

# Optimal distribution of charging stations for electric vehicles

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[wp.bcamath.org/esgi150](http://wp.bcamath.org/esgi150)



# Challenge Presentation

- What is the optimal deployment of the interurban network of public charging stations?

With different chargers disaggregated by type

- BASE CASE**

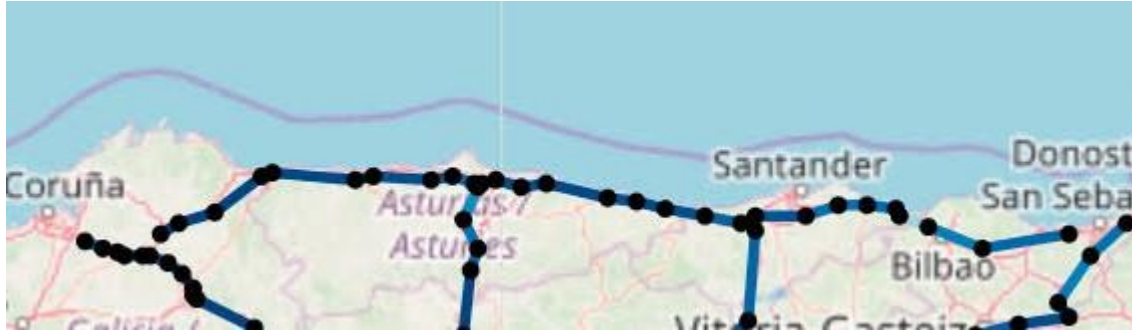
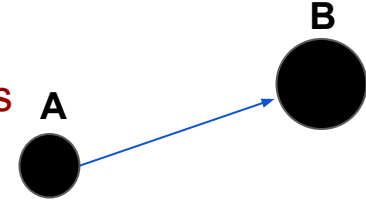
Considering 65 charging stations are already available



# Assumptions

#A2. We focus on the interurban behavior → Road by road approach

- Cities have their own charging stations
- Commuter model, IMD based, **other approach, gravity models**
- IMD measurements are “dense”



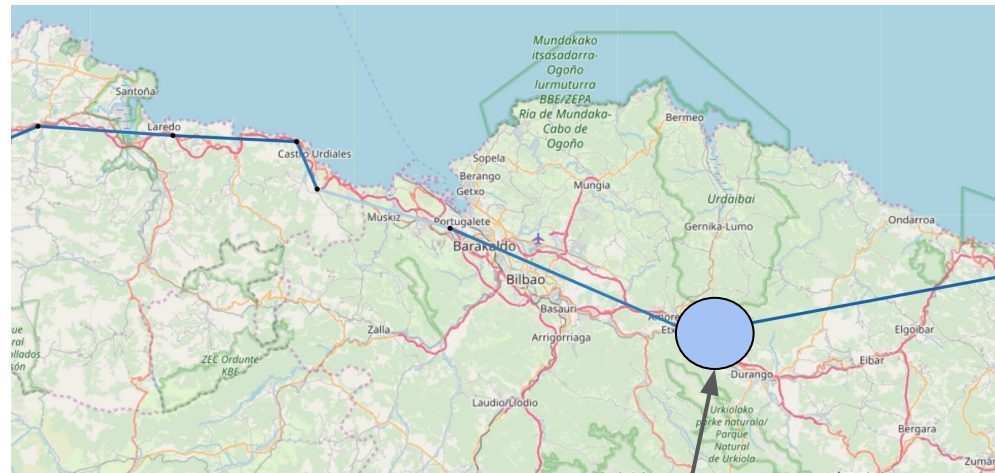
# Input Data

Number EV

Battery size of the vehicles

Coordinates of IMD

#A1. Fixed Range! (100Km)



Mean Day Intensity

% of Light Vehicles

# Station information

	T1	T2	T3
Power (kW)	50	150	350
<b>N° vehicles simul*</b>	2	3	6
Charging t (min/vehicle) in 2018	30	10	5
<b>Installation cost (€)</b>	28900	289000	578000
Charging cost (€/kWh)	0,15	3	8



# Modelling?

We decided to focus on **two goals**:

