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2018
MCM/ICM
Summary Sheet

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Leading the Charge: Generation and Analysis of Future Electric Vehicle Infrastructure

With recent leaps forward in technology, Electric Vehicles (EVs) are becoming increasingly popular, with reasons for purchasing EVs spanning environmental to economical. With the increase in EV adoption, it is important to keep pace with the increasing demand for relevant infrastructure. Electric charging stations are an important part of encouraging EV use, so better charging station locations will stimulate more EV usage. However, when building infrastructure for charging, it is important to place chargers in the optimal locations, to maximize usefulness and minimize required costs for full coverage.

Our model uses a genetic algorithm to determine several best solutions to this problem. While these solutions are not unique, they allow a country to choose from solutions based on factors such as existing infrastructure and politics. Our model can also be easily modified to explore different factors. This model was tested on two case studies, Ireland and Singapore. While these countries are small, the ideas explored can be expanded to problems of any size, from large countries to single cities. The model is purposefully general to allow differences in the goal number of superchargers, the goal distance between superchargers, and other considerations a country may have.

The genetic algorithm used in our model looks at a map created by simulating traffic flow through a small country. We focused on the large scale of towns and highways, and manipulated variables to explore the sensitivity of our results. We discovered that when focusing on traffic flow, the best locations for charging stations were outside major population centers along popular routes for travel. We also found that superchargers were more effective in rural or suburban areas, as opposed to large cities or population centers. This distinction appeared in our model as well as several corresponding papers on the subject. We were able to corroborate the results of these papers by investigating generated tour data and determining best locations for charging centers.

This also showed that destination chargers would appear primarily based on population, within urban centers, rather than spread evenly across rural areas. Our model was primarily designed to analyze the placement of supercharger stations, rather than these destination chargers. Instead of focusing on the sustained population of EVs within a city, which would use the slower destination chargers, we looked into rapid charging stations that focused on the total flow through a city. This allowed us to focus on superchargers, with destination chargers located where people would stay for longer.

Using the generated solutions, we determined the best locations within Ireland and Singapore and came up with a generalized plan for shifting a country to electric vehicles.

Contents

1 Introduction

As technology advances and the world becomes more environmentally conscious, electric vehicles (EVs) are becoming more widespread as personal vehicles and as public transport. To encourage EV use and to keep up with the growing number of EVs, charging stations must be available to increase the range of EVs and therefore their appeal. Countries who are moving to encourage more EVs will need to understand the impact of charging stations on consumers, and put careful consideration into the placement of these stations. If a country better understands how the charging stations affect drivers, the switch to EVs will be smoother and quicker, and allow the country to embrace the next step in transportation.

1.1 Background

The shift in the paradigm surrounding transportation is one of great interest to researchers. Previous work in the area of EV charging stations primarily deals with node-based or flow-based algorithms. Node-based models determine placement by social factors, such as where people work or live, or determine how many chargers there should be per station. In flow-based algorithms, the station locations are determined using the routes drivers take, following research that most EV drivers refuel on their way to destinations[1]. These two methods also lead to important distinctions between different types of EV chargers. EV chargers come in two types: destination chargers, which take a long time to charge, and superchargers, which can charge a vehicle in a half hour. Other researchers have found that node-based models work better for destination chargers, while flow-based are more useful for the superchargers[2]. This is supported by the charging habits of people who already have EVs and the fueling habits of people in general-EV owners tend to recharge on the way to their destination, instead of when they arrive[1], while people in general tend to fuel at their destinations, especially close to work or home[3]. While models used vary greatly, genetic algorithms have not been widely used to find the best locations. Research has found that genetic algorithms can be useful in finding locations[4], and genetic algorithms allow for more theoretical modelling that explores different dynamics in a very flexible way. In this paper, we will expand on this work by using genetic algorithms to approximate best locations for superchargers.

2 Tesla in the United States

2.1 Existing Infrastructure

Tesla charging stations already exist across much of the United States, in addition to the other EV charging stations available. A huge number of cities already have destination charging, and supercharging stations are already evenly distributed across many major highways. Tesla is also working to create supercharging stations within urban spaces, although they do encourage owners to install home charging for convenience. With the increase in interest and the high sales of Tesla's new model 3, it seems like consumers want to buy EVs. However, the price of these cars and the lack of charging stations could be holding back many buyers.

