Addressing Electric Vehicle Charging Station Problems using Networks

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ABSTRACT

Climate change has become more prevalent than ever. With the amount of disasters such as forest fires, and unexpected weather conditions, humanity is starting to view the results of climate change. Numerous policies have enacted to prevent further damage to Earth, and one very large contributor is gas-powered vehicles. As national policies demand for their citizens to switch to electric vehicles, the infrastructure of electric vehicle charging stations is of upmost importance.

To address the concerns of electric vehicle charging infrastructure, this report seeks a solution and proof of concept to heuristically install charging stations for sufficient coverage around the USA given the current charging station network. This report will be taking the Nation Renewable Energy Laboratory dataset on fast charging stations, creating the network, classifying the problem into a geographical grid network, and finally using different measurements such as closeness and greatest connected component size to provide maximum coverage.

KEYWORDS

electric vehicle charging stations, graphs, network analytics, dataset, transportation networks, optimal placement

1 INTRODUCTION

1.1 Motivation

Governments have promoted the use of "green" automobiles to minimise pollution because transportation activity accounts for roughly a quarter of worldwide Carbon dioxide emissions [5]. Despite the fact that the number of electric vehicle owners has been steadily increasing in recent years, the worldwide EV (electric vehicle) industry continues to expand at a moderate pace. The biggest impediments to widespread EV adoption, according to [5], are car purchase price, restricted driving range, and insufficient charger availability. The electric car's driving range, or the greatest distance a vehicle can travel with a fully charged battery, is a source of "range anxiety" for drivers [7]. Many of them view the number of times they must stop for battery recharging during a trip to be inconvenient, and they may be concerned about running out of battery before reaching their destination. Drivers may be put off by the long wait times and recharge times associated with electric vehicles. Because of this, for the purposes of this project we are only considering DC fast charging stations, which can fully charge most electric vehicles in approximately 30 minutes or less.

The urgency for electric vehicles is higher than ever. A crucial part of the demand for electric vehicles is due to climate change policies. In Canada and USA, policies have been implemented to promote electric vehicles to combat carbon emissions. As USA has promised half of all automobile sales to be electric or hybrid[4], and Canada's implementation where all new vehicles and passenger trucks are to be zero emission by 2035[1].Accessibility and range reliability for charging station infrastructure are critical to such policies attaining their full potential, and this project aims to aid in achieving those goals.

Our project focuses on this problem of electric vehicle charging station infrastructure. The switch from unsustainable fuel to electricity will be difficult for those without accessibility. Equally important is the need for connecting routes where current infrastructure does not support such routes. Our main motivation stems from the need to make EVs more adoptable on a larger scale for long distance travel. Accompanied with mandating electric vehicles lies the need for a foundation of adequate charging stations provided by the public sector in order to ensure climate policy success[6]. Our goal with this project is to determine the best locations for future EV charging stations based on criteria which are outlined in the following section.

2 PROBLEM DEFINITION

The network will be represented by a weighted, undirected network graph with parameters:
N: node, the existing charging stations in the network,
E: edge, which will be present between a node if there exists a road network route between the nodes and they are within the full charge distance. This distance determines edge weights.
Full charge: the maximum distance between any two nodes in our graph. This represents the furthest distance the average electric vehicle can travel on a full battery, and will be determined by a percentage of the average maximum distance of an electric vehicle, as specified by our research. Based on this, the range that was chosen is 250km.

The problem this project is focusing on is connectivity of charging stations through various routes to assure adequate infrastructure of charging stations using states in the USA and Canada as case studies. We have defined our problem as a coverage problem because we want to solve the "range anxiety" problem. In short, we want to decrease range anxiety by increasing the coverage of EV stations in an area.

A secondary objective of this project is to increase the closeness of the network. The lack of infrastructure that plagues electric vehicle travel not only affects what places are accessible, but how accessible places are. If a given travel route is, for example, 400km long, but requires an electric vehicle take a 1200km route to avoid running out of battery, this is very inefficient. By increasing the closeness of the network, the EV station network can be more reliable and useful, and further decrease energy consumption.

Problem 1: Given a network of EV charging stations, figure out where to add the new nodes which represent the EV charging stations to maximize the size of the GCC of this network. Our result should be a GCC that all edge weights are ≤ EV range R.

Problem 2: Decrease range anxiety problem described in **Section 1.1** by adding additional EV charging stations (increasing coverage).

Problem 3: Identify locations for new charging stations that would maximize the closeness of the network.

