Optimal Placement of Charging Stations Using Evolutionary Algorithms via Congestion Configuration

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Abstract

This work develops a method for optimal placement of charging stations of electronic vehicles in a transport network. The optimisation is done via configuring the congestion in each edge of the network graph. Betweenness centrality is used to estimate the optimal placement. The solution methodology is illustrated by an example.

1 Introduction

The 2030 Agenda for Sustainable Development, *#Envision2030* [1] adopted by the UN General assembly includes seventeen goals to promote prosperity of our

[1] `https://www.un.org/sustainabledevelopment/development-agenda/`

planet while protecting it. Development of sustainable cities and communities is the 11th goal of *#Envision2030*. Promoting the use of the electronic vehicles (EVs) is highly recommended in making of a green and sustainable city. Along with increasing the energy efficiency and reducing pollution emission in the environment, EVs also help to enhance the security and economics of the power system concerned by coordinating with intermittent renewable energies, such as wind generation [4]. Optimal placement of the charging stations (CSs) for EVs is one of the important concerns in this respect.

Economic planning of the CS infrastructure is needed to cater the dramatically increasing user-demands and helps to have an efficient transport network. Analysis of the the traffic flow in the transport network will help to determine the possible candidate locations of the CSs. The congestion in each part of the network may be controlled to make use of the full capacity of the CSs. For the optimal placement with a limited budget of the CSs, a centrality measure of the network graph must be considered. We use the *betweenness centrality* for each node of the network which is the number of the shortest paths that pass through the vertex.

In this project, we aim to to provide an optimal placement of CSs in a transport network when congestion is a decision variable. We use an evolutionary algorithm that uses genetic operators (numeric mutation and crossover). The project was carried out at the SIGevo Summer School - 3, 2019 by the ヌCiti team, held at Prague, Czech Rupublic . The codes and the data is available open-source at `https://github.com/nuciti`.

The next section gives an overview of the state-of-the-art. The rest of the paper is organised as follows: the problem statement which defines the problem, the solution methodology, results, and the concluding remarks.

2 State-of-the-art

This section describes several recent studies which aim to develop the placement of CSs in a transport network. Liu et al. [4] develop a mathematical criterion to balance the environmental factors, such as land price, service radius of a station (i.e., how much the battery gets discharged to get to a station), investment, maintenance, and operation costs. The constraints limit the infrastructure properties as to how many stations can be connected to one power supply. The objective function minimizes the total costs associated with the EVs. The optimisation is done by using a method which combines a two-step screening method and a primal-dual interior point algorithm.

The paper by Lam et al. [3] proposes a formal definition of the problem (Electric Vehicle Charging Station Placement Problem). In the paper, it is proven that the problem is NP-complete by a reduction from the Vertex Cover Problem. The city is represented as a graph with a distance metric, where each car has a maximum reachable distance, and the capacity of a station is more than the average demand in the neighborhood of this station (which is estimated from density). The problem is then solved using the Mixed Integer

Programming, and a greedy heuristics is provided.

The paper by Mehar & Senouci [5] again formalizes the problem based on congestion, infrastructure costs, transportation cost, station capacity, and power grid capacity. The paper uses a genetic programming algorithm. The genetic information has two parts - first car index assigned to a station (0 means that the station is closes), and the second relates to cars. The problem is then solved by a modified genetic programming algorithm.

Xiang et al. [6] formulate an economic planning model for optimal placement of CSs for electric vehicles. The origin-destination traffic flow data is considered in the optimisation problem in order to determine the location of the CSs. The capacity of the CSs is determined after obtaining the equilibrium traffic flow on each road. A queueing model is considered for the service system of CSs, in which the arrival of vehicles in a certain CS is a Poisson process. Load capability constraints are also included in the model. Jin *et al.* [2] also use a genetic algorithm to optimize the placement of CSs. A bi-objective problem has been considered with objectives denoting the cost of constructing the charging stations and the cost for drivers to reach their nearest charging station. Candidate solutions are encoded as bit strings: There are ten possible station locations, and five of these are chosen for each individual.

Our work builds on these scenarios, but however uses simpler assumptions by focusing on the city graph and general graph properties, so we formulate the problem in a slightly different way which we will present next.

3 Problem Statement

We aim to optimize the location of charging stations on a road network. In order to do this, we vary the congestion on the network in such a way that we maximize the betweenness centrality of the n nodes with the highest betweenness centrality (that is, the most central nodes). We then place the charging stations on these nodes. This means that the charging stations will be placed in the most central locations.

The betweenness centrality of a node x is defined as the number of shortest paths in the graph $\mathcal{G}$ which pass through the node x [1]. More formally, the betweenness centrality of a node x is defined as

$$B(x) := \sum_{s \neq x \neq t} \frac{\sigma_{st}(x)}{\sigma_{st}}$$

where σ_{st} is the number of shortest paths from s to t, and $\sigma_{st}(x)$ is the number of these paths which pass through x.

4 Solution Methodology

We based our work on the Python `networkx` library for the purpose of building graph and accessibility to graph operations such as betweenness centrality. A population of solutions represented as vectors of weights is generated randomly at the beginning of our algorithm. We then apply an evolutionary algorithm to this population using crossover and mutation operators.

The *mutation* operation iterates all weights in a vector, and each weight is changed with probability 0.1. The distribution of the new weight is uniform random. The *crossover* operator takes as input two vectors of weights and produces a new vector where each field is independently and randomly taken from one of the input vectors.

The overall flow of the algorithm starts with a random population of vectors. In each generation, we select 40 % of pairs of individuals, calculate their crossover with a randomly selected individual. Half of the new individuals is modified by the mutation operator on those. The new generation also contains the mutation operator applied to 10 % of the old generation.

