled the complex problem of electrical vehicle charging stations placement. Focusing on a specific city, La Baule-Escoublac, our approach followed two parallel paths. In the first one, we tried to estimate the demand of charging stations from users. We conducted a thorough data analysis, allowing us to calculate two distinct types of demand: the first based on the number of electric vehicle owners, and the second on energy needs estimated from the population's travel patterns. In the second path, we implemented different algorithm to solve the NP-hard optimization problem of placing the stations. We used two approach, a greedy and a genetic one. Our final results are consistent with already existing stations and profit values. All our codes and experiments can be found in the associated GitHub repository [1].

1 Context

The main objective is to **optimize the positioning of charging stations for electric vehicles across France.** Specifically, this involves determining the optimal distribution of stations, charging points, and power levels based on client requirements and key points of interest.
This question is significant for Vinci, the mentor, because optimizing the EV charging infrastructure:

- Ensures efficient resource allocation and better coverage for EV users.
- Supports the transition to sustainable mobility by reducing range anxiety.
- Enhances infrastructure planning through data-driven decision-making.
- Improves station fleet supervision for better management and scalability.

For this project, we decided to build the model and test it on a single commune, which for our case is La Baule-Escoublac.

2 Data

At the beginning of our project, we were provided the following data :

- **French cities boundaries (Data.gouv.fr)** – Geographic boundaries of cities
- **French road network (IGN TOPO** – Geographic dataset containing road infrastructure
- **Charging station in France (IRVE)** – Geographic dataset of existing charging stations
- **Vehicle fleet per city (INSEE)** – Information on vehicle fleets (including EVs)
- **Origin-Destination matrices from INSEE** – House-work trips for workers per city

In addition to these datasets, through our research and discussions with the mentors, we realized that we needed to add a new database with the finest and most information-rich partition possible. We then found two promising possibilities, both with fine population-related data. Figures of each division can be found in Appendix A.

- **Population per IRIS zone (INSEE)** – A zoning system, used by INSEE for statistical analysis, divides areas into neighborhood-sized zones.

- **Population per 200m or 1km squares (INSEE)** – A geographic zoning system, aggregating population data, enabling precise spatial analysis (200m or 1km grid squares)

Both datasets provide valuable insights such as population density, revenu distribution or housing data (see Appendix A). The grid-based dataset (200m or 1km) offers higher spatial resolution for micro-level analysis, while the IRIS zones provide a more structured division, useful for urban planning.

3 Demand estimation

One of the main challenges in solving this problem is accurately estimating the energy demand for electric vehicles in the city. Proper demand estimation is crucial for strategically placing charging stations in high-demand areas. If the demand is miscalculated, charging stations may be underutilized, leading to financial losses for the company.

3.1 Population demand

Our first approach involved estimating the demand with the population inside each zone. This is a first approximation, made by [2] in the city of Hong-Kong. However, by doing so we overestimated a lot the demand as everybody does not have an electrical vehicule. Unfortunately, we don't have access to a clear database of electric vehicle owners, which is leading this route down a blind alley. However, this first estimation helped us the provide first approximated results and develop our algorithms.

3.2 Energy-based demand

To address the latter, we leveraged the previously presented data to estimate an energy-based demand based on two primary sources: Resident demand (energy consumption from city inhabitants and commuter demand (energy consumption from individuals who live outside the city but work within it). By adding these two sources, we obtained an estimate of the total energy demand per zone in the city, expressed in kWh per day.

Resident demand We estimated the daily energy demand for each zone using the following equation:

$$\text{Demand}_{\text{residents}} = N_{inhabitants} \times \left(\frac{N_{apartments}}{N_{houses}} \right) \times R_{EV} \times D_{avg} \tag{1}$$

where:

- $N_{inhabitants}$: number of inhabitants in the zone,
- $\frac{N_{apartments}}{N_{houses}}$: ratio of apartments to houses,
- R_{EV}: proportion of EV drivers per inhabitant,
- D_{avg}: average energy demand per inhabitant, with $D_{avg} = 6$ kWh (30km).

