Finding an efficient strategy to solve the charging point placement problem

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Bachelor of Technology

by

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Abstract

In this thesis we present a mathematical model for the Multi-objective optimization charging point placement problem, which deals with demands of the city on an average basis, rather than considering a simulated environment. A model which runs purely on the expected demand in a city. It also discusses about the optimal analysis, an optimal exponential and an approximate greedy solution, and compared their performance on generated test cases.

Contents

Chapter 1

Introduction

Electric vehicles cost less compared to conventional gas vehicles each year. As the cost of electric cars becomes the same as or less than existing vehicles the choice to 'go electric' will be obvious. Since electric cars have zero tailpipe emissions, we can look forward to cleaner air when there are more electric cars on the road. Cleaner air means less disease in the world, which means less stress on public health systems, hospitals, and so on. In addition, fewer greenhouse gas emissions will save the ozone layer and reduce our carbon footprint. If we can't stop global warming, we can certainly slow down the onset, and EVs are nothing if not a good start. Implementing EVs faces a challenge of placing charging points throughout the country, due to the long charging time (compared to conventional fueling time) which can make the life of EV owners difficult.

There is a growing literature addressing the issues relevant to EV charging station placement. References [1]–[4] formulated charging station placement as an optimization problem. However, they did not take into account the impact of EV charging on the electric power network in their works. Whereas the reference [5] took into account the above mentioned factor, while running a simulation to simulate a real-time environment to understand the charging demands of the city and satisfy the needs accordingly. This gives us an idea to create a mathematical model, which deals with demands of the city on an average basis, rather than considering a simulated environment. Even though such a model might not consider the extreme cases, but can give us a statistical lay out of charging point placements which are stable in a longer run.

Chapter 2

Formulation

2.1 Problem statement

Given a city map, and a statistical layout of its charging demand spread across tentatively defined candidate charging points. We need to find a subset of charging points which satisfy the charging demand of these candidate locations, at the same time minimizing a multi-objective function involving multiple costs.

2.2 Input parameters

- G(V, E) - Graph
- A candidate nodes subset of V.
- $demand[]$ - array of demand values for candidate nodes
- roc - Radius of coverage per charging station
- α - Travel penalty coefficient
- β - Grid penalty coefficient
- λ_1, λ_2 - Penalty factors
- ϵ - Randomness coefficient
- Partitions of the candidate locations connected to respective grids.

2.3 Concepts used

1. Concept of Travel penalty
   (a) The penalty incurred due to the redirection of traffic (demand) from one candidate location to another.

(b) This happens when a candidate location can satisfy the needs of another nearby candidate location.

(c) Input parameter used - α called travel penalty coefficient.

(d) Travel penalty given by, $tp[x] = \alpha * demand[x] * dis$
where,

- x - A candidate node whose demand is redirected.
- dis - Distance between x and the node to which the demand is redirected

2. Capacity of a charging station

(a) Every charging station has a capacity c, which means that a charging station cannot satisfy more than c demand per hr.

(b) Also note the input demand for any candidate location can't be more than c (i.e) $demand[i] <= c \; \forall i$