A. Low total cost of building the charging stations:

$$\text{Cost} = (\text{Number of stations}) \cdot (\text{Prize per station})$$

*Cost is easy to model and good for algorithms (Linear Optimization)!*

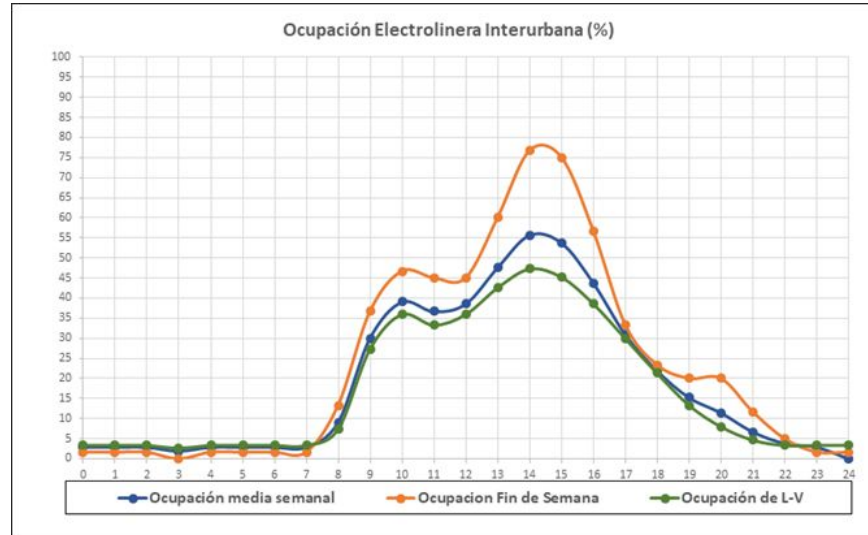
B. Low maximum waiting time at all stations:

**Problem:** How can we compute/model the waiting time at a station?

A detailed description requires **queueing theory**. We used a simpler approach!

# Energetic Approach I - Peak Traffic

Traffic has two phases: Peak traffic / off-peak traffic



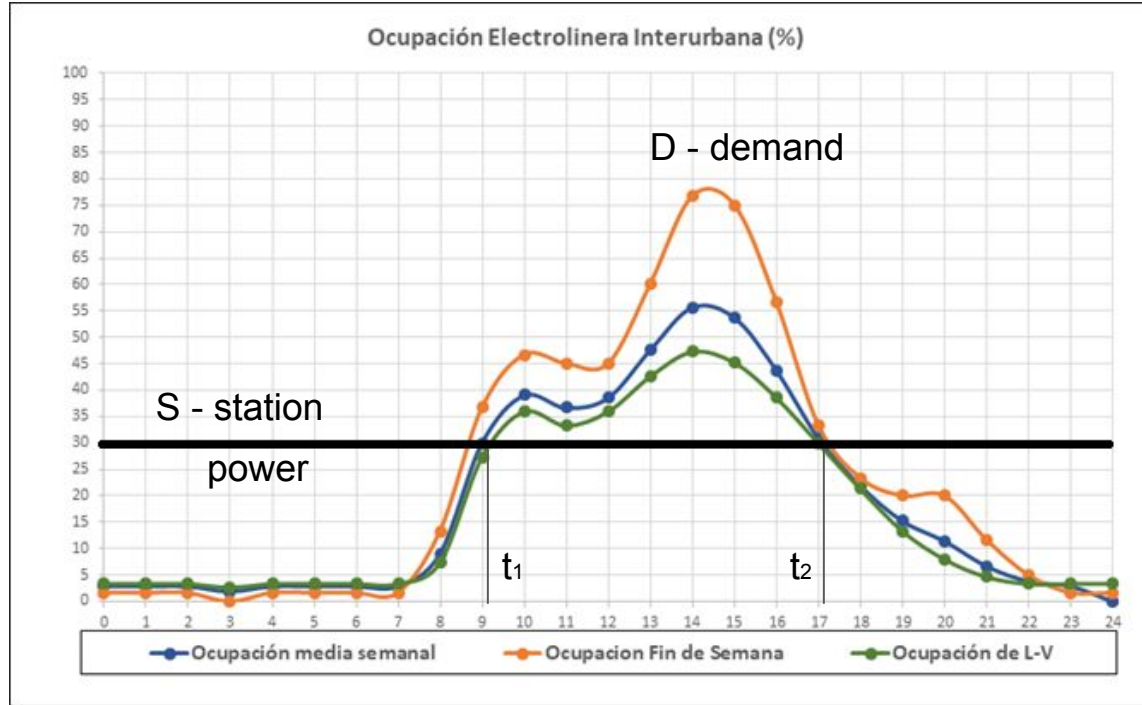
(Peak time traffic diagram by Iberdrola)