3 RELATED WORK

3.1 Using Mobility Data

An interesting work that our project is related to is Optimizing the deployment of electric vehicle charging stations using pervasive mobility data[7]. This paper proposes a method for meeting an urban region's demand while minimising the hurdles that vehicles face. These barriers could be based on the drivers' total additional driving distance to reach a charging station, the associated energy overhead, and the number of charging stations available. However, current infrastructure deployment is not taken into account when formulating the new optimal arrangement, therefore any potential gaps between the current state and a blank canvas is left unexplored. Our project will consider the current charging locations when deciding where to best place the future charging locations. This paper also introduces using a geographical grid in regions of interest to minimize the total number of charging stations needed. The paper defines the grid as non-overlapping cells $\alpha = \{ C_1, C_2, ..., C_N \}$. Although instead of using a genetic algorithm to decide which cells are more important to install new charging stations, we're using this grid cell layout to solve our coverage problem of currently unreachable EV range for the average EV.

3.2 Using Minimization Techniques

Another paper related to our research is Optimal Placement of Charging Stations for Electric Vehicles in large scale Transportation Networks[3].This paper describes a novel practical approach for allocating charging stations in large-scale transportation networks for electric vehicles (EVs). The issue is especially pressing in order to satisfy the charging needs of the rising fleet of alternative fuel vehicles. The study considers the Route Node Coverage (RNC) problem, which seeks to determine the smallest number of charging stations and their locations in order to cover the most likely routes in a transportation network. Our project will try to solve these problems and check the validity by applying them to real world networks that exist in the US and Canada.

3.3 Using Transportation-related attributes

Furthermore, in the paper Determination of charging infrastructure location for electric vehicles[2], in order to address local requests, a weighted multi-criteria strategy was proposed that took into account both existing stations and the varying costs associated with each location. When you look closely at the information around each place, you'll notice that each node has environmental, economic, and transportation-related attributes. Many aspects, including the optimal number of chargers in an area and the type of charger, have to be determined later using local knowledge, according to the paper. Incorporating real-time traffic flow data, into the decision of where new charging stations should be placed, is one of the areas of further research highlighted in the paper. We want to move away from this issue in our decision-making process, and with more research, and change the problem to a coverage problem instead. Hence, that is what we will explore further in this paper.

4 METHODOLOGY

This section will include the details of how we plan on solving the problems we described in **Section 2**.

Solution to Problem 1:A larger GCC would mean more reachable coverage, as an electric vehicle would be able to traverse more area without running out of charge before reaching its destination (because it would have more places to recharge). Essentially, this boils down to maximizing the size of the GCC by first identifying it, and then adding new nodes (charging stations) in a way that would allow disconnected components to then be connected to the GCC.

Solution to Problem 2: Decreasing Range Anxiety for the purposes of this paper means increasing the density of charging stations so that drivers can worry less about running out of charge before reaching their destination, and allow for less detours when making long trips that require a recharge mid-way.

Solution to Problem 3: Similar to problem 2, increasing density would allow drivers to take less detours when attempting to reach their destination. Adding nodes to increase the closeness of the graph would achieve this. The closeness of a node u in the graph is defined by

$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)}$$

where $d(v,u)$ is the shortest path distance between v and u, and n is the number of nodes that can reach u. The closeness of the graph is the average of all the closeness values of each node in the GCC of the graph.

4.0.1 Process. We follow a three step process:

(1) Extract the dataset from the NREL API (details in **Section 4.1**). The API provides several criteria so we may use multiple datasets- for example, we can look at only the fast charging stations, or other subsets. For the calculations we perform, we use only DC Fast charging stations. The dataset contains approximately 7000 charging stations across North America
(2) Using the latitude and longitude of the data points for each charging station, as well as displacement data to determine