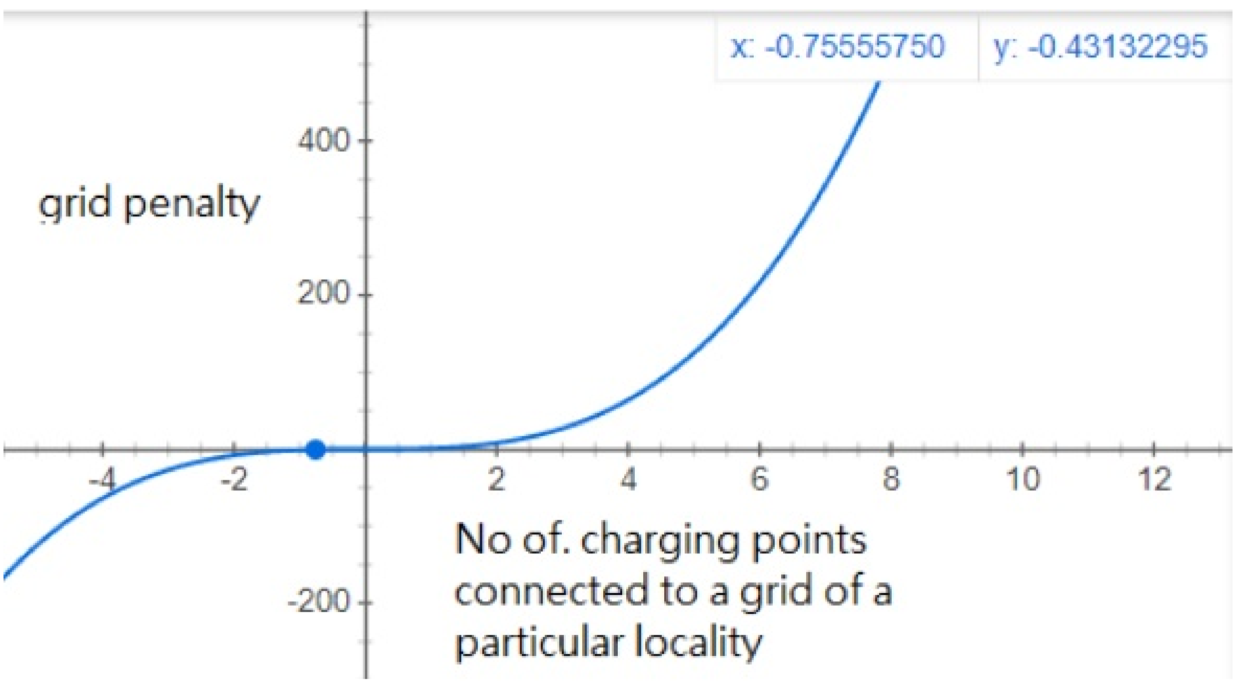

Fig. 2.1: An example of grid penalty curve, $y = x^3$

3. Concept of grid penalty

(a) The penalty incurred on the power grid due to placing multiple charging points in the same locality.

(b) We assume the grid penalty in a locality follows a non linear polynomial function.

(c) Input parameter used - β called grid penalty coefficient.

(d) Grid penalty given by, $gp = \beta * f(n)$ where,

   - f - A non linear function
   - n - No. of charging points connected to the grid.

   (e) Figure 2.1 shows an example of grid penalty curve.

4. Reduced multi-objective optimization

   $Z = \lambda_1 * tp + \lambda_2 * nc + (1 - \lambda_1 * \lambda_2) * gp$

   where,

   - Z - objective to be minimized
   - λ_1, λ_2 - penalty factors
   - nc - no. of charging points
   - tp - total travel penalty
   - gp - total grid penalty

Chapter 3

Optimal analysis

To prove the problem we are having in hand is NP-Hard, we choose Set cover problem (well known NP-Complete problem) and reduce it into our problem, in polynomial time. For that we just need to find two polynomial converters X and Z.