# Energetic Approach II - Approximation

- We approximate waiting time with energy demand at each point
- Assumptions:
  - Energy demand at each point is proportional to the car movement density
  - Waiting time at each point depends on the power balance



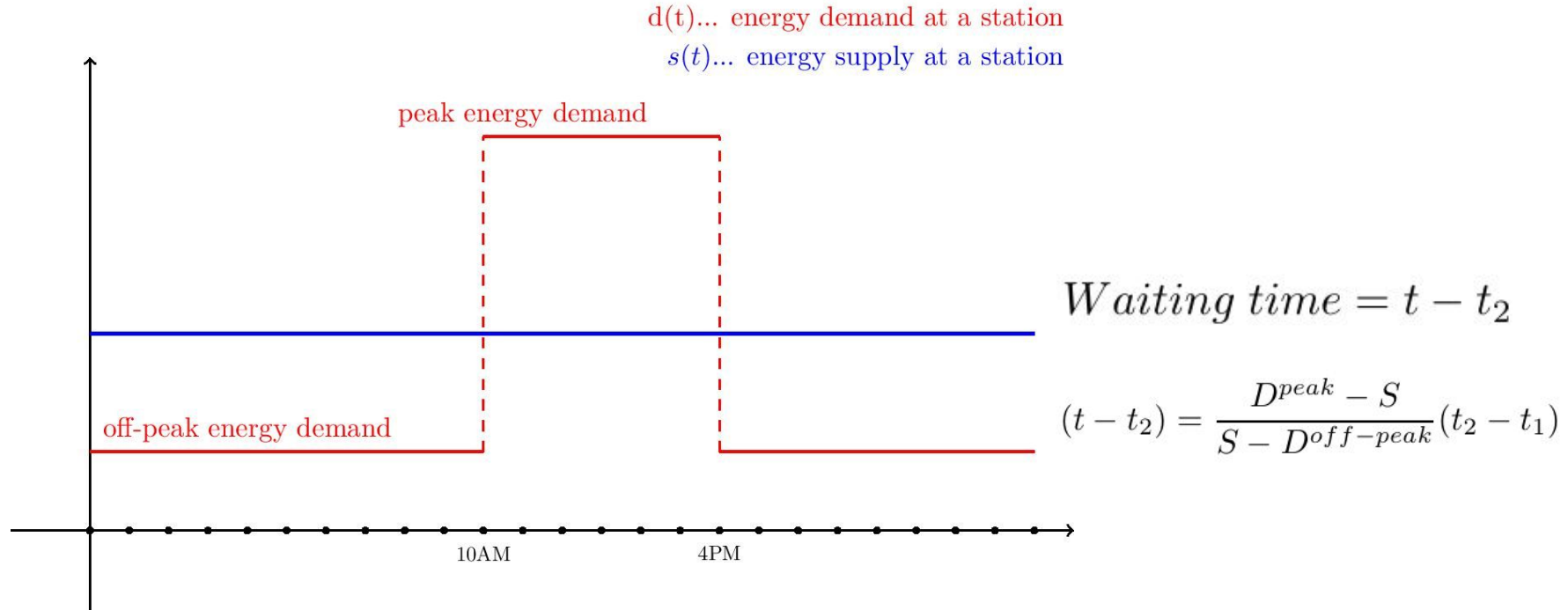
# Energetic Approach III - Approximation



