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2018
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Summary Sheet

Electric Vehicle Revolution: Predictions of Charging Station Placement and Evolution Process

Electric vehicles have emerged significant potential for enhancing energy security, reducing carbon emissions, and improving local air quality. To fully exert the advantages of electric vehicles, we desiderate a comprehensive scheme. Spelling out in simple terms, the question at our hand is to estimate the number, the placement and the distribution of charging stations and to predict the process of this electric evolution. We found that the step of given tasks is actually a step of loosening the assumptions and including more variable factors. Therefore, we herein develope our paper following the sequence of questions.

Based on some reasonable assumptions, we first considered the imaginary situation that no transition time required. We seek to develop a mathematical model which coherences production capacity and charging station supplement at its core. To do this, we estimated the capacity, dug out the crucial factors. So, with the shapefile include both data of population density and road distance, we could write program to simulate many dots which represent the cars on the road. We also tried 3 different kinds of cluster analysis and finally used the Monte Carlo algorithm. After getting the processed data, we could count the number and conclude the distribution.

Next step, we took the need of time into consideration. That is, measuring the speed of evolution. The main points we considered are: GDP, population growth, annual growth rate of car ownership, annual growth rate of electric vehicles and annual car elimination rate. We introduced a stop time as common parameter and 3 formula to form our model. This way, we can illustrate the timeline of the evolution.

In our third step, we enhanced the scalability of our model. Based on our constructed model and assumptions, we classified different countries by 3 dimensions---geography, wealth, and population. As a result, we were able to fit all the countries into our model.

Having considered the endogenous variables, thinking about exogenous variables may make our model more applicable to the developing world. Car-share, Ride-share, Self-driving cars, Rapid battery-swap stations, Flying cars and Hyporloop begin to gain influence. In this part, we used a qualitative analysis method, analytic hierarchy process. And the resulting weight vector is correspond with common sense.

Meanwhile, we deeply analyze the strength and weakness of our model, hoping to consummate some day.

Key words: charging stations, road density, distribution, timeline

Contents

1 Introduction

Given the imbalanced environment, given the forethought of economy, reducing the utilization ratio of fossil fuels becomes increasingly valued. To follow the trend of development, we are facing an unprecedented transition from conventional gasoline and diesel cars to electric vehicles and therefore need to have a sufficient number of vehicle charging stations in all right places so that people can use their vehicles for their daily business, as well as making occasional long-distance journeys.

Countries now are considering building a network of charging stations that can support the full adoption of all-electric vehicles. Apparently, the basic factors (the number of stations, the locations, the number of chargers at the stations, and the differences in the needs of different areas) should be all taken into consideration. The growth and evolution of the charging stations network over time is also important as we should fit the establishment of network into city construction.

1.1 Statement of the Problem

We are first tasked to determine the number, placement, and distribution of charging stations of given different countries under relatively simple assumptions that for the United States, we regard all cars are Tesla electric cars. As for Ireland, we postulate the country could migrate all their personal passenger vehicles to all-electric vehicles instantaneously. Based on these studies, we are asked to loosen the assumptions step-by-step. Not only the time-line of the complete switch should be taken into consideration, but also flexibility plays a significant role in our model because many countries are under different situation, which means we should consummate our model to accommodate to more flexible factors.

2 Analysis of the Problem

In this section, the problem will be divided into two parts and analysis will be done to help form the model.

3 Task 1

As tasked, we mainly focus on the super charging stations and destination charging stations.(ignore the charging stations installed at home) According to the introduction and distribution of Tesla's official website, we found that super-charging piles are mainly used for long-distance travel and distributed on expressways. And the purpose of destination charging piles is mainly used for additional supplements at leisure, mainly in restaurants, cafes and out of entertainment places. Based on these, we put forward and validate some assumptions. As long as these assumptions get clear, we are able to use the database we have collected or estimated to calculate the number of charging stations we need.

3.1 Assumption and Justification

Assumption: About Super Charging Station:Tesla's existed supercharging stations are equidistantly distributed on the highway.