2.2 Distribution of Charging Stations

The current map of Tesla charging stations is similar to a population map - the areas of the country with a high population density, like the east coast and California, have a higher density of charging stations than the less-populated plains states. There is a big difference between the slower destination charging stations and the quick supercharging stations. Destination charging stations exist in or near cities, while the superchargers cover the highways in addition to urban centers. There are supercharging stations existing or planned at regular intervals along major highways, to allow drivers to make major treks without having to worry about where they can charge. The existing system seems to assume that destination chargers will be used when drivers reach their destinations, while the supercharger stations allow them to fill up on the way. Tesla' website claims to be working on building urban infrastructure, so owners can charge anywhere. However, they also emphasize that buyers should install home-charging rather than depending solely on supercharging. With the current distribution and the plans they have for future sites, it seems Tesla is well on the way to creating a vast and reliable world-wide network of charging stations. However, when looking at a closer scale to much of the US, it becomes clear that even in major cities, there are only a few places for users to charge their vehicles. Although a Tesla thrives close to home, where charging is easily available, once the owner wants to travel a bit further it becomes inconvenient. In addition, electric cars are still very much a luxury car. The vast majority of the US is unable or unwilling to spend over $35,000 on a Tesla. However, with the Model 3, Tesla is transitioning to a more accessible car. The average cost of a 2017 model car was $33,000, meaning the Tesla is in range for people looking to buy new cars. Increasingly, the saved cost of using electricity instead of gas and government subsidies are making the cost of EVs less of a concern. Analysis of EV sales show that government subsidies can increase the rate of change-over to EVs from fossil-fuel cars. By creating "Demand-focused" subsidies, governments can increase consumer interest in EVs. Norway, the current world leader in EV market share, has many incentives to encourage consumers, including purchase subsidies and other incentives like exemption from toll roads and free parking. They had a EV market share of 22% in 2015.[5] There is also the option of "supply-focused" incentives, which encourage car manufactures to increase availability and improve research of EVs. With these incentives, it is possible to greatly increase the adoption rate of electric vehicles, and once enough of the market share has accepted the difficulties that come along with early adoption of new technology, the infrastructure required for wide-spread adoption will follow. With support from the US government, 100% EV ownership in the US could occur much more quickly, but judging from the sales of Tesla's electric cars, the country is still on track for 100% adoption.

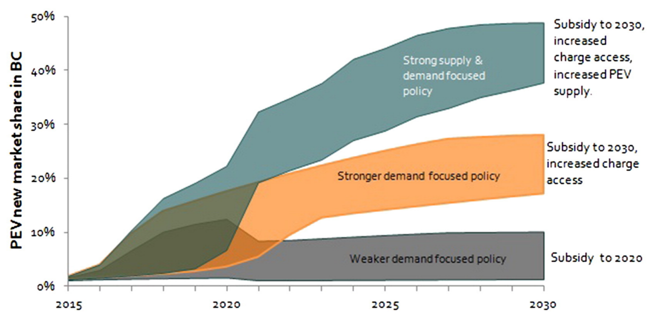

Figure 1: Model of EV adoption with Policy Support[5]