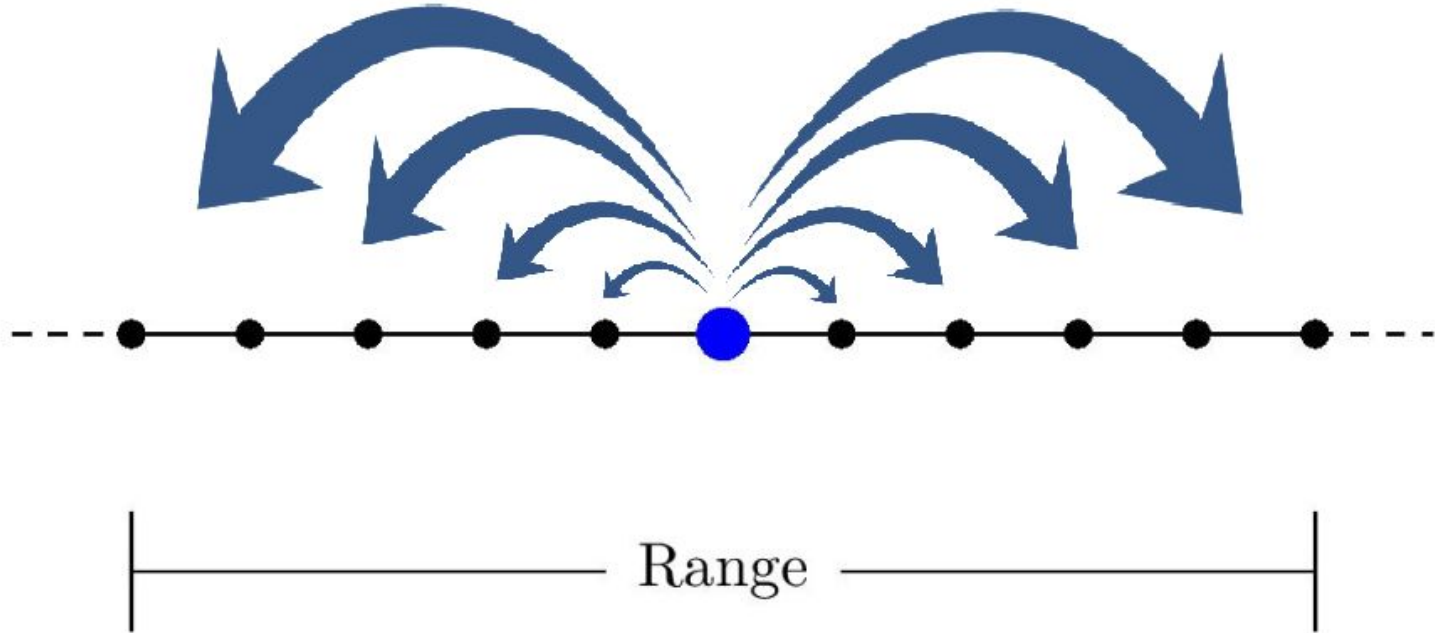
Waiting time =  $t - t_2$

$$\int_{t_1}^{t_2} D - S = \int_{t_2}^t S - D$$

# Energetic Approach III - Approximation



# Energetic Approach III - Demand



# Energetic Approach III - Demand

- General formulation

$$\int D_k = \sum_{\substack{j \in X \\ \|j-k\| \leq R}} IMD(j) \cdot D_{j \rightarrow k} \cdot P_{j \rightarrow k}$$

- Application

$$\int D_k = \sum_{\substack{j \in X \\ \|j-k\| \leq R}} IMD(j) \cdot C_e \|j-k\| \cdot \frac{1}{NSR(j)^2}$$

# What is the genetic algorithm?

It's a particular type of evolution algorithm where an initial population of solutions is repeatedly modified, such that it evolves toward the local optimum.

Useful terminology:

- **Fitness function:** the objective function to be minimized.
- **Individual:** a specific solution.
- **Population:** array of individuals.
- **Parents and children:** parents are the individuals selected within the population to produce the next generation.

