ESGI 150 IBERDROLA CHALLENGE

October 2019

1 Problem description: Optimal design of the EV's public charging network.

We would like to determine what is the optimal design of the EV's public charging network in the Spanish territory with the data facilitated by Iberdrola.

Since we are optimizing the design for interurban mobility and not for each city particularly, we will optimize per road. The road system in Spain is formed by 10 roads, 8 central ones from Madrid and 2 peripherals going around the peninsula.

This assumption of optimizing per road and not the whole graph was done as a first simplification of the problem and since it is assumed that each vertex or city would have its own charging stations and we are not taking into account any smaller secondary road which would result in intersections.

In addition, Iberdrola would like to take into account the stations that are already available on the network. We will first propose and solve the problem without taking them into account as introducing them will be equivalent of restricting the solution once the problem is posed.

2 Description of the optimization problem: the objective functions

To determine the optimal design of the EV's public charging network, we simultaneously focus on two goals:

(1) Minimize the building cost of the network.

(2) Minimize the maximum waiting time throughout the network.

More precisely, we are dealing with a multi-objective optimization problem with two objective functions g_1 and g_2, which model the total building cost of all stations and the maximum waiting time over all stations. In addition, we constrain ourselves to solutions such that there is a at least one charging station every 100 kilometres (the type of the station does not matter in this constraint).

In the following, we describe our choice of the objective functions g_1 and g_2.

2.1 Building Cost

The objective function describing the building cost is given by

$$g_1 = \sum_{k=1}^{3} v_k b_k. \tag{1}$$

Here, for any $k = 1, ..., 3$, v_k denotes the number of stations of type k and b_k is the building cost (in euros) of one station of type k, given by

$$b_1 = 28900, \qquad b_2 = 289000, \qquad b_3 = 578000. \tag{2}$$

2.2 Waiting time

The objective function describing the maximum waiting time in the network is given by

$$g_2 = \max_{i:\exists \text{station at the node } i} W_i, \tag{3}$$

where W_i is the maximum waiting time of an electric car at the station at the node i. Hence it remains to model W_i in a suitable manner. Whereas other sources employ queueing theory to describe the waiting time (see [1]), we use an *energetic approach*:

2.2.1 Total energy demand

First of all, we consider the total energy (in kWh) demanded at a station at the node i during one day, denoted by D_i. We assume that each electric car can only travel a certain distance without charging. For simplicity, we assumed that all electric cars have a range of 300 km. Converting this to the combinatorial distance (recall that nodes are assumed 15 km apart from the next one), each electric car can travel

$$R = 20 \tag{4}$$

nodes without charging. Having this assumption in mind, we describe D_i by

$$D_i = \sum_{\substack{j:\exists \text{ station at the node } j \\ \text{and } d(j,i) \leq R \\ \text{and } i,j \text{ are on the same road}}} d(i,j) \cdot c \cdot \mathrm{IMDEV}_j \cdot p_S(j) \cdot p_J(j,i). \tag{5}$$

Here, the appearing quantities are defined as follows:

- c... cost of energy (in kWh) for an electric car to go from one node to the next one, that is, to go 15 kilometers; We assumed that $c =$ (!!! I'm not sure what we used in the simulation?)

- $d(i,j)$ ... defined for two nodes i and j; it's the "combinatorial distance" between i and j; = the number of steps to go from i to j (for example, $d(i,i+1)=1$))
- NRS_i ... defined for a node i; the number of stations, which are reachable from the node i in $\leq R$ steps and are on the same road;

  $\mathrm{NRS}_i = \#\{j : \exists \text{ station at the node } j, d(i,j) \leq R \text{ and } i,j \text{ are on the same road }\}$
- $\mathrm{IMDEV}_j = \mathrm{IMD}_j \cdot 0.1$ .. total number of electric cars passing at the node j during one day; we assume 10% of all cars are electric
- $p_S(j)$... the probability, with which an electric car passing the station at the node j stops to charge
- $p_J(j,i)$... the probability with which an electric car which has charged at the station at j chooses the station at i to charge next

The idea behind the formula (5) is the following: a car stops with probability $p_S(j)$ at a station at the node j. Hence the total amount of cars stopping at j in one day is

$$\mathrm{IMDEV}_j \cdot p_S(j).$$

After charging at the station j, the driver chooses randomly a station within its range to charge next. Hence the total amount of electric cars in one day arriving at the station i coming from the station j is

$$\mathrm{IMDEV}_j \cdot p_S(j) \cdot p_J(j,i).$$

The arriving electric cars want to charge the energy that they used since their last stop at the node j. This is exactly

$$d(i,j) \cdot c.$$

To simplify our model even further (and make it easy to implement), we assume

$$p_S(j) = \frac{1}{\mathrm{NRS}_j}, \qquad p_J(j,i) = \frac{1}{\mathrm{NRS}_j} \tag{6}$$

(Intuitively, a driver is less likely to stop at a particular station, if there are many others close to it.) Altogether, we end up with the following expression

$$D_i = \sum_{\substack{j:\exists \text{ station at the node } j \\ \text{and } d(j,i) \leq R \\ \text{and } i,j \text{ are on the same road}}} d(i,j) \cdot c \cdot \mathrm{IMDEV}_j \frac{1}{\mathrm{NRS}_j^2} \tag{7}$$