2.2.1 Methods for Rolling Out Charging Stations

One roadblock to widespread adoption of EVs is the requirement for charging stations. Although most EV owners charge their vehicles at home, making it possible to own an electric car without access to nearby chargers, the fact remains that any long journey requires widespread charging infrastructure to complete. This infrastructure is not yet in place, although it is becoming increasingly common to see stations for charging EVs. Many consumers could be reluctant to buy a car that they can't drive anywhere, particularly one as pricey as an EV. Therefore, it seems that infrastructure must be in place before any sort of wide-spread adoption of EVs. However, despite the popularity of the model 3, there are only 100,000 Teslas in the United States, and around 700 supercharging stations[6]. Although electric vehicles are a promising technology, there still isn't a high demand for charging stations for the average consumer. It's a chicken-and-egg problem: until there are enough charging stations, consumers will inevitably shy away from purchasing EVs, particularly since most electric cars still have a range that leaves much to be desired. Yet without increased demand for EVs, the demand for infrastructure is low. Another way of encouraging consumers to purchase EVs is to increase the number of charging stations to ensure that an EV isn't limited to its range. We propose following Tesla's lead and emphasizing the placement of superchargers along major highways, while increasing the number of destination chargers within urban areas. This would allow owners to make long trips and stay in other cities, away from their home chargers. Since destination chargers are primarily built by owners of hotels or other places where people would be staying, this kind of charger should exist primarily in Urban areas. It is expected that more drivers will be going to and staying in high-population areas, so this should be the priority for destination chargers. Superchargers, on the other hand, are more for fast charging. Although these would be useful near shopping centers and other areas for congregation in urban centers, is is preferable to have fast charging along areas where cars will be going from one place to another, not in places that drivers are usually staying. Therefore, these should primarily exist in rural areas. Finally, we have to consider suburban areas, where there is a denser population than rural areas, but also more space than urban ones. These areas are most likely where the drivers will be living, and therefore close to the home chargers they have installed. We argue that these areas don't need chargers as much as rural or urban centers - but there is still a niche for superchargers as an extra convenience for people visiting stores in the area. Overall, the primary goal should be breadth over depth - it is more important to have regular spacing along major highways than it is to have lots of stations in one place.

2.3 Switching to Entirely EV in the US

Should the entire US make the switch to entirely EVs, more stations will follow. In the case of every car in the US switching, with equal numbers of transference, there will be 247 million EVs on the road in 2030. However, due to dropping need for transportation and in increase in ride-sharing and self-driving technologies, it's been predicted that there will only be 44 million cars on the road by 2030[7]. If this is the case, of course less charging stations will be needed. The European Clean Power for Transport directive recommends 1 charging station for every 10 EVs by 2020. If this is the case, with 44 million cars, there will have to be 4.4 million charging stations to support them, in a well-organized network. If each charging station includes 10 spots for charging, there will have to be a network of 440,000 charging stations to support every EV in the US[8].

2.4 Applying our Model

If we wanted to explore where most of these stations would reside, we could run a large-scale model on a graph of US major highways and cities to discover where charging stations could be placed. It would likely look like the current map of charging stations in the US, with stations spaced evenly across major highways and clustered in cities. More specific placement would have to occur on a place by place basis.

3 The Model

We used a genetic algorithm to determine the best positions for each supercharger. This allowed us to use a flow-based model where nodes were intersections of major roads. This was the best way to model this in terms of time, accuracy, and allowed for the best way to understand differences in parameters. This algorithm allowed us to quickly vary parameters and explore the impacts of weighting parameters differently, while still having the freedom to investigate unexplored elements.

3.1 Thesis

By generating car movement data based on population information and mapping, we created an algorithm to explore the best places for EV charging stations without costly data gathering. Our methods for estimating this information allows researchers to quickly explore different elements that come along with different areas. By working solely from mapping and population data, our model can quickly explore different ideas for countries large and small, with largely rural or largely urban populations, and anything in between.

3.2 Assumptions

First, we assume that any car going from one place to another will choose the shortest path to get there.

Next, we are not including the cost of building the chargers in our model. We look at where the optimal placement would be for different numbers of chargers, but we do not include price in our solution.

Next, we assume that the traffic to and from an area is directly proportional to the population of that area. This is based on the census data from Ireland, which also included the number of cars in a location.

We assume that once we have determined a location, the number of charging stations at that location can handle any cars that come through. This simplifies the problem to two steps, determining where the supercharger should go, and then determining how many charging stations should be at that location. This also serves to split our problem into flow-based (location) and node-based (number of stations.)

We also assume that the range of EVs are 350km (220mi) on a single charge, which is the accepted value for current high-end electric cars like the Tesla.[6]

3.3 Data

The data used in our model includes census data and geographical data of Ireland[9]. This comes from the 2011 census, and includes the population of towns and counts of car ownership. In addition, we used census data from Singapore to analyze the use of our model on different scenarios, such as a country with primarily urban population as opposed to primarily rural.

3.4 Generating a Graph

First, the graph was generated from a map of the major roads within Ireland. We converted OpenStreetMap[10] data into a graph with roads as edges and intersections as nodes. This process is straightforward, as OpenStreetMap's internal structure is highly similar to a directed graph. To account for our limited computation power and time, we restricted the roads included in our map to motorways, major highways, and primary roads. This means the scale of our model is larger, without getting caught up in the differences between streets in a city. Given the location of current Tesla superchargers, including only these roads should result in our model producing a similar distribution to a model with every road included, because the range of EVs is on the order of hundreds of kilometers.