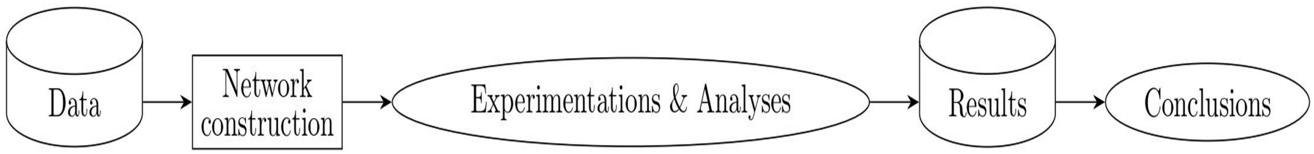
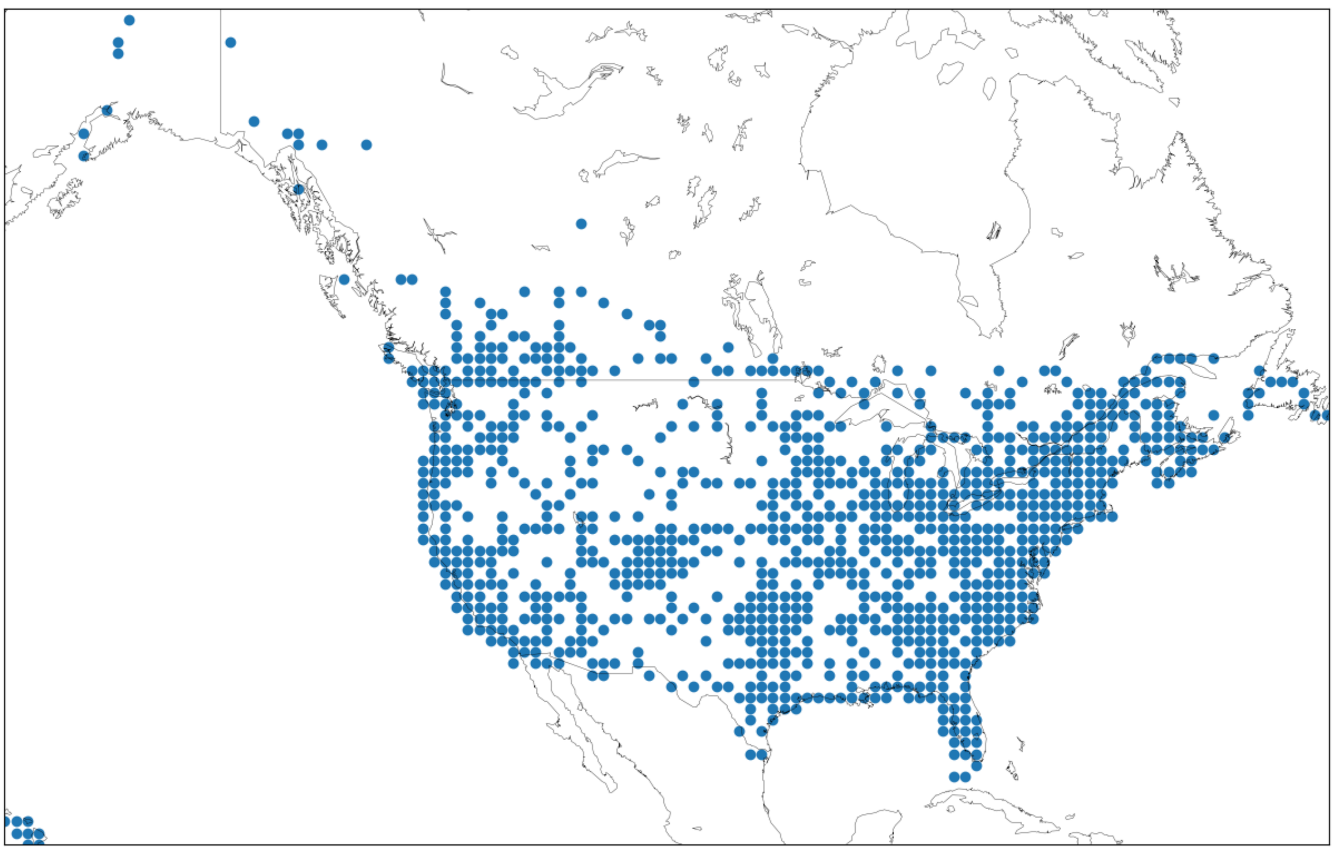


Figure 1: The high-level framework to attempt to solve the problem as discussed in Section 2 involves four major steps: (1)Acquisition and Analyses of Data, (2) Network Construction, (3) Experiments Analyses, (4) Results and (5) Conclusions.

Figure 2: Division of North America into $100km^2$ cells containing EV charging stations



edges in the network, construct the network itself. Details can be found in **section 4.2**

(3) After we have the whole chosen charging station network, we can then evaluate the results and determine the best locations to add new charging stations. The way we quantify the best location as well as details on how this is accomplished are discussed in Section 4.5 and 4.6 thoroughly.
(4) With the new insight, we can generalize some parts of our methodology, as well as describe additional potential uses for the data and the networks we construct.

In simple terms the above steps can be summarized into, choosing an area to work with and get all the charging stations in that area. Then, to generate the edges, we will use the NREL API to get the id of all the stations within a predetermined "travel distance" of each station. This distance will be represented by the maximum distance an electric car can travel on a single charge. We then form edges between the initial station and each other station by considering two factors. The first would be the distance between the stations must be less than our predefined network diameter. The second condition is that a road network must exist between these stations for an edge to be formed.