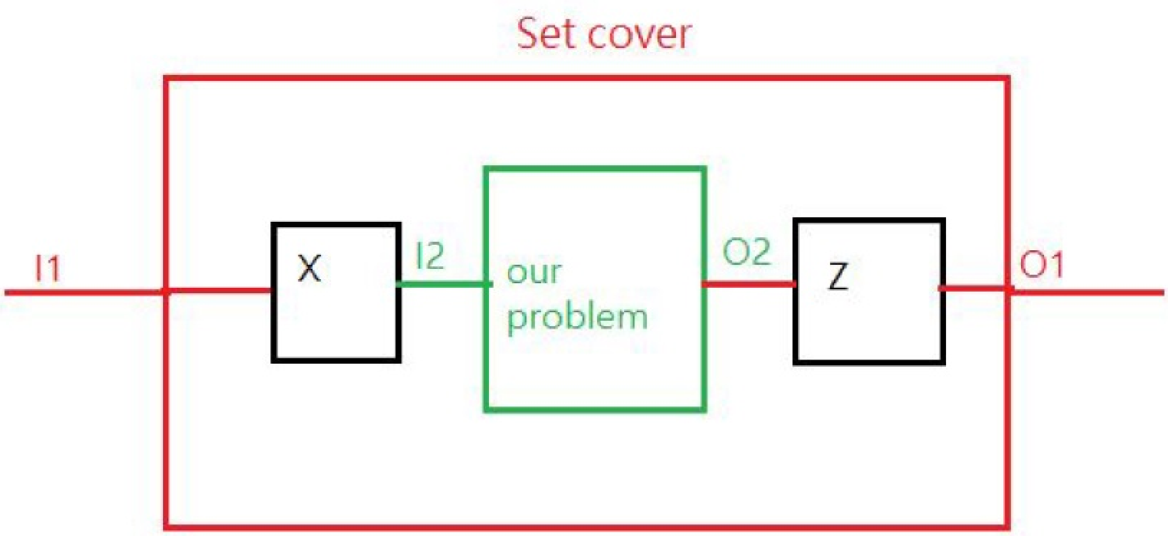

Fig. 3.1: Reducing Set cover problem to our problem.

Figure 3.1 shows a visual representation of our optimal analysis.

I <u>Set cover problem:</u>

Let's say our Set cover problem has the following description:

i Universe:
$S = \{s_1, s_2, \ldots., s_n\}$

ii Subsets:
$A_1, A_2, \ldots.., A_n$ where $A_i \subseteq S\ \forall i$

iii We need to find an optimal set:
$O = \{B_1, B_2, \ldots., B_k\}$ satisfying,

- $\exists\, i, j$ *such that* $B_i = A_j$
- $\bigcup_{i=1}^{k} B_i = S$
- k is minimum possible

II Converter X:

i Set : $roc = 1,\ \alpha = 0,\ \lambda = 0$

ii For each element s i in the universe of set problem create a node in the graph with:

- $Capacity = 0$
- $Demand = 1$

iii For each given subsets ai of the set problem create a node in the graph with:

- $Capacity = \infty$
- $Demand = 0$

iv For each $s_j \in A_i\ \forall i, j$ create an edge of length $= roc$ in the graph.

III Converter Z:
Trivial, just reverse map the charging point nodes that were selected in the graph, to the subsets of the set cover problem. And the given list of subsets is the optimal solution for the set cover problem.

IV Analysis:
This means the set cover problem can be poly-time reduced to our problem. Which means our problem is at least as hard as set-cover problem, which is a well known NP-complete problem. This implies that our problem belongs to NP-HARD.

Chapter 4

Solutions

4.1 Optimal solution

Created an exponential time optimal algorithm test the performance of our proposed solution.

I Algorithm:

- Make all 2m subsets.
- Let's take a subset:
  - For all the nodes not selected, we try to put it's demand in its neighbour selected nodes.
  - Just like distributing balls to boxes.
  - We choose the best compatible assignment which has least cost.
- Among all the subsets we choose the least cost compatible assignment.

II Time complexity:

$T(N) = O(2^N D^{KN})$

where,

- N - no. of vertices.
- D - the maximum demand value.
- K - max no of roc neighbours.

4.2 Proposed solution

The proposed solution involves a greedy approach.

I Concept of UV:

- Uselessness Value

- Tells us how useless it is to place a charging point in any location i.
- $uv[i] = \alpha * (\sum_{v \,\in\, rn[i]} free\_capacity[v] - demand[i]) \; + \beta * grid\_penalty[grid[i]]$ where,
  - $rn[i]$ is roc neighbourhood of i.
  - $grid[i]$ is grid to which i is connected.

II Algorithm:

- Maintain a tree DS containing the candidate nodes sorted on the highest uv first .
- While DS not empty, pick a node from the top of the DS (say u):
  - Give away it's demand to its roc-neighbours in the nearest first order.
  - Update the uv values of the nodes that were affected in the above step and its roc neighbours.
  - Refresh the DS with the changed uv values.