Justification: The entire U.S. highway total length is about 77017 km and the distance between two super-charging stations adjacent to each other is about 182.4 km. Therefore, there should be 422 super charging stations on the highway. According to the data given by Tesla's official website, There are 468 charging stations, which satisfies our assumption just right

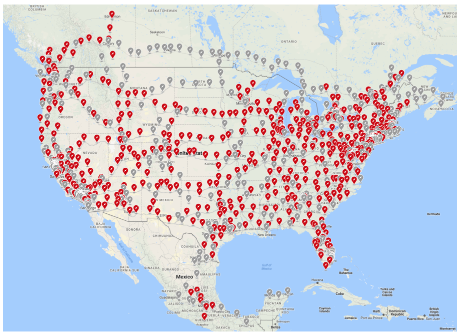


Figure 1: Super Charging Stations

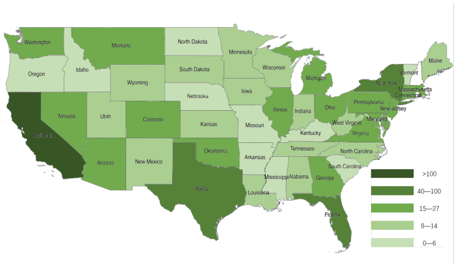


Figure 2: Super Charging Stations Distribution

Assumption: Super charging stations are less likely to distributed in cities.(only a few are distributed in well-developed states) And the coming soon super charging stations are also constructed mainly in well-developed states.(the US has already completed the supercharging construction on the high way)

Justification: Since we have discovered the potential connection between the number of supercharging piles and the local economic level, we compared the number of supercharging piles (both under construction and completed) to the GDP across the states. To quantify the relationship, we first standardize the two data which were classified by states and then use them as two standard vectors. Thus we can know the correlation by calculating the cosine angle of the vectors. We concluded that these two factors are highly correlated.

Assumption: Destination charging stations, which is the primary access of charging electric cars inside the city edges, are mainly distributed in the cities.

Justification: A destination charging pile costs only US 500 dollars, which is well below the cost of a super charging pile of $ 100,000, thus it is the city's main choice. We can confirmed by Tesla's official website that there are 3308 Charging stations, far more than Super charging stations.

Assumption: If all cars in the United States are now fully converted to electric cars, then to a large degree it will be made up of Tesla Model 3.

Justification: Model 3 is Tesla's lowest-cost product in need for large-scale promotion, which full charged mileage is 362. For super charging piles, it will take 0.866029 hours to fully charge a model 3. As for destination charging piles, it will need 6.033333 hours.

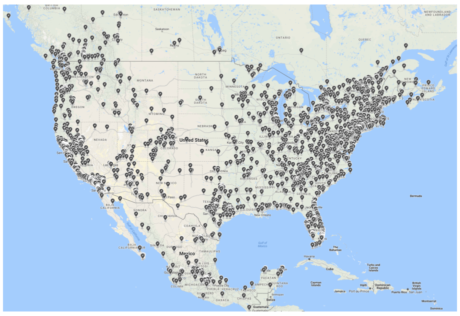


Figure 3: Destination Charging Stations

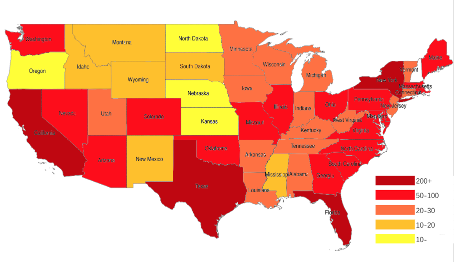


Figure 4: Destination Charging Stations Distribution

Assumption: The vast majority of car owners will go to the charging station only when the battery is running out, and at each time they will fully charge the battery.

Justification: In the United States, the vast majority of car owners charge in the garage every night. The average daily mileage for each car in the United States is 37.5 miles and one charge a week is enough. We can know that there is no need for additional supplements for most people. So, the group of long distance drivers is the vital users of destination charging piles(like taxi drivers, Uber drivers and Lyft drivers)

3.2 Is Tesla on track to allow a complete switch to all-electric in the US?

To achieve the nationwide electrification of vehicles, Tesla need to solve two main problems: laying out the charges in time and solving the production problems.