Workers demand To estimate the energy demand from commuters, we used the INSEE dataset on work-home mobility patterns. These datasets allowed us to quantify the number of trips made by workers and deduce their daily charging needs. We assumed that the proportion of electric vehicle (EV) drivers among workers is the same as the national average in France, enabling us to calculate the additional energy demand generated by commuters. Moreover, we distributed the commuter demand based on the intersection of travel routes with different city zones. This approach ensures that high-traffic areas, such as main roads, receive a higher demand allocation than more peripheral locations.

4 Methods

Parameters Our algorithms rely on different parameters to find the best charging station locations. These parameters are estimated thanks to the data analysis and exploration previously made. First, we considered the 3 different cuttings of La Baule. Each zone is a potential placement for a charging station. In order to run our algorithm, which are based on graph theory, we need the adjacency matrix of the locations, which we computed using the distance by roads in the city. Then we need an estimation of the demand per location. We first considered two different estimations: by population, and by kWh. But after our experiments, we found out that the demand in population led to inconsistent profit results so we only kept the demand in kWh.

We need a whole list of other parameters, that can be found in appendix B.

4.1 Greedy Approach

We initially attempted a greedy approach based on the method described in [2]. This approach involved starting with stations everywhere and systematically removing them while ensuring demand satisfaction. We then evolved this method to a variation where we began with no stations and selectively placed them based on maximizing profit. Algorithm 4.1 shows how it works.

Algorithm 1 Greedy Algorithm for Charging Station Placement

```
Initialize all nodes to 0 (no charging stations placed), best_profit to 0
Get existing charging points
while best_profit can increase do
    Set best_node to None
    for each node in the network do
        Simulate the profit of the network with an additional charging point in this node
        if profit is better than best_profit then
            Update best_node and best_profit
        end if
    end for
    if no improvement is found then
        Break the loop
    end if
    Add a charging point to best_node
end while
return the final solution
```

4.2 Genetic Approach

In order to have different methods to compare, we wanted to implement a genetic algorithm, taking inspiration from [3].

Moreover, this new approach allowed us to take into more constraints like being able to place more than one station in a location, and more importantly, taking into account already existing stations.

The idea is to start from a random set of solutions and generate new slightly modified solutions from the best previous ones. The best solutions are determined with a *fitness score* which we modeled with a combination of coverage and profit. The solutions are modified with mutations and crossovers. A mutation is a random modification of a specific point of the solution, while a crossover is a merge of two previous solutions. We define the fitness of a solution s as following:

$$fitness(s) = coverage(s) + profit(s) \tag{2}$$

A solution s corresponds to $(x_i)_{i \in I}$ where each x_i correspond to the number of stations at location

i in the set of possible locations I. $coverage(s)$ corresponds to the proportion of the demand which has access to a nearby station. It can be mathematically defined as:

$$coverage(s) = \frac{1}{D} \sum_{i \in I} d_i v_i \mathbb{1}_{\{\exists j \in I : i \in \mathcal{C}_j\}} \tag{3}$$

where d_i is the demand in i and $D = \sum_{i \in I} d_i$ is the total demand. $\mathcal{C}_j$ is the set of locations reachable from j with an electrical vehicle and v_i is a function which takes into account y_i, the number of existing stations, defined as:

$$v_i = \begin{cases} 1, & \text{if } x_i = 0 \\ \frac{x_i}{x_i + y_i}, & \text{otherwise} \end{cases} \tag{4}$$

The $profit(s) = pD(s) - c$, with p the price for the user, c the cost of the charging station and $D(s)$ being the total demand actually satisfied by the solution s. This demand is computed with the coverage and the capacity of the charging stations.

We run this modification of solutions for a fixed number of generations, and hope that the final solution will combine the best aspects of each generation. We also allow the algorithm to place several stations in the same place when the demand is to high to be fully covered by only one charging point. Algorithm 4.2 explains how it works.