# Classic algorithm vs Genetic algorithm

Classic algorithm (ex. line search)	Genetic algorithm
<p>At each iteration it generates one solution.</p> <p>The sequence then converge to the optimum.</p>	<p>At each iteration it generates a population</p> <p>The best individual (the one with the least fitness value) converges to the optimum</p>
<p>Points in the sequence are computed analytically</p>	<p>Next generations are computed using random generators.</p>

# Three types of rules

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At each step the next generation is computed according to three types of rules:

- **Selection:** It selects the parents.
- **Crossover:** combines the selected parents to form children.
- **Mutation:** Apply changes to parents to form children.

# The algorithm

It begins with a random initial population.

Then at each step it creates a sequence of population as following:

- Computes the fitness values of the current population.
- Based on the values, it selects the parents.
- Children are produced from parents, with crossover or mutation.
- Replace the initial population with the new children.





# Goal

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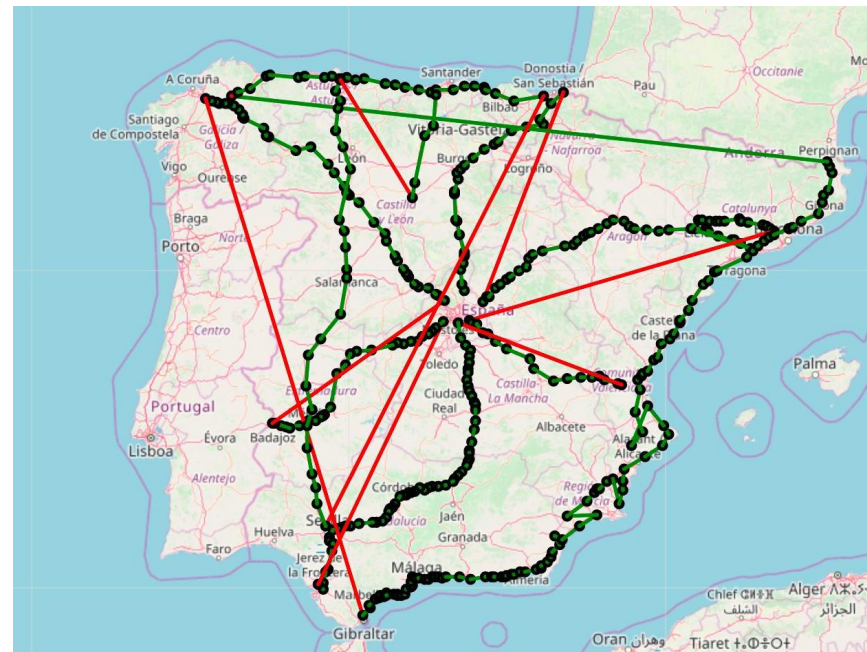
The optimization problem formulated falls in the class of nonlinear integer programming (INLP) problems.

The goal is to apply the genetic algorithm to both single and multi-objective cost functions.



# Data Cleaning

- One point is placed in the wrong road
  - Close to Marbella the street is divided in two streets
  - Loops
    - Near Barcelona
    - Near Cartagena
    - Near Lleida
- Clean up the data
- Correct and remove odd points



# Pareto and Genetic algorithms

- Genetic algorithms create many solutions and filter out good ones
- With two objective functions, sometimes it is unclear what solution is “best”
- Overview over all solutions and exclude “dominated solutions”
- This creates the “Pareto Front”, solutions which are candidates for “best”
- Sometimes this produces a good picture, sometimes not



# Solutions for Road A2

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Road A2 has a clear Pareto Front, but which solution to choose?

- Low waiting time and high cost?
- Medium waiting time and medium cost?
- High waiting time and low cost?