Prodution

Tesla's current annual production is:500,000 per year. Because Tesla uses full-automatic factory production, its production efficiency is beyond average. According to Tesla CEO, Musk, Tesla production capacity will reach 5,000,000 in 2022. Moreover, along with the prosperity and development of electric vehicle market and the policy of banning fossil fuel cars, the Big Three would change their tune to product more electric cars. All of the factors above will contribute abundant production capacity in the near future.

Tesla now occupies 0.75% car market share and 63% electric car market share in the United States. As self-driving car introduced, not only the need of human labor but also traffic accidents would reduce. This will serves to make greatly stimulation to the development of electric vehicles.

Charging staion

According to our analysis of the super charging station, Tesla's existing distribution network of super charging piles has largely met the needs of long-distance travel, but the number of destination charging piles in the city is far from enough. However, the price of a destination charging pile price is only 500 US dollars, thus it would be very easy to produce and very fast to reach a full coverage.

Conclusion: Through out the analysis, the nationwide electrification of vehicles must be enforced. With a keen insight, Tesla is on top of the electric vehicle field. Although Tesla is not likely to monopolize the US electric vehicle market, Tesla has indeed succeeded in vigorously promoting the process of U.S. comprehensive electrification.

3.3 The distribution and umber of charging stations

Based on assumptions, we use logarithmic normal distribution to estimate the number of charging stations. For the distribution of charging stations, we compare the K-Means algorithmïijŇthe weighted-network model along with the Monte Carlo algorithm. We found the latter one appears more convincing. In consideration of the population density, GDPïijĹper capita), road density, traffic congestion, radius of charging station, a few considerations are readily apparent to be highly correlated. This strategy can be constructed in the following way:

(1) First we consider the super charging stations. It is mainly used for long-distance travel. The data of existing highways showed that the distance between two adjacent super charging stations is 182.4 km, a 32 minute driving distance.

In well-developed states, it is reasonable to assume that the super charging pile should be increased to 1130 .

Sub-conclusion: After all the electric vehicles in the United States have been electrified, a total of 1130 super-charging stations need to be built.

(2) Now consider the destination charging stations. The majority of vehicles run inside the city, absolutely. And remove the cars which mostly charge at home, the destination charging stations seem the only supplement to charging vehicles. The number of destination charging stations is apparently larger than super charging stations. There are two main reasons:

1. The cost of a super charging pile is 200-500 times of a destination charging pile.

2.Tesla establish a preferential policie that they will offer 2 destination charging piles to the recreation areas(such as restaurants and cafes) for free or at a low price.

Based on the assumption, we estimate that there are about xx% cars are in need of extra charging.(daily mileage more than 352 km. So, there are about (233760558 * 0.0151709) cars are using the destination charging piles daily. As seen, the graphs(divided by mileage) below can clearly demonstrate the distribution of the destination charging stations.

Time	Ration
0.5	0.0033302
1	0.0026624
1.5	0.0021466
2	0.0017441
2.5	0.0014272
3	0.0038603

Figure 5: Time Ration

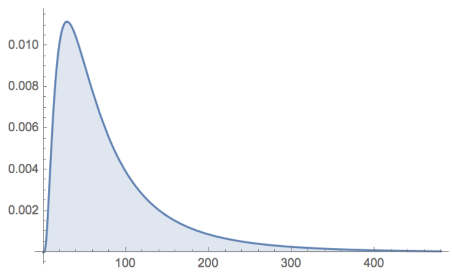


Figure 6: Drving Distance Distribution

According to this table, assuming that a destination charging pile works 24 hours a day, the number of vehicles that can be serviced by one destination charging pile is 13 per day. Thus a station is able to serve 26. Besides knowing there are 233760558 in the US, we can estimate that about 8990790 destination charging stations are needed across the country.

As for the distribution of charging pile in urban area, we construct a model of weighted network, considering the population density, road density, traffic volume and traffic congestion.

Our algorithm for building a network is as follows:

We suppose the logarithm of car owner's daily mileage obbey normal distribution. The mean is defined as μ and the variance σ. What we know now is the $\mu = 4.094344$. Thus, we can calculate $\sigma = 0.857835$,and then know the distribution.