3.5 Generating Cars

In order to simulate traffic through a country, we generated cars to drive along the roads to see where most people would need to refuel. Each town node generated cars, which would then "drive" through the graph by selecting an end destination and finding the shortest path there. The towns we used were found in the Irish census data, which included 824 cities and towns. Of these, we determined the latitude and longitude of each town and used this to align them with the closest node in the graph. This resulted in 725 nodes that aligned with towns in Ireland that we could use to run our car model. In addition, a number of randomly-chosen nodes sent off set numbers of cars to ensure a more even coverage, and to account for general travel to and from rural areas. For each of these locations, we then generated destinations from the other saved towns, with probability proportional to the population according to the census data for the town. Randomly chosen nodes had a small but non-zero chance for choice, meaning they could be chosen as a destination, but rarely. For each pair of (source, destination) nodes, the shortest path was determined and every node along that path had the following information added to it: Car count: The number of cars passing through the town was recorded to determine the popularity of the destination. Total distance: The distance travelled by each car to get to the given node was recorded. The idea behind this is that areas on longer stretches of road, or where it takes longer to get from area to area, would need charging stations more than areas where most journeys were shorter than the range of the car. Type of town: This was a way of classifying places as rural, suburban, or urban without having to separately go through each node in the graph. As the algorithm passes through each node, the population is examined and a ruling is made about the type of town.

This information is all saved as part of the graph. We generated data this way to closely reflect the actual number of cars going through each town. Simply looking at the census data for number of cars in each town wouldn't take into account towns that are on major routes of travel and therefore see a lot of temporary traffic. These locations could be key spots for analysis, and therefore, this method is crucial for determining not only which spots are the most populous, but also the spots which are key to many journeys. We then use this data in the evaluation step of our genetic algorithm. One good thing about this system is how simple it is to generalize. It isn't geared to Ireland specifically, although one could imagine that for larger countries with higher populations, the runtime complexity would increase a great deal. It might not be easy to generate enough data to be meaningful for areas with a lot of towns, or, alternatively, for extremely rural areas without a lot of population. However, this data allows us to theorize about different populations. For example, if there are a lot of random nodes, the population is more spread out in its movements, and if different percentages of the car population is moving around, it can simulate a population with different percentages of electric cars.

3.6 Determining Best Locations for Superchargers

Once we have data on the estimated number of cars visiting a given node, we use this model to determine the best placements for the superchargers. This is where we took into account parameters such as distance between nodes, number of cars that would be serviced there, and what area it was in. A sample of locations were chosen as potential supercharging positions. Then, each location received a weight based on the parameters. Once the locations were scored, we either kept them, discarded them, or generated new nodes from them, using the score to determine how good the placement was. Each round, a number of random nodes would be generated to keep the total number of nodes steady, and to allow for additional variation that could lead to a better spot for a station. With the following variables, we can define a function for the score.

$$
\begin{aligned}
v_t =& \text{Total Number of Vehicles} \\
& \text{Through Node} \\
d_t =& \text{Total Distance Each Car} \\
& \text{Traveled to Get to the Node} \\
m =& \text{Max Distance a Car Could Travel} \\
C =& \text{The Set of Nodes Classified as City} \\
S =& \text{The Set of Nodes Classified as Suburban} \\
R =& \text{The Set of Nodes Classified as Rural} \\
n =& \text{The Current Node} \\
c_n =& \text{The Weight Given to City Nodes} \\
s_n =& \text{The Weight Given to Suburban Nodes} \\
r_n =& \text{The Weight Given to Rural Nodes} \\
l_n =& \text{Location of Current Node} \\
l_m =& \text{Location of Nearest Node} \\
& \text{to Current Node}
\end{aligned}
$$

The score function was defined as follows:

$$
\left(\frac{d_t}{v_t \cdot m}\right)\left(\frac{1}{|(l_n - l_m)|}\right)\begin{cases} c_n & n \in C \\ s_n & n \in S \\ r_n & n \in R \end{cases}
$$

This score is driven in first iterations by how much the driver would want to charge given by the $\frac{d_t}{v_t \cdot m}$ term. In successive iterations, the distance between nodes would be the largest term, meaning once it has found good nodes, it will create a lattice of good nodes to fill the necessary area.