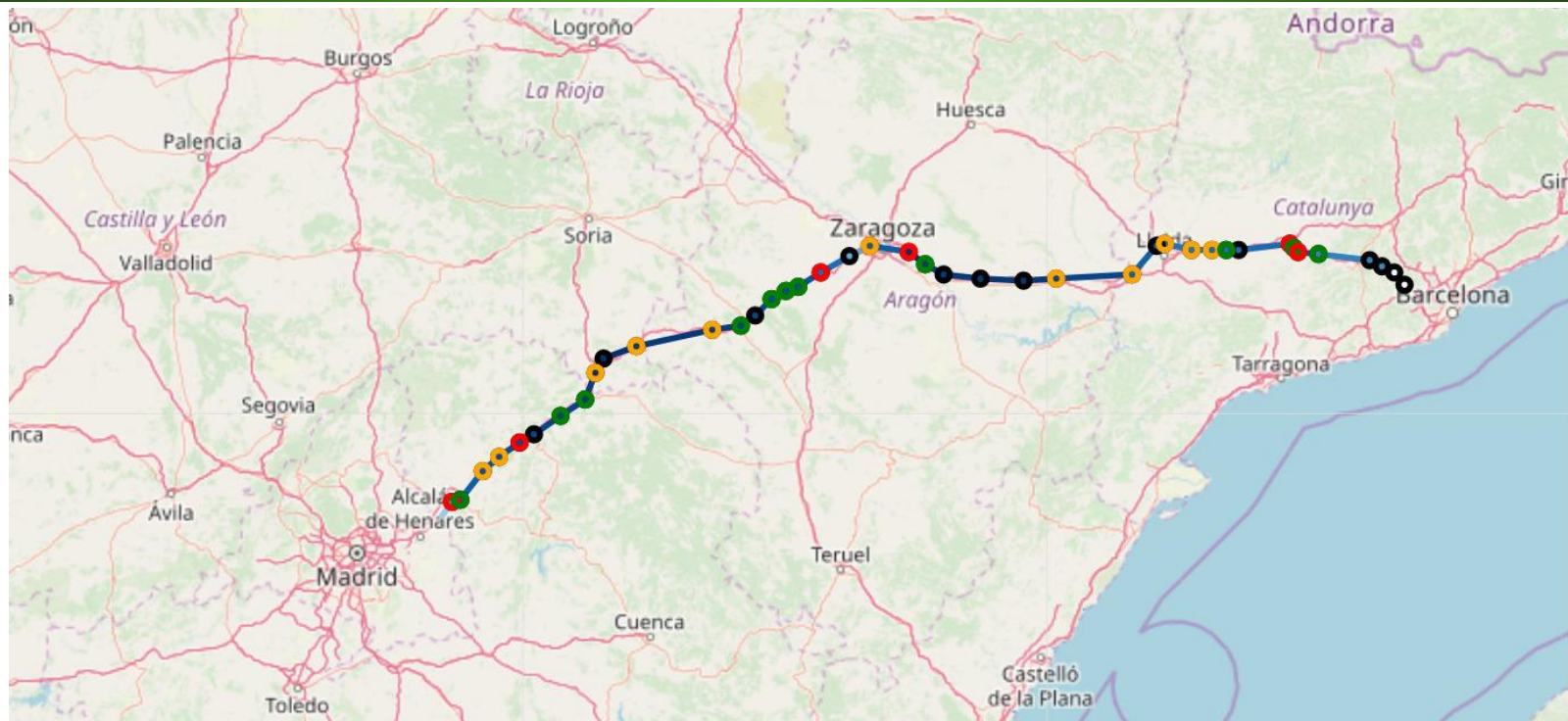
Note: We assume only one charging station per location.