2.3 Modelling of Waiting Time by Energetic Approach

The total number of electric vehicles varies during the day. Denote by $N(t)$ - the distribution of numbers of cars that require charging in the particular point of the road at time t. The total required charging power is given by

$$P(t) = \sum_{i=n}^{N(t)} P_i$$

where P_i denotes the power of $i-th$ vehicle at time t. We simplify the model by assuming that all electric vehicles have equal power. Hence, the total power is given by the formula

$$P(t) = N(t) \cdot C$$

for a fixed constant C. The total energy demand D_{t_1,t_2} at the interval $[t_1,\ t_2]$ is given by the integral

$$D_{t_1,t_2} = \int_{t_1}^{t_2} P(t).$$

Let assume that the installed charging

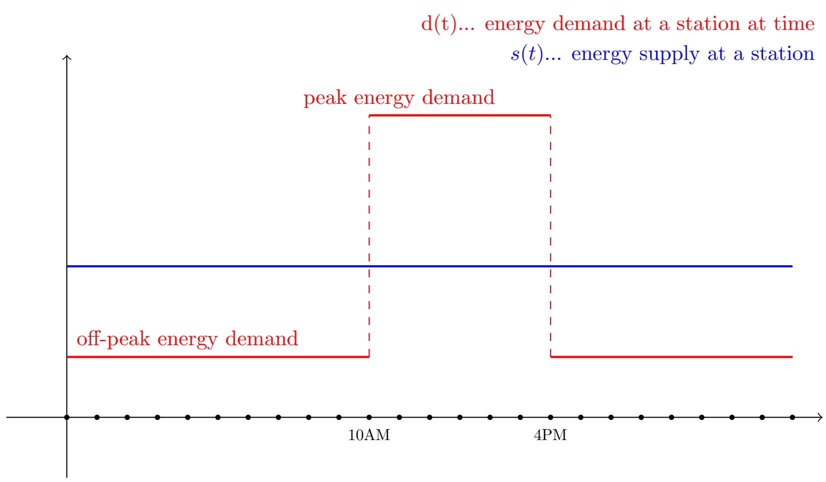

Figure 1: Energy demand/supply during one day

3 The genetic algorithm

A possible tool to tackle this optimization problem is the genetic algorithm. It's a particular type of evolution algorithms (heuristic-type optimization, inspired by natural evolution) where an initial population of solutions is repeatedly modified, such that it evolves toward the local optimum.

3.1 Useful terminology

When employing evolutionary algorithms, there exists a standard terminology that facilitates the comprehension of the various steps involved in the algorithm. We present them briefly:

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

3.2 Genetic and gradient-based algorithms

To highlight the main aspects of the genetic algorithm, We consider some of the main differences with respect to gradient-based algorithms (e.g., gradient descent).

Gradient methods:

- At each iteration it generates one solution;
- The sequence then converge to the optimum;
- Points in the sequence are computed analytically;

Genetic algorithm:

- At each iteration it generates a population;
- The best individual (the one with the least fitness value) converges to the optimum;
- Next generations are computed using random generators;

3.3 Steps of the algorithm

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 begins with a random initial population. Then at each step it creates a sequence of population. Each individual is a solution of the problem we would like to solve. The fitness function determines how fit an individual is. Therefore it gives an information on the single individuals, and how they compete between each other in the selection phase.The probability that an individual will be selected for reproduction is based on its fitness score. The highest the fitness score,the highest the chance to be selected for reproduction. A crossover point then is chosen randomly.The algorithm terminates if the population has converged, meaning that there is no significant difference from the previous generation. To summarize the steps:

- 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;

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.

4 Reading the results

Genetic algorithms always produce an array of possible solutions. Usually it is easy to then choose the best or the top 5 solutions among those. Since we were running optimisation with two objective functions, i.e. trying to optimise two functions at one time, this was not as simple. All of the possible solutions are two-dimensional with one value for the first objective function and one value for the second objective function. By removing "dominated" solutions, i.e. solutions for which there exists at least one other solution where the values for both objective functions are better, a so-called "Pareto Front" emerges. These are all the candidates for the final best solution.

4.1 First approach

In the first approach it was assumed that each location can hold only one charging station. In reality, this might not be applicable, but rather "charging lots" would be built holding multiple charging stations at one location.

The following figure shows two visualisations of all solutions of the genetic algorithm. In the first picture the Pareto Front is clearly visible running from top left to bottom right in a curve. In the second picture the Pareto Front is unclear, which can be a hint to something going wrong in the optimisation.

[Here I want a figure with the two pictures from the presentation, slide 20, but I don't know how to include pictures.]

Still, the questions unanswered by the algorithm is: Which of those solutions is the most desirable, since they can be very different?

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

- High waiting time and low cost?

[Maybe have the three pictures from slides 22, 23, and 24 here? but not necessary.]

Often, it is necessary to take into account additional constraints on budget, service or time to answer this. Since the optimisation was run on each road individually, it is necessary to choose one solution for each road and then combine these to create the whole grid of charging stations. Future work on this problem might take into account the influence of roads on each other.

4.2 Second approach

In the second approach one location can now hold up to one charging station of each type. This approach leads to a more complicated optimisation problem, but is closer to reality. Although we did not work on this approach very long, there were some promising programming ideas and we produced a preliminary result, shown in the following figure.

[Here I want a figure of the right picture from slide 28]

For future work, in an even more realistic model, it would be possible to have each location hold any number of charging stations.

References

[1] H. Hanabusa, R. Horiguchi, *A study of the analytical method for the location planning of charging stations for electric vehicles*, LNAI **6883**, 596–605 (2011).