III Randomness:

- Do random picking of nodes, rather than pure greedy picking with highest uv first.
- Do our normal greedy with probability $1 - \epsilon$ and random picking of node with probability ϵ

IV Time complexity:

$T(N) = O(N(N + K^2 log(N)))$

where,

- N - no. of vertices.
- D - the maximum demand value.
- K - max no of roc neighbours.

Chapter 5

Testing and results

5.1 Implementation

- We have implemented the algorithm in c++.
- Used the pre-existing STL library for the DS required.
  - $std :: set$ for the red-black tree implementation required for the algorithm.
  - $std :: vector$ for adjacency list of the graph.
  - Output is a vector of nodes, which correspond to the charging point locations, which are minimum in number and also minimize the travel penalty.
  - The implementation is available online in https://github.com/viskey98/Btp-EVgithub.

5.2 Results

- Due to the exponential complexity of the optimal algo, we run on smaller test cases ($n < 15$) to compare the results of our greedy algo with the same.

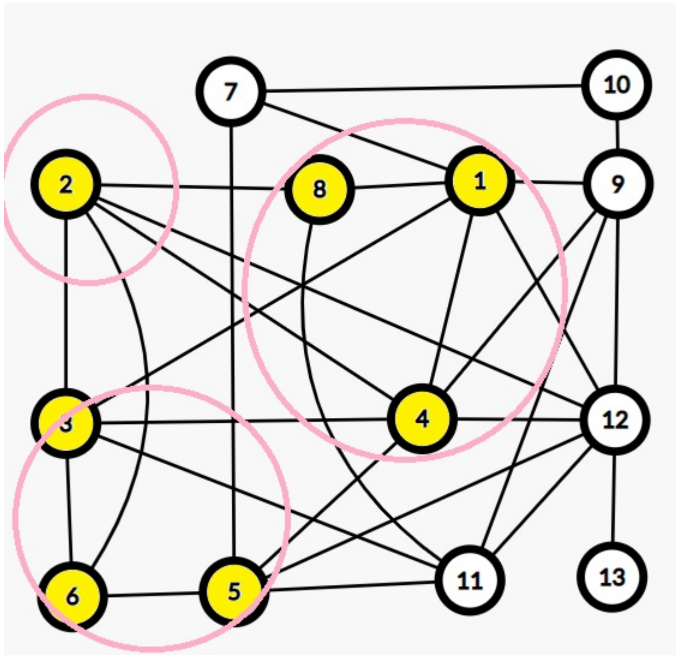

Fig. 5.1: An example test case.
— indicates candidate nodes;
— indicates nodes connected to same grid.

- An example test case is shown in Fig 5.1.
  - No. of nodes = 13
  - No. of candidate nodes = 7
  - No. of edges = 28
  - Edge weights varying from: 5 to 26 units
  - roc = 29 units
  - $\lambda_1 = 0.025$
  - $\lambda_2 = 0.8$
  - c = 10
  - $\alpha = 0.2$
  - $\beta = 0.5$
  - $\epsilon = 0$
  - A custom generated grid network.

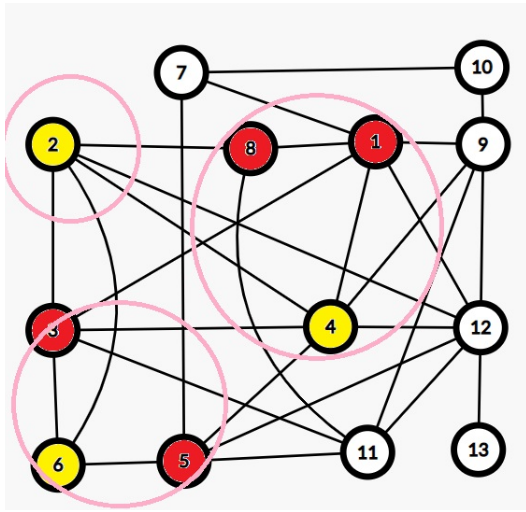

Fig. 5.2: Placement of charging points by optimal algo.
— indicates nodes where charging points are placed;