Due to the continuity of geographic data, we simplify the problem by converting the described network into a grid to allow for discrete calculations. This is further explained in section 4.3

4.1 Dataset

The dataset used in this project is extracted through the NREL API. NREL is the National Renewable Energy Laboratory, a US-government national laboratory of the U.S Department of Energy. This dataset contains complete information of every electric vehicle charging station such as Name of the Station, Street Address, Intersection Directions, City, State, Zipcode, Latitude and Longitude. In our case, we are concerned with the current fast-charging/DC fast charging station network as the most commercially viable option, charging electric vehicles in under an hour. The information that we utilized was the latitude and longitude for each station which we used to plot out the stations in our network and place them based on their position. The API lets us freely acquire all the information we need for this project.

4.2 Network Construction

To model the charging station network, every node is a charging station, positioned at its latitude and longitude, and an edge is determined based on the route distance between two nodes:

Algorithm 1 CALCEDGE (lats,lons)

```
G ← newGraph
len ← numOfNodes
i ← 0
j ← 0
for i < len do
    for j < len do
        dist ← distOf(Lat[i], Long[i], Lat[j], Long[j])
        if dist ≤ EVrange then
            G ← edge(i, j)
        end if
    end for
end for
```

Since we have to compare every node's distance to each other, we use this algorithm to determine which nodes have edges by comparing each node to every other node. Once we do this for all states, we combine each state's graph to form the whole USA charging station network. To calculate the distances between nodes based on their latitude longitude co-ordinates, we use the Haversine Formula:

$$d = 2rsin^{-1}(\sqrt{sin^{-1} * (\frac{\gamma_2 - \gamma_1}{2}) + cos(\alpha_1)cos(\alpha_2)sin^2(\frac{\alpha_2 - \alpha_1}{2})})$$

Where (γ_1, γ_2) and (α_1, α_2) denote two different (latitude,longitude) co-ordinates, and r indicates the Earth's radius (Approx. 6371km)

First we will also define our method to constructing and adding nodes to our grid abstraction.

4.3 Problem Simplification

Because this is a graph augmentation problem, we cannot simply look at a world map and decide where to put a new node- there are infinitely many possibilities. To simplify our problem, we can project the positions of the charging stations onto a Mercator map and acquire an (x,y) coordinate for each one. Note that the Mercator projection does cause some distortion but it is not very significant. We also account for it by dynamically calculating the resulting distance conversion from latitude/longitude coordinates to grid plane coordinates. This allows us to display the network on a coordinate plane, and partition the network into a lattice of cells. This means that each cell represents a "square kilometer" area based on a decided length of L^2. In order for this to represent a network, nodes would be added based on indices of the established 2D array if there is a station within a grid cells geographical area, and would connect only to adjacent nodes. In other words, the nodes can only exist on a grid, and a node will only exist if there is at least one charging station within its corresponding area. This means that the area of each node would be square, and the dimensions of a grid cell would be restricted by the maximum range of an electric vehicle, as we defined in **Section 2**. By simplifying the problem in this way, we can ensure that edges between nodes are definitely reachable by the range of most electric vehicles. This also allows us to produce a discrete answer, a particular grid cell, in which it would be optimal to place an additional charging station. By using a generous approximation, this simplification allows us to mostly ignore the imperfections of road networks and continuity of geographic positioning while still partially accounting for the roundness of Earth.

4.4 Grid Network Construction

This section will further specify our methodology of constructing the grid network. First, all of our latitudes and longitudes are projected into (x,y) coordinates using a Mercator projection. This yields a set of arbitrary x and y value coordinates for each station. To identify the distance, we use the Haversine formula mentioned in section 4.2 to first calculate the distance between two arbitrary stations using their latitude and longitudes. Then, we can use that distance to determine how many units on the (x,y) coordinate plane that distance corresponds to by using Pythagoras' theorem on the same two stations. This gives us a factor, which we labeled the Grid Size Factor (GSF), which allows us to determine how many kilometers the coordinate plane distance between two points corresponds to. We will be defining our grid by 100.7KM * 100.7KM squares. Then once we have our established distance in in coordinates, we integer divide (divide and truncate) the x and y coordinates of each station by our GSF length of 100KM. For a 100KM square length, this results in a dynamically sized matrix of width 96 and height 61. This area includes all the states, therefore the 2D grid stretches from Hawaii to the most eastern portion of the USA, and from the heights of Alaska to the bottom of Hawaii (the most southern part of USA), and everything in between. The code for this is described in Algorithm 2.