# Low waiting time, high cost





# Medium waiting time, medium cost



# High waiting time, low cost





# Combined solution

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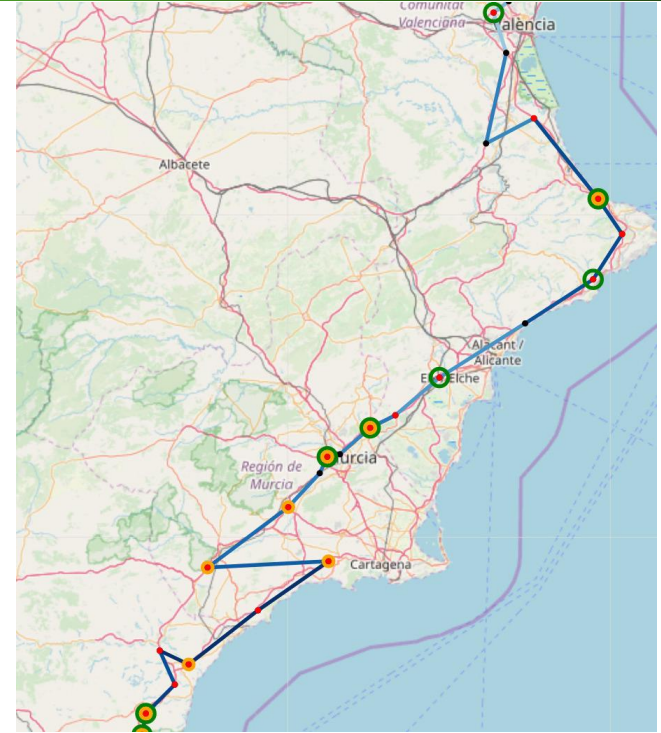
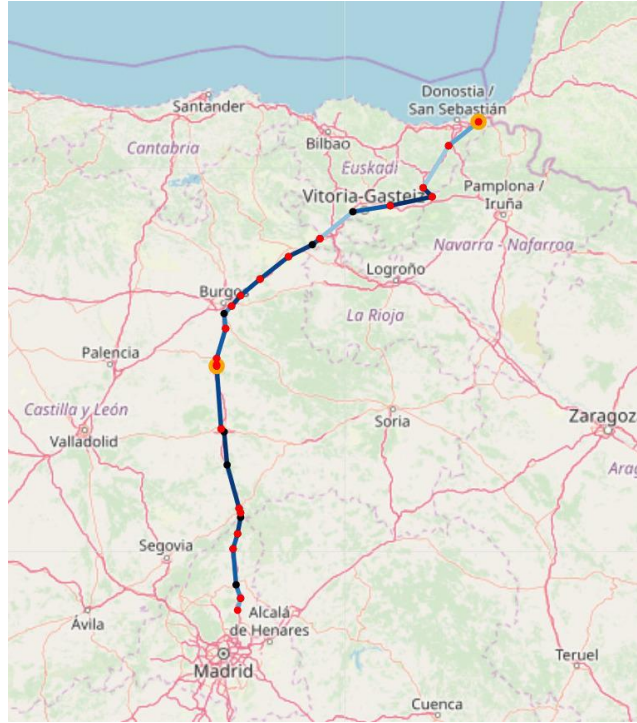
- Select **a** best solution from every individual simulation for each road
- Combine these solutions into a whole grid of stations



# Multiple charging stations per location

- At one location, there can be more than one charging station
- This leads to a more difficult optimisation problem, but is closer to reality
- Very promising ideas for programming

# Multiple charging stations at one location



# Future work

Distinguish between regions depending on

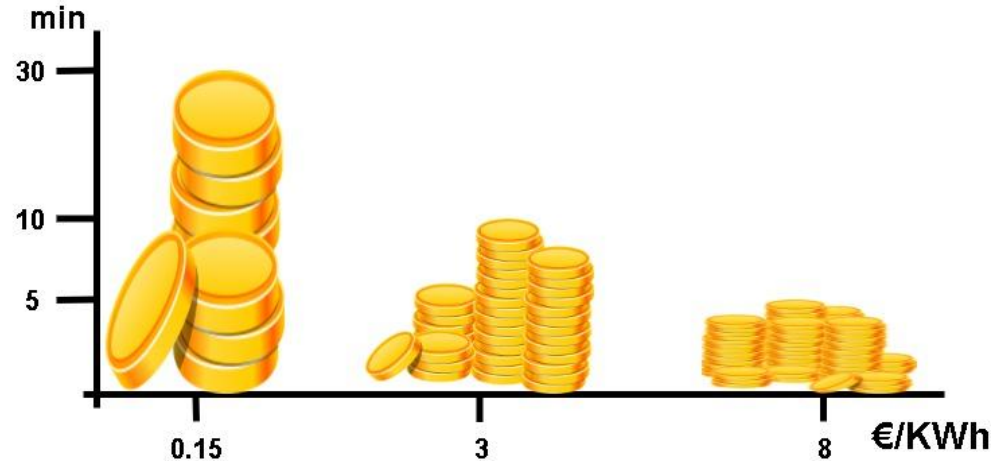
The wealth

Number of electric cars

The traffic

Decrease charging time

Consider locate more than one  
type of charge station per place



# Thank you!