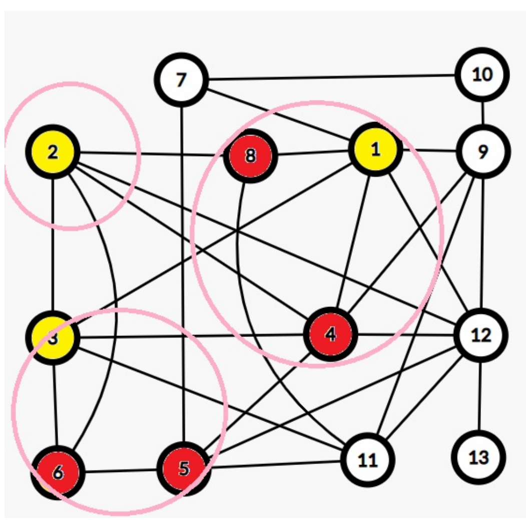

Fig. 5.3: Placement of charging points by greedy algo.
— indicates nodes where charging points are placed;

- Output of optimal algo is shown in Fig 5.2.
  - No. of charging placed: 4
  - Charging point locations: 1, 3, 5 and 8
  - Travel penalty: 16.0000 units
  - Grid penalty: 50.0000 units
  - Total reduced cost: 12.35 units
- Output of our greedy algo is shown in Fig 5.3.
  - No. of charging placed: 4
  - Charging point locations: 4, 5, 6 and 8
  - Travel penalty: 200.0000 units
  - Grid penalty: 50.0000 units
  - Total reduced cost: 16.95 units

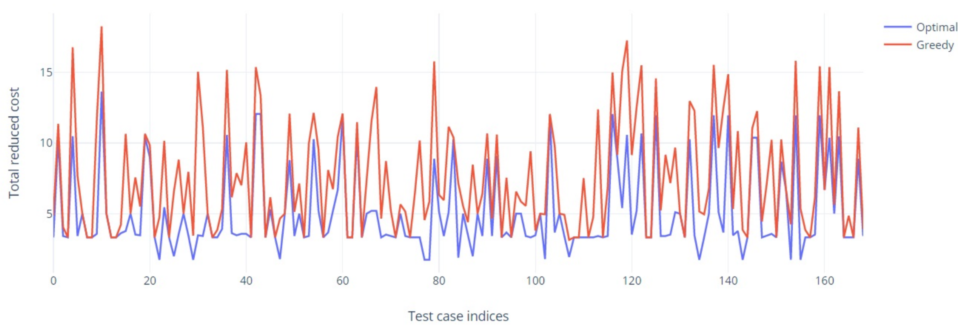

Fig. 5.4: Comparison plot for the costs of optimal vs proposed algo.

- We also Tested with 170 test cases similar to the one given above.
- Fig 5.4 shows the comparison of the costs given by optimal and proposed algorithms.
- Observed approximation factors:
  - Best: 1.000
  - Average: 1.642
  - Worst: 4.292

Chapter 6

Conclusion and future scope

- A good mathematical model works with average case demands rather than the simulation models out there.
- The formulations were kept as simple (like same capacity for all stations, simple grid penalty etc) and sustainable, which can be easily extended without much change in the solutions.
- Focus was given more on the proposed solution and it's competence with the optimal solution.
- Observed very good approximation (with average around 1.64) factor.
- Can be tested with actual city map input, to check the performance in production.
- Future work can include making the model more complex, with incorporating quality of service (QOS), locational factors and different costs of installation etc.
- Good generators can be made to test this model, by using some machine learning techniques which learn several real-life city test cases and output a similar test case.
- The model can be made complicated by making it a game between multiple charging service providers, who play to optimize their cost functions respectively.

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