Grid indices are classified by subtracting a station's coordinates by the minimum X and Y co-ordinates, then dividing by the 100KM co-ordinate length GSF resulting in the index the station belongs

Algorithm 2 FILLGRID(Grid, X, Y, GSF, minX, minY)

Input: 2D integer array initialized with zeroes and size W*H, X and Y denoting lists of Mercator projected co-ordinates, GSF denoting a co-ordinate distance of 100KM, and minX, minY denoting the smallest x and y coordinates.
Output: 2D integer array denoting the number of stations within geographical area of every cell.

```
len ← # of stations
for i < len do
    Grid[int((X[i]−minX)/GSF)][int((Y[i]−minY)/GSF)] += 1
end for
```

to on the geographical grid. The filled grid then represents all stations located within each geographical grid cell. We use this filled matrix to then construct the grid network by adding nodes to cells that are greater than 0 and connecting them to any adjacent cells. Furthermore, this report will discuss the augmentation of the grid network.

4.5 Network Augmentation

To augment the network (adding charging stations that are connected), we will be using a couple different methods to locate best spots that would increase overall connectivity and GCC coverage, as well as closeness of the networks GCC.

Firstly, we convert the the grid matrix mentioned in section 4.4 into a network by placing a network node on each non-zero matrix cell. Then we connect any adjacent nodes to each other to form our network. This results in a network as depicted in figure 3, with the largest connected component highlighted blue, and the second-largest component in red.

Once the network is constructed, nodes can be added to it. The addition of a node to the graph would represent a DC Fast charging station being added somewhere within the 100km bounds of the grid cell represented by the node.

The approach we used when checking the efficacy of an added node was to simply add the node and then check our criteria again. For optimization, a node was only added to an empty grid location if there was at least one adjacent node, since all of our problems involve augmenting the GCC of the network.

5 EVALUATION

5.1 Network Analysis

5.1.1 GCC Analysis. Now that we have established our different augmented networks, we will begin analysis. The first analysis we wish to perform is on the Giant Connected Component (GCC) of the graph. As given by the algorithms mentioned above, the single best location with the dataset and information outlined above is within the 100km grid cell containing the latitude and longitude coordinates (31.948962356280216, -101.99881421355937). This location is shown in figure 4 and the corresponding graph is displayed in figure 5 and zoomed in figure 6. The algorithms can be re-run to produce different results depending on the size of the squares chosen, the dataset, and locations chosen.

Algorithm 3 CONSTRUCT_NETWORK(Grid)

Input: The grid produced from Algorithm 2
Output: Graph: a NetworkX graph representing the grid input

```
w ← grid width
h ← grid height
i, j ← 0
for i < h do
    for j < w do
        if Grid[i][j] > 0 then
            Graph ← node(i, j)
        end if
        if Grid[i − 1][j] > 0 then
            Graph ← edge((i, j), (i − 1, j))
        end if
        if Grid[i][j − 1] > 0 then
            Graph ← edge((i, j), (i, j − 1))
        end if
    end for
end for
```

Algorithm 4 ADDNODE(Graph, x, y)

Input: Graph, x and y coordinates of spot to add a node
Output: Graphcopy, a copy of Graph with a new node at (x, y)

```
Graphcopy ← node(x, y)
Graphcopy ← edge((x ∓ 1), (y ∓ 1)
```

Algorithm 5 EXPAND_GCC(Graph, Grid)

Input: Graph with at least 2 separate components and Grid corresponding to the given Graph.
Output: The location that would yield the largest GCC if it had a node placed in it.

```
location ← (0, 0)
biggestSoFar ← emptyGraph
for each empty spot in Grid with at least one adjacent non-empty spot do
    test ← ADDNODE(Graph, x, y) where x, y is the current empty spot in Grid
    if GCC(test) > GCC(biggestSoFar) then
        biggestSoFar ← GCC(test)
        location ← (x, y)
    end if
end for
```

Further analysis can be performed by altering the algorithm to add n new nodes at once. This would increase the complexity exponentially and would likely require heavy optimization to be feasible, but it could allow "reaching" further and connecting components that were unreachable by adding only one node.