3.6.1 Distance Between Superchargers

The distances between superchargers were weighted based on an ideal distance. The ideal distance was determined from findings that drivers using alternative fuels would refuel with more left in their tank than other drivers[1]. So, ideal distance was given by how far a driver could go on 3/4 of a charge. However, with more research into the driving habits of EV owners, particularly as the number of charging stations increase, this parameter could change. It could be that anxiety about finding a place to charge their EV is what drives EV owners to fuel earlier - if there are more stations, it could change these habits.

3.6.2 Number of Cars Serviced

The number of cars serviced was based on how many cars went through the node and how ready they were for charging. This was determined by finding the ratio of the average distance a car had travelled to the total range of an EV.

3.6.3 City, Suburban, or Rural

This number gave a weight to try to offset the population differences between the different types of locations and to determine whether focusing building in certain types of places would be better than others. This was determined using the population of the town during the car model generation, for the following values:

$$\begin{cases} Population < 1500 & \text{Rural} \\ 1500 < Population < 4000 & \text{Suburban} \\ Population > 4000 & \text{Urban} \end{cases}$$

3.6.4 Generating New Nodes

One key element of any genetic algorithm is the generation of additional superchargers. Once the best stations are determined, additional stations are created to try and improve the solution. The low-scoring superchargers are removed, and additional ones are created. In addition, if the charger was within some threshold distance of another, the higher performing charger was kept. This allows for more spread-out superchargers and reduces redundancy in our solution. Since we were looking for the best locations for the superchargers and not the number of charging stations at each location, combining nodes like this helped determine the best locations for superchargers. If a supercharging station was far away from other stations, but its score was high enough to keep, the station would generate new superchargers around it. This allows us to investigate if the position is the best place for an area that requires a station. This would also mitigate the potential for superchargers to die out if they were in an area with no other superchargers around it, but still served a needed community. Finally, stations are generated in randomly-chosen nodes, to give other areas the opportunity to shine. The generation of these superchargers addresses the particular needs of the model, while still allowing for random creation. In this way, we have adapted the traditional genetic algorithm methods of breeding and mutation to create a system that addresses goals specific to the problem.

4 Electric Vehicles in Ireland

4.1 Optimal Locations

Although our simulations did not converge to a single solution, the solutions given by our model could be used to determine the best supercharger locations for the country. The reason for these multiple solutions was how a good solution from our model depended on distance to other superchargers. Two locations very close together could score highly, but since they were close, the model would choose only one of these. So the solutions could vary to get both a spread and good locations. The graph below shows the most common places that were chosen by our model.

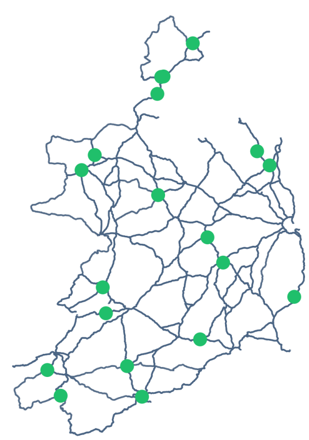

Figure 2: Frequently Chosen Locations

Note these points are some that came up most often, this is not a solution graph.

The solution iterations worked toward a good solution. Since the fitness value of a supercharger depended on the distance to other superchargers, the model did not converge to a single best solution. However, this works in our favor since we can generate many good maps and then choose the one that fits which communities have more electric cars, or where it would be easiest to build. The first iteration of the algorithm and the last are shown below.