We define a weighted network graph

$G =< V, E, W_V, W_E >$
E represents all state-level highways in the state, V represents the intersection of all the highways in the state,$W_V$represents the dot weight of intersection, andW_E represents the side weight of the highway.

Point weight setW_V is defined as:

W_v is defined as:

$$W_v = \frac{Adj_v}{\sum\limits_{<v,u>\in E} \frac{1}{W_{ij}}}$$

We find that population density and traffic volume are positively correlated with the density of the road network. Therefore, W_V reflects the density of the adjacent road where the node is located, and because the usage of the harmonic mean, the road with largest density of all the adjacent roads have a great impact on the dot weight.

Side weight set W_E is defined as:

W_e is defined as:

$$W_e = \frac{W_u + W_v}{2} (< u, v >= e)$$

This is because the density of the area where the edge is located at and the density of its neighborhood are always the same, approximate.

Based on the definition above, we use GIS and Python to simulate the weekly traffic distribution:

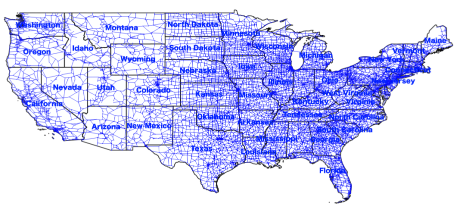


Figure 7: US Traffic Flow

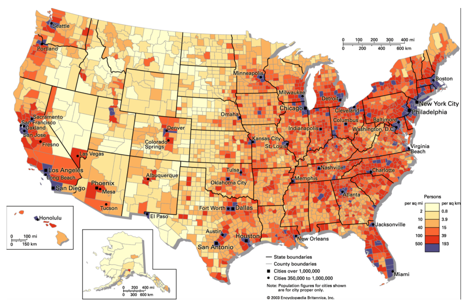


Figure 8: Population

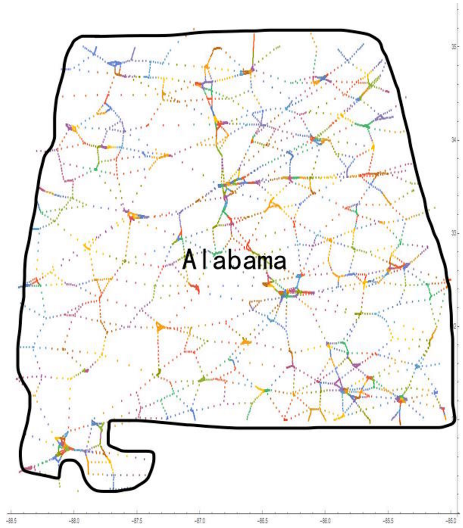
Comparing the number of charging piles available in each state with the distribution of population density in each state, it can be considered that our conclusion is reasonable.

After that, we compared two kinds of algorithm for calculating the location of charging stations— K-Means and Monte Carlo search algorithm, and finally chose Monte Carlo algorithm.

Take AL State for example:

1.Using K-Means:

This result generally guarantees the approximate same radius, but the drawback is that this algorithm can only aggregate the adjacent dots as one. But more charging stations should be set in the areas where vehicles are more densely distributed.



Kmeans Result

2.Using Monte Carlo algorithm:

Therefore, we use the Monte Carlo algorithm, and our added restrictions are as follows:

1. Each charging station serves more than 26 vehicles.

2. Every charging station is equally distributed.

3. Add the "penalty", making the charging station away from the intersection to avoid traffic jams.

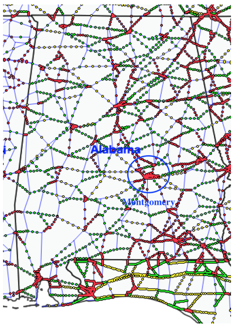
The penalty is defined as:

For one state: We use Monte Carlo to simulate $stateCarNum/26$ destination charging stations.

Comparing the map of the state, we can clearly see that the charging stations are well located in various cities.