5.1.2 Closeness Analysis. The second analysis is on the closeness of the graph. Algorithm 6 explains our approach to improving

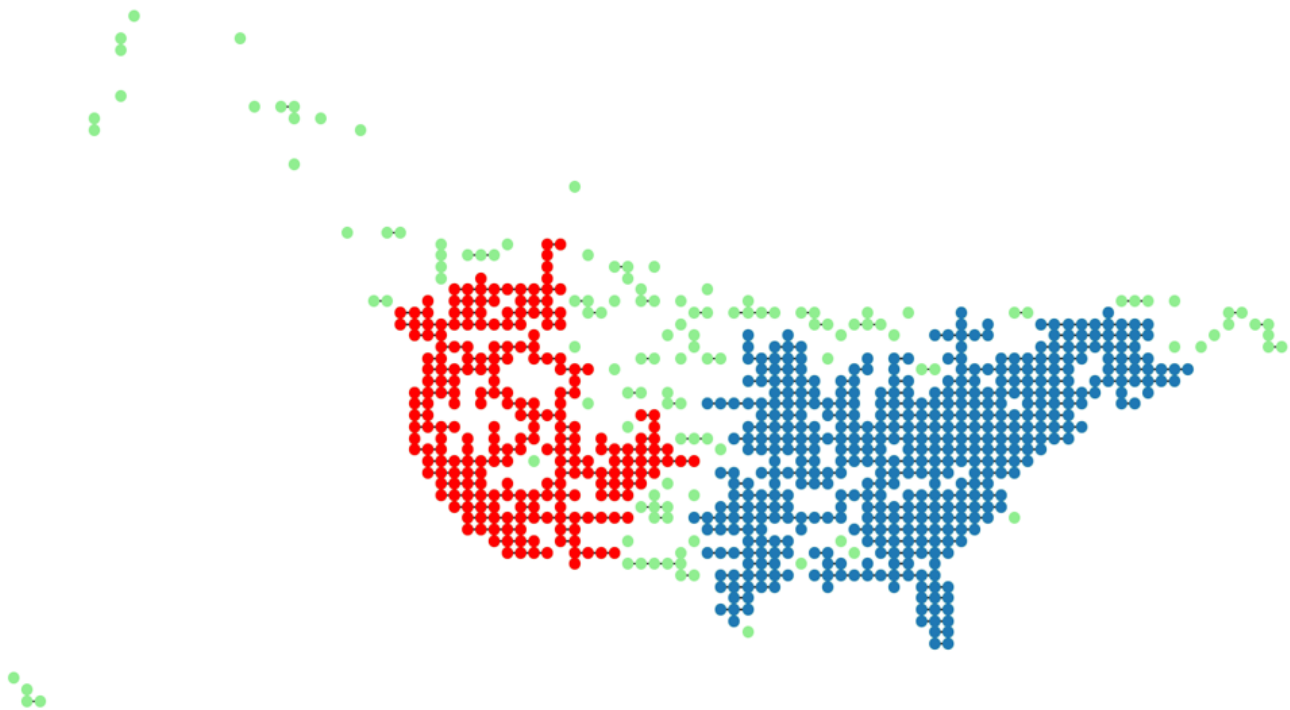


Figure 3: EV Grid Network - Each node represents a 100.7km * 100.7km square - Blue: largest connected component, Red: 2nd largest

Algorithm 6 IMPROVE_CLOSENESS(Graph, Grid)

Input: Graph with at least 2 separate components and Grid corresponding to the given Graph.
Output: The location that would yield the highest graph closeness if it had a node placed in it.

$location \leftarrow (0, 0)$
$bestCloseness \leftarrow 0$
for each empty spot in Grid with at least one adjacent non-empty spot **do**
  $test \leftarrow ADDNODE(Graph, x, y)$ where x, y is the current empty spot in Grid
  if CLOSENESS(test) > bestCloseness **then**
    $bestCloseness \leftarrow CLOSENESS(test)$
    $location \leftarrow (x, y)$
  end if
end for

the closeness of the graph. The result it provides is a node at position denoted by latitude and longitude (43.255205334055624, -87.67711089544706). This is shown in figure 7 and the corresponding graph is shown in figure 8. An important note is that the resulting node happened to be in lake Michigan, which suggests that the best spot for a new charging station would be one that connects both sides of the lake. For electric vehicle travel, this would improve the closeness the most. This highlights one of the weaknesses of our algorithms and methods in that they are unable to distinguish the

Figure 4: The center of the grid cell in which a new station would provide the most efficient coverage expansion