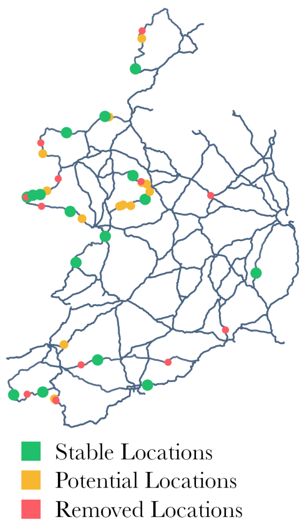

Figure 3: Superchargers after the first iteration

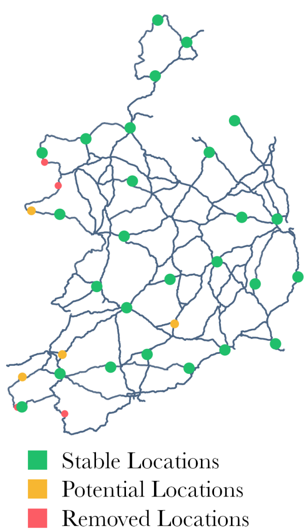

Figure 4: Superchargers after the last iteration

4.2 Rural, Suburban, or Urban

One thing that came up as we ran many simulations was that cities were not chosen for a supercharger very often. When supercharger locations were chosen near Dublin, for example, they were often moved to a location farther away from the city on subsequent iterations. This implies that a rural or suburban area would be a better location for superchargers. Many successive runs also gave a statistically significant proportion of rural or suburban to city. Most runs only chose about 0.1% cities and kept the rest as suburban or rural. This fits a social argument as well; a city is most likely an origin or destination, a place where a driver would want a longer charger. Within a city, a node-based or other flow-based model could be applied to determine the best locations for chargers within a city. Changing some of the parameters of our model could find solutions in the city, an argument laid out below with Singapore. Models such as that laid out by Xi [11] for maximizing use of chargers could be used to determine how many and where chargers should be located within a city.

4.3 Optimal Number

We found that the optimal number of chargers was between 15 and 30. When the model was run on numbers less than 15, the model would not come to a conclusion because the chargers were too spread out. When the model was run with more than 30, the chargers would get too close and would not come to a conclusion. Since we were looking for a good cover, and not an eventual solution that would want more chargers, we found this number of superchargers to provide the best range.

4.4 Timeline to Charging Network

Building a supercharger station takes between 12 and 20 weeks to build, and a cost of \$100,000 to \$175,000 (USD) to build.[12]

Consequently, it would be unrealistic for a government to build all 15-30 supercharger stations at once. Based on the results from our model, we have identified four tiers of superchargers based on their usefulness values. Note that these are approximations of locations.

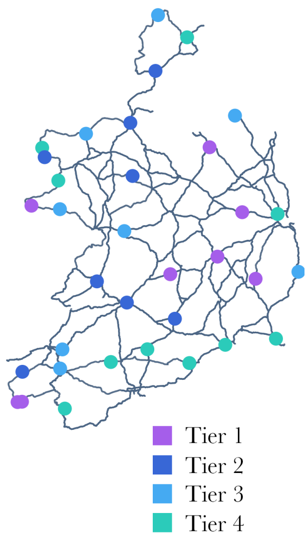

Figure 5: Tiers of Supercharger Locations

Ideally, Ireland would build the tier 1 stations first, followed by the tier 2 stations, and so on. Given an aggressive push by the government to build out supercharger infrastructure, all 30 charging stations could be built in as little as 2 years.

Other research shows that policy, alongside infrastructure, is very important in moving forward with EVs. Researchers have found that with policies such as subsidies, increased access to home chargers, and increased variety and availability of EVs, the market share of EVs could increase by up to 49% by 2030 [5].

5 Expanding the Model to other Countries

Since EV adoption is mostly determined by availability and less by socioeconomic factors [13], our model expands well to countries with different wealth distributions.

5.1 Model in Singapore

As a case study, we used Singapore to explore how our model could be used at a different scale. The most significant change was the ideal distance between nodes. Because Ireland was much larger, nodes could be spaced in relation to the EVs' range. Singapore, however, is much smaller and so the range did not matter as much. The distances were then found by approximating how many charging stations were wanted and how how far apart they should be, based on the area of Singapore.

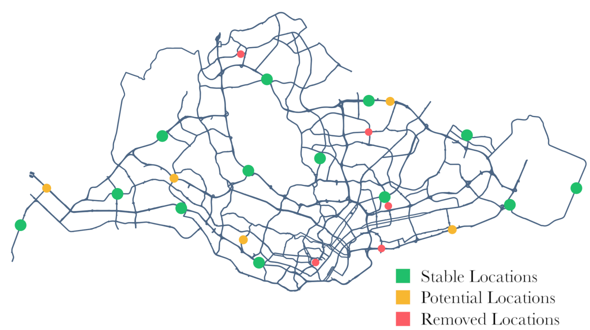

Figure 6: Locations for Superchargers in Singapore

The model is not able to determine an estimate for the best number of superchargers in Singapore, because it is so small, so it cannot use the distance a fully charged EV can go as a metric.