For the Mongtgomery city in AL state:

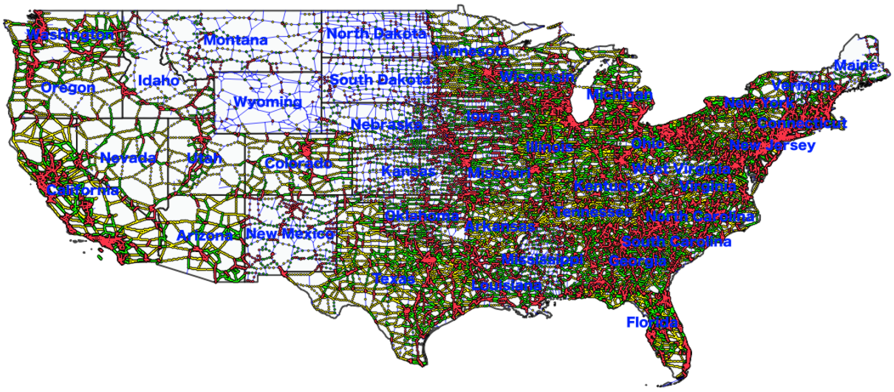
Comparing the map of XX city, we can see that the charging stations are distributed more in the high-density traffic flow area, and most of them are far away from the intersection, which meets the demand. The distance between charging stations is also reasonable.



AL station

The other states' and cities' distribution is also related with the car ownership, GDP and population density distribution.

This is clearly a piece of information that reflects the distribution of the United States charging stations.



US Charing Stations

Add up to 131810 destination charging stations are needed in conclusion.

Charging pile distribution ratio between urban and rural areas:

Based on US's definition of urban, suburban and rural areas, and based on our previous calculations, the results are as follows:

Country_urban_station Number	77942
Country_suburban_station Number	41450
Country_rural_station Number	21536
Country_urban_station Ration	0.5715317
Country_suburban_station Ration	0.3039437
Country_rural_station Ration	0.157919

Urban, Suburban, Rural Distribution

3.4 Conclusion

We can now come to conclusion:

1.Through out the analysis, the nationwide electrification of vehicles must be enforced. With a keen insight, Tesla is on top of the electric vehicle field. Although Tesla is not likely to monopolize the US electric vehicle market, Tesla has indeed succeeded in vigorously promoting the process of U.S. comprehensive electrification.

2.After all the vehicles in the United States are electrified, a total of XX super charging stations and XX charging stations need to be built.

3.For the charging pile distribution, x% should be built in the cities, x% should be built in suburbs and x% should be built in rural areas.

4 Task 2

4.1 Charging station placement

In this task, we choose Ireland as our research objective. As in Task1, we use the same model. From database, we could tell the total highway mileage of Ireland is 22425 km, thus the amount of equidistant chargers is 122. Meanwhile, the amount of extra needed superchargers due to population density and GDP is , thus, the amount of planned superchargers is 178.

According to the amount of car ownership and the analysis of daily driving distance of a car in Task1, we assume that the amount of planned destination chargers is 1124. On the basis of the enactment of algorithm in Task1, our key factors are: GDP Per Capita

From the optimal algorithm same in Task1, we figure out the total number of the Charging station is: $122 + 1124 = 1246$
, and the Percentage of each type of area is :

urban: 21.3746%

suburban: 43.1273%

rural: 35.4980%

4.2 Building strategy of charging stations

As for the sequence of building chargers, as far as we are concerned, the process of chargers construction are carried on pari-passu between urban and rural areas, but their purposes of construction are not the same.

In the beginning, chargers should meet the requirements of counties, as well as the basic requirements of the small amount of electric cars in urban areas. Therefore, superchargers should be distributed on highways and a small quantity of destination chargers in urban areas.

When we achieved the goals mentioned above, we should focus on development in urban areas for about 60% people live in cities, as well as most cars. For the reasons above, large quantities of chargers should be promoted until the number of them rise to 1134 which just meets the minimum standard.

In our opinion, the construction of chargers is the top priority. In terms of the existing technical level, the main factor restricting the popularity of electric vehicles is that the charging time of electric vehicles is much slower than that of gasoline vehicles in addition to policies. Therefore the density of charging piles and charging speed will directly affect people's desire to buy electric vehicles. In the view of the policies of the US, China and Germany (For example, Germany claims to forbid fuel cars in 2030), the development of new energy vehicles in the world and Tesla's strategy, we think that it is imperative to make electric vehicles completely electric. Therefore, we should first build a complete charging network to stimulate people to buy electric cars, which speeds up the popularity of the electric vehicles.