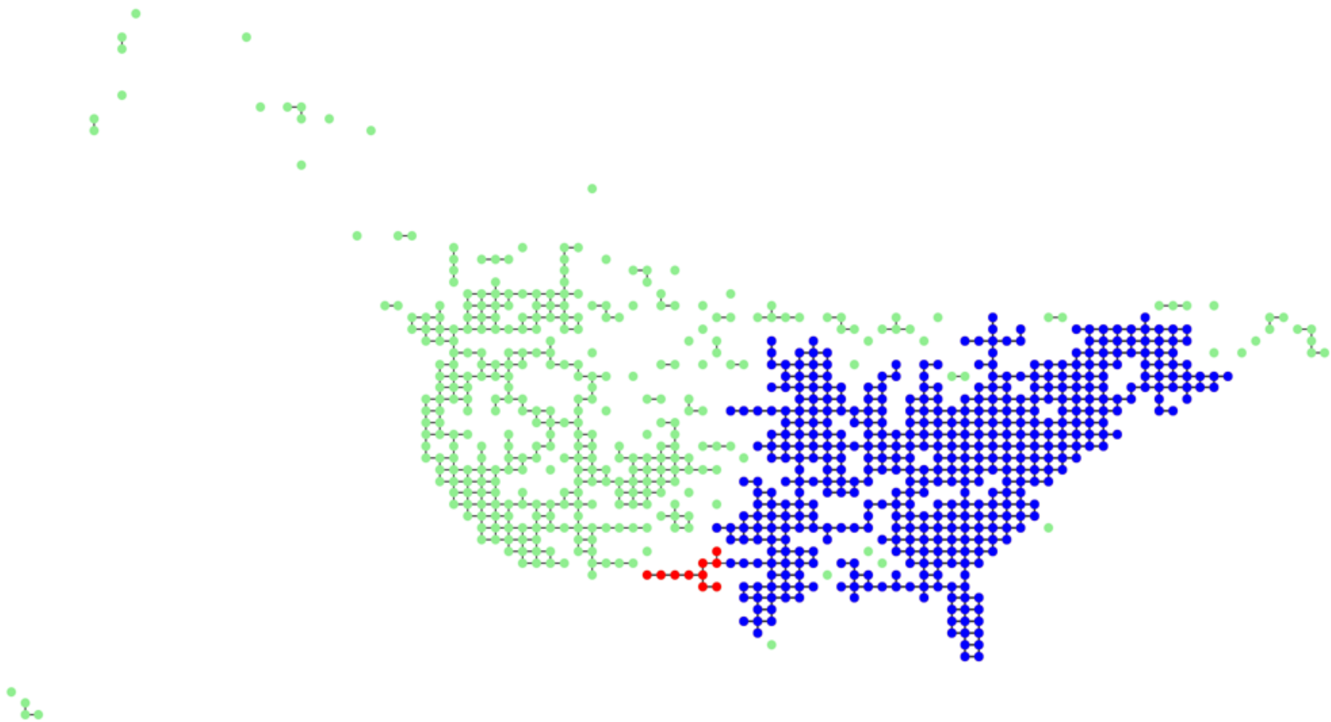


Figure 5: Greatest connected component expansion result - Blue: Original GCC (462 cells), Red: newly added GCC (+10 cells). The first red node connecting to the blue is the node added by our algorithm.

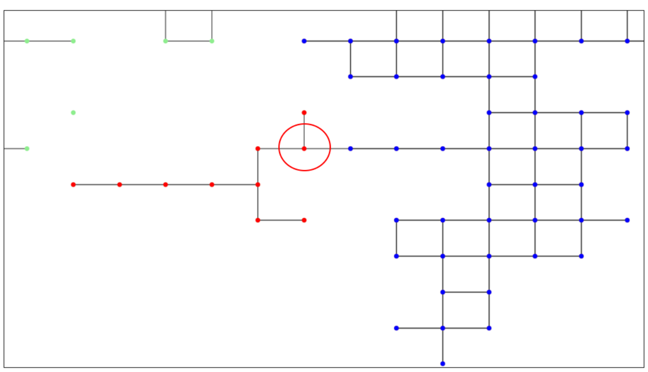


Figure 6: Newly added GCC

Figure 7: The center of the grid cell in which a new station would improve the closeness of the network

geography of the terrain. This can be improved upon by simply "blacklisting" those nodes which are primarily water, preventing them from being candidates for new stations, but this is beyond the scope of this project.

5.2 Comparison

5.2.1 Coverage Comparison.

Within our first method of getting the larger greatest connected component through adding adjacent nodes to. the result from brute-forcing every possible adjacent node beside the current greatest connected component yielded a greatest connected component of **472** nodes, compared to the original size of **462** nodes. Each node is defined as a grid cell, therefore coverage increased from 4620000 km^2 to 4720000 km^2. With greater computation ability, we would be able to test out adding more than 1 node at a time and resulting in a greatest connected component that would optimally extend the GCC even further. The spot that our algorithm chose to include a station which ultimately extended the GCC at the point mentioned earlier in Texas.