Looking at the order in which the superchargers should be built, we notice an interesting pattern. The nodes to be built first form a good cover of the city while those in later tiers fit between them.

Figure 7: Tiers of Supercharger Building

5.2 Model in Other Places

If we were in a country that included mostly rural areas, such as Australia, our model may be skewed towards the areas with less people. In a large country, our model should weight towards the locations with a higher population. The downside is that our model seeks to create a cover of nodes, which might not be feasible in a large country, especially in areas that might not even have vehicle traffic.

A country whose roads did not create a connected graph would also be challenging for this model. In this case, we would have to run the model on each island or be very careful about how the distance parameters are defined.

6 Sensitivity Analysis

Our model worked in general terms. Each solution could vary wildly from others, especially if the parameters were not set well. The distance between each supercharger affected the final solutions a good deal. When run on smaller areas, if the distance is set too high, the algorithm will not settle on an optimal solution. When run on larger areas, if the distance is set too small, the algorithm will find a good solution in a small area but might disregard large sections of the country.

Our model runs from generated car tours, if car tour data was available as it is in some cities, this map could give more accurate solutions.

Our model also looks only at a subset of roads. This gives only solutions along major roads and could be improved with longer runtimes.

Since our model created these car paths, if done on a larger graph, the runtime will grow in terms of $O(E + Nlog(N))$, where E is the number of edges in the graph and N is the number of vertices. For larger graphs, the runtimes could be costly, especially when generating multiple solutions.

7 Alternative Technologies

While the shift towards EVs from gas-powered cars seems inevitable, we should also consider other developing technologies that could affect how a country builds out its infrastructure. For example, the growing ride-sharing industry could indicate that the concept of car ownership could become a thing of the past, greatly reducing the number of cars (and therefore needed charging stations) on the roads. Paradigm shifts in transportation like the Hyperloop would significantly change our analysis as well, as the usage of roads that our model takes into account would be very different with these technologies than they are currently.[14]

8 Conclusion

Electric vehicle charging stations are increasingly important to encourage EV use and support those who already own EVs. It is necessary to position the charging stations to relieve range anxiety and supply EV drivers.

To help find the best charging station locations, we created a genetic algorithm to iterate and find solutions. The basic parameters we used were the drivers' want to charge, the distance from other chargers, and the location.

Further work could be done to determine other parameters to include, such as cost in building them, distance from the shortest path, including the drivers' willingness to drive up to 9 minutes to recharge[1].

EV use is primarily dependent on access to charging stations[13] and incentive programs [8]. Countries that wish to encourage electric vehicles should plan infrastructure and incentives to prompt consumers to make the switch.

To the Attendees of the International Energy Summit

When the steam engine was first created, it started the globalization that continues to this day. When Ford first created the Model T, it increased mobility of the individual to the astonishing degree that we currently enjoy. Now, we approach an exciting new frontier in transportation technology.

Electric vehicles are becoming a clear next step in our goals to decrease dependence on fossil fuels and mitigate climate change. With the support of government subsidies and incentives, the number of electric vehicles will quickly grow until a country no longer depends on gasoline. One needs only to look at Norway to see how quickly consumers switch to electric vehicles with the support of government policies. Norway has aggressive policies to encourage electric vehicle purchasing, and as a result, in 2015 22% of the market share was dominated by electric vehicles.

To support electric vehicles, careful consideration must also be placed on charging stations. As demand for charging stations increases, the demand for gasoline decreases. By understanding the different kinds of charging stations and the multitude of research going into placement of these stations, countries can develop infrastructure and remove one of the largest barriers to widespread adoption. Each country will have to analyze the different needs for the population to determine the placement, number, and kind of charging stations they will need. These will depend on population, density, and size.

Another key factor to the adoption of electric vehicles is home charging. For people to switch to an electric vehicle, they must have a system within their home to charge their vehicles. These systems are costly to install, and would benefit greatly from policies to incentive their adoption.

Any county on the forefront of this revolution will be well-prepared for the eventual domination of electric vehicles on the market. With proper consideration, gasoline cars could cease to exist within a century of their creation, and we could move forward to a brighter, cleaner future.

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