To complete the transition from gasoline to electric vehicles, there are key points as followed:

Per capita GDP growth, Population growth, The growth of annual vehicle ownership, The growth of electric vehicle annual capacity, Annual car elimination rate.

4.3 Analysis the pace of the replacement procedure

Define $StopTime$ as the time when the policy of forbidding fuel cars is implemented:

As for year t, we define funtion $f(t)$ as the car number, $g(t)$ as the number of fuel cars which still funtions normally , $h(t)$ as the number of fuel cars considering the abandon rate of fuel cars due to the increase of electric cars. And all K_i are constants.

$$f(t) = k_1 + k_2(k_3)^t$$
$$g(t) = k_4 \cdot f(StopTime) \cdot (1 - Abandon_{rate})^{t-StopTime}$$
$$h(t) = k_5 \cdot g(t) \cdot (1 - Increase_{rate})$$

All we need to do is to solve the equation below:

$$1 - \frac{h(t)}{f(t)} = P\,\%$$

5 Task 3

As known, diffierent countries have very diffierent geographies, population density distributions, and wealth distributions. In our model established in Task 1 and 2, no matter when we talk about the number, the distribution or the timeline of a country, we all took these three factors into account. So, when we want to study countries with various conditions, the only thing we need to do is to change the parameters, which means our model has good scalability. From our perspective, these three factors trigger the choice of diffierent approaches to growing the network in three diffierent dimentions. Therefore, ultimately, the question at hand is, how to establish a classify system to help a nation determine the general growth model they should follow.

5.1 classify system

To demonstrate a general growth model, there are 3 dimentions: the number and the distribution of charging piles and the timeline of electrification. As we have known the exact data of the US, we will use the US as a referenced standard in the following part.

1. **Geographies:** the factor that measures the number of charging piles.

We divide the geography of the US into 3 levels, in which has different percentage of plain.(level 1:0-30%; level 2:30-65%; level 3:65-100%) Suppose in each level, the number of chargers are x_1, x_2, x_3 and the acreage of each level are S_1, S_2, S_3. Then, for per unit of area of level 1 to 3, the percentage of total chargers number are $\frac{\frac{x_1}{S_1}}{\sum_{i=1}^{3}\frac{x_i}{S_i}}$ Once we know the geography of a country, we can calculate the acreage of diffierent levels, using result we have calculated and the charging pile demand, it is easy to find out the number of charging piles the country need in diffierent areas.

In reference to the obtained data, the plain areas are more likely to have more road and more population, thus require a higher demand of charging piles. Consequently, using this to measure the number of charging piles is reliable.

2. **Population density distributions:** the factor that measures the ratio of super charging piles to destination charging piles.

Making use of the opproximate population density boundary between urban and rural area, we discriminate the country as 2 parts.(urban:more than 50 people per square kilometer;rural:less than 50 people per square kilometer) From the data of the US, we assume the acreage of rural area and urban area are A_1, A_2, and the ratio of super charging piles to destination charging piles in the US is k. Then when we get the database of another country which acreage of two areas are $a_1 and a_2$, we can estimate that the ratio in this country is $\frac{k*A_2*a_1}{A_1*a_2}$.

It is known that super charging stations merely deposited in rural areas and destination charging stations mainly placed in urban areas, so use the acreage ratio to represent the number ratio is also reasonable.

3. **Wealth distributions:** the factor that measures the speed of vehicle electrification.

GDP reflects the wealth distribution of a country. Take the US as an example, it has almost the highest GDP around the world and consistently it has the highest speed of vehicle electrification. From the data collected on the Internet, we can also conclude a similar result. Cause the actual speed of vehicle electrification is restricted by too many kinds of factors(like government policy, geographic convenience and so on), it is irresponsible to quantificat the speed. However, GDP does have a relevant influence on it. Hence force, we can use GDP to probable compare the speed of diffierent countries.

6 Task 4

In this section, we will focus on factors that were regarded as exogenous variables in the previous tasks. With the rapid development of technology, new modes and new