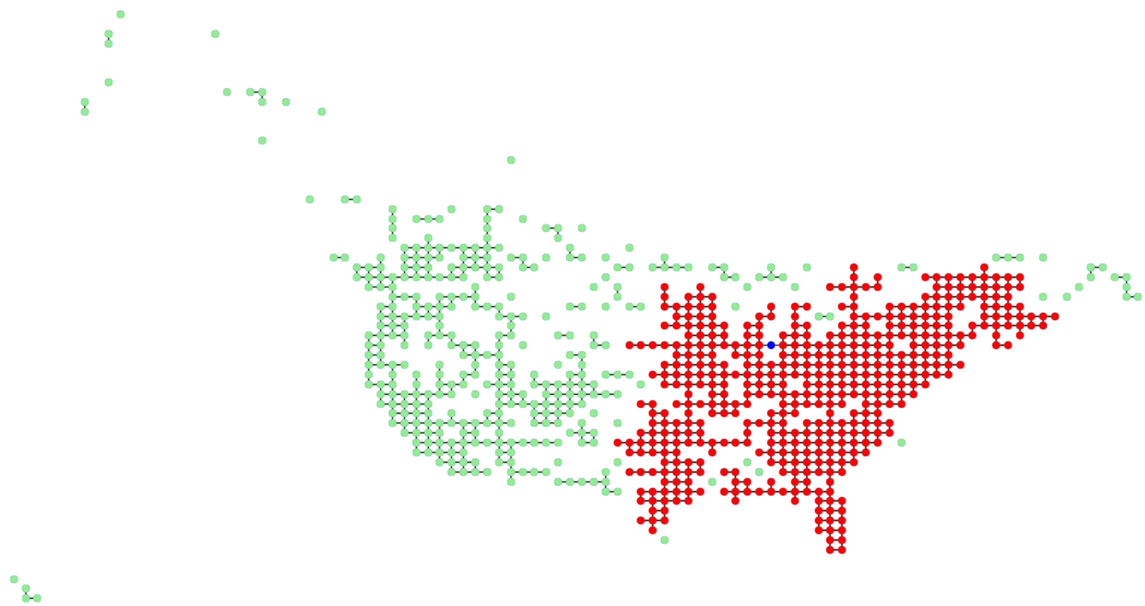


Figure 8: Closeness improvement result - Red: GCC, Blue: New node which provides the biggest increase in closeness to original graph.

5.2.2 *Closeness Comparison.*

The closeness of the original network was a value of 0.05392. Algorithm 6 gave a seemingly meager improvement of only 1.34% to 0.05464. However, this is not so meager because the cell size of 100km is rather large, and although it would not affect many long distance trips, the effect it would have on the few it does is significant. The blue node in figure 8 can cut down some trips by up to 400km - instead of taking the 600km detour, drivers can take the 200km straight path.

5.3 Future Experiments

One method that we wanted to attempt was a targeted approach. Within the grid network, we could obtain all the connected components, and find which connected components are nearest to each other based on their leaf nodes using pairwise distances on our grid matrix. Once comparing all connected components to each other, we can obtain a list of pairs of connected components, and a pair of leaf nodes of each of the respective connected components. With this information, we may perform a Breadth First Search starting from connected component 1's leaf node to the next nearest connected component X's leaf node. In conclusion, this would result in all connected components connected through a shortest path. Paths could also be ranked based on length versus how many of the grid cells along the path are already covered, thus lowering the amount of stations required for bridging that connected component. This method was explored although we could not implement a reliable solution resulting with what we envisioned. The implementation of this method is included at the end of the code.

6 CONCLUSION

To summarize, what we've accomplished is through use of the NREL API dataset, we classified the whole of USA into a geographical grid network. To obtain the grid network, we identified stations that would be in the area of each cell. Using this result, we could then determine if a cell is covered, if so, add a node in that grid cell. Once all nodes are added, connect all adjacent nodes within the grid with edges. Once the grid network is established, we worked on solving the problems we outlined.

The first was expanding the GCC of the network, which we achieved by adding a node to each possible adjacent node within the greatest connected component in the grid network to obtain an extended greatest connected component. With this method, by only restricting to adding 1 node in total, we obtained a GCC of size 472 versus the original 462 cells. The second method we used was to maximize closeness using similar ideology of adding a node to each possible adjacent empty cell from a node cell in the greatest connected component. This resulted in an increase of closeness from 0.05392 to 0.05464. For incomplete methods, we propose another method by matching connected components to their nearest neighbours and connecting them through the shortest path of their respective leaf nodes. Additionally, re-running the methods already performed with multiple nodes added instead of just one can also serve to provide more insight on this topic.

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