Algorithm 1 Pseudocode of the used algorithm

```
Generate a random graph structure
Initialize the first generation randomly

while not converged do
  Form the new generation
    • Select 40 % of pairs of individuals and crossover them with a randomly
      selected individual
    • Apply mutation on 50 % of individuals

  Keep half of population size from the old generation sorted by fitness
  Keep half of population size from the new generation sorted by fitness
end while

Report the individual with the highest fitness
```

The selection operator selects from the union of the parents and offspring the half of the individuals with the higher fitness.

Let us define the set of solutions $S = \{s_1, ..., s_n\}$, the set of nodes in a given graph $G = \{g_1, ..., g_m\}$. For a given solution s, the values of betweenness centrality is defined as follow $BC(s) = \{BC_1^s, ..., BC_n^s\}$. Finally the subset $b(s) = \{b_1, ..., b_x\}$ contains the x highest values of the $BC(s)$. We then define our fitness function as follows:

$$F(s) = \sum_{i=0}^{|b(s)|} b_i$$

5 Results

The considered transport network is randomly generated using a Watts-Strogatz small world method and has 100 nodes. A limited number of CSs need to be placed optimally, (i.e., 10 in the considered network). Our algorithm has a population size of 20 and a mutation rate of 0.2. The algorithm is run for 200 generations.

A visualization of the solution is provided in figure 1. The red dots represent the optimal placement of the CSs in the considered network graph while the blue dots represent the possible candidate locations. Please bear in mind that closeness in network terms need not correspond to closeness in terms of real distance, but this chart shows what could be an optimal placement for 10 stations, a number that has been chosen arbitrarily.

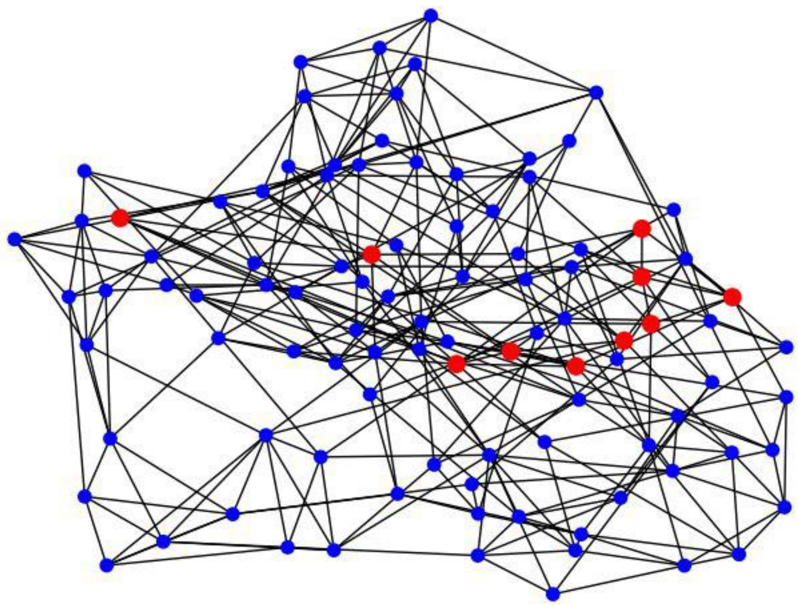

Figure 1: Central placement for charging stations. Red nodes represent the location of charging stations.

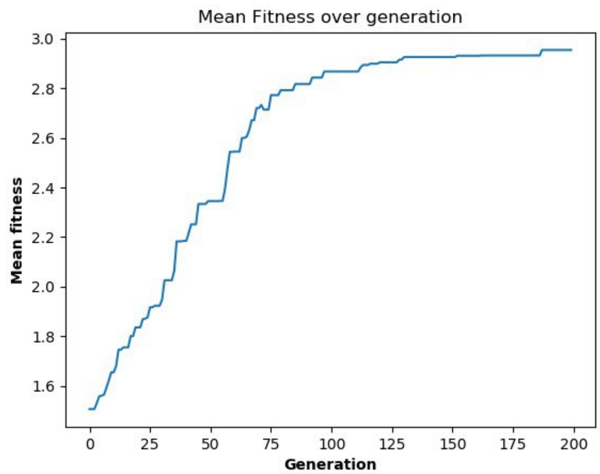

Figure 2: The variation of mean fitness over the generations

The mean fitness increases as the generations of the algorithm progresses. The figure 2 depicts the variation of the mean fitness, showing that the number of generations is probably enough to find a good enough solution. However, it's a big search space so we would probably need some tuning in order to get the best possible evolutionary algorithm.

6 Conclusion, Discussion and Future Work

In this paper, we present a methodology to optimally place the charging stations for electronic vehicles in a transport network. In our optimisation problem, we consider the congestion as a decision variable. We exploit the betweenness centrality of the network graph to identify the best possible locations to place the CSs. This makes the stations be in the nodes that are going to be reached optimally in (optimal) runs through the city.

Establishing the *congestion* of the city streets allows the city planners to have a decision variable for changing the load in the roads according to accessibility to the charging stations. Obviously this is never the only decision variable when designing a city; it is actually a multiobjective problem where you need to increase livability and also accessibility to other facilities in the city. In the future, we can approach this problem using these different angles. We will also need to make the abstract city graph more realistic, by incorporating different city typologies that need not be represented by a small world complex network.

This work is mainly intended as a proof of concept, with no attempt to tune the evolutionary algorithm operators and parameters, complex network parameters, or representativity of any of those values. In the future, this will be a line of work we intend to pursue.

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