Algorithm 2 Genetic Algorithm

Initialize a population P of n random individuals
Evaluate each individual $s \in P$ using fitness function $fitness(s)$
while number of generations not reached **do**
  $P' \leftarrow \emptyset$ {New population}
  while $|P'| < |P|$ **do**
    Select two parents $p_1, p_2 \in P$ based on fitness
    $c_1, c_2 \leftarrow$ Crossover(p_1, p_2) with crossover probability p_c
    for each child $c \in \{c_1, c_2\}$ **do**
      $c \leftarrow$ Mutate(c) with mutation probability p_m
      Evaluate $fitness(c)$
      Add c to P'
    end for
  end while
  $P \leftarrow P'$
  Preserve the best individual found so far
end while
return the best individual in P

5 Results

In the end, our two algorithms do not work exactly in the same way. Indeed, in the greedy algorithm, we add charging points until we cannot increase profit or we reached a maximum number of points. In the genetic one, we impose a maximum number of stations to get the maximal fitness score. Thus we did not really compared the same optimization problem for both algorithm, but we can still compare their results.

We can see in Table 3 that the profit we get from our stations is consistent. In the computation of the coverage, we can see that for the divisions of 200m, we have a very low coverage. This can be explained by the already existing stations which, in the calculation of the coverage, take into account market shares. However, the profit is not impacted as the stations are still fully exploited by the demand. In figure 2, we can see an example of station placement with the genetic algorithm.

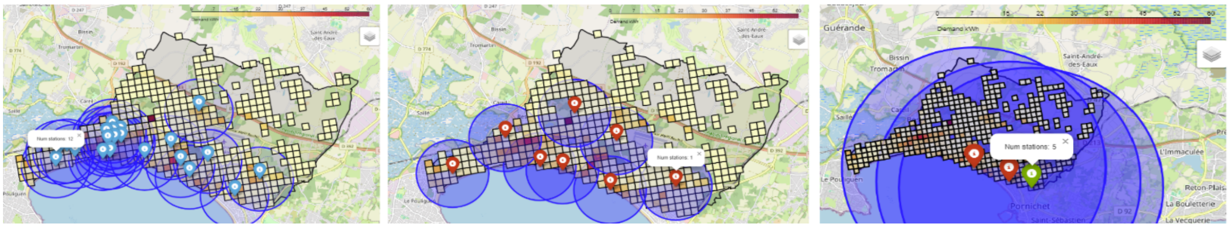

Figure 1: Positioning of charging stations superimposed on estimated demand. **Left**: actual station placement. **Middle**: greedy result for a radius of influence of 1 km. We can see here that the placement of our stations is very similar to existing stations. **Right**: greedy result for a 5 km radius of influence. Red dots indicate 1 charge point. Green dots mean 5 charge points. The blue dot can signify several values.

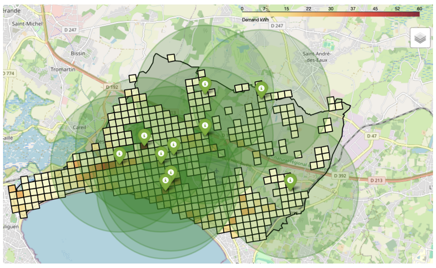

Figure 2: Station placement with genetic approach, for a maximum of 10 stations. The area of influence of each station is displayed.

Division Type	**Coverage (%)**	**Profit (€/day)**
Iris	98.95	583.04
1 km	73.75	651.56
200 m	28.10	649.04

Figure 3: Results for the Genetic algorithm, with αD = 1km and a maximum of 10 stations, considering existing stations for the 200m division. In this table, we do not display the result with existing stations for other divisions.

6 Conclusion

We managed to produce significant results, but our work still has some notable limitations. In our current model, we only consider one type of charging station with a fixed capacity. In reality, however, Vinci offers three types of charging stations (Normal Charging Stations, Fast Charging Stations, and Ultra-Fast Charging Stations) and integrating this distinction would make our model more reflective of real-world conditions. Moreover, our model assumes that the stations are in continuous use, which, of course, is not necessarily the case. This would help us more accurately gauge the demand that charging stations meet, whether we're talking about existing stations or new ones we add to the network. Furthermore, it would be interesting to test our models on different cities to assess its behaviour in diverse settings.

All of these limitations present clear opportunities to enhance our model, making it more realistic and robust.

Organization within the team After our initial meeting with Vinci's team, we each reviewed relevant research papers and shared our findings, which helped align our understanding and define the project's scope. We divided the workload, with some team members focusing on data sourcing, integration, and feature selection, while others worked on developing and testing models. We maintained constant communication through a text group and held group calls before or after meetings with Vinci to align our thoughts.

While roles were initially assigned, we remained flexible, assisting each other as needed based on task complexity or availability. Weekly meetings with Vinci helped refine our direction and keep us focused on what mattered most. This organization allowed us to progress steadily, with Vinci's ongoing feedback ensuring our work stayed relevant and aligned with the project goals.

References

[1] Emma de Charry, Anas Chaoui, Eliott Henry, and Maxime Moutet. `https://github.com/MoutetMaxime/capstone-vinci`. GitHub repository.

[2] Albert Y. S. Lam, Yiu-Wing Leung, and Xiaowen Chu. Electric vehicle charging station placement: Formulation, complexity, and solutions. *IEEE Transactions on Smart Grid*, 5(6):2846–2856, November 2014.

[3] Mohammad M. Vazifeh, Hongmou Zhang, Paolo Santi, and Carlo Ratti. Optimizing the deployment of electric vehicle charging stations using pervasive mobility data. *Transportation Research Part A: Policy and Practice*, 121:75–91, March 2019.

A Data

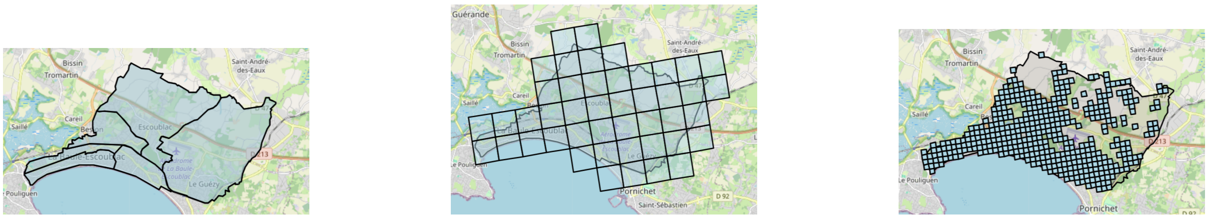

Figure 4: The Iris partition, 1km x 1km partition and the 200m x 200m partition.

Where there is no square, it means the area is uninhabited, and therefore no data is available.

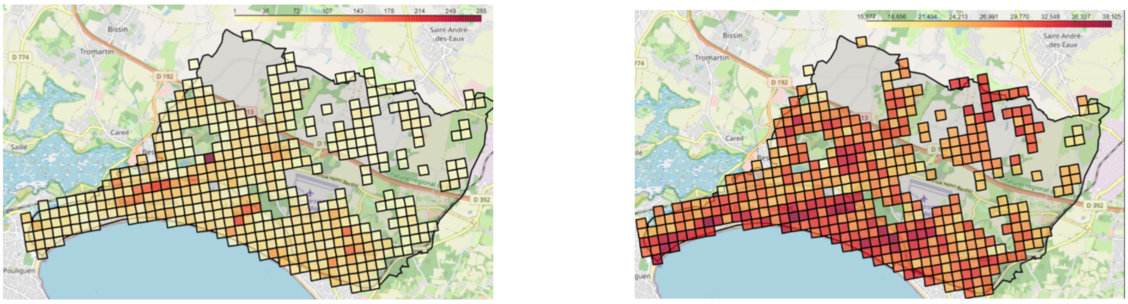

Figure 5: Population distribution (left) and revenue distribution (right) on the 200m x 200m partition.

B Parameters list

We have common parameters for both types of demande (population/kWh):

- **Cost**: cost for the firm of placing a charging station. It is computed with the price of the station, smoothed over the entire lifespan of the product.
- **D**: The average distance traveled by an electric vehicle without charge.
- α: A parameter that indicates the risk aversion of users to breakdowns. A value close to 1 means that users are prepared to travel the distance D before recharging, while a value of 1/2 means that when the vehicle is at half charge, users will go to a charging station.

We then have parameters depending on the type of demand we consider:

- **Price per kWh**: price paid by a user per kWh (0.25 €/kWh)
- **Price per charge**: price paid by a user for a complete charge (20€)
- **Station capacity in kWh**: Number of kWh a station can deliver over a day. This number depends on the station, but we used an intermediate value of 60kW over a day of 8h.
- **Station capacity in population**: Number of people a station can charge in a day. To estimate this parameter, we used the value from [2], which is the inverse of the density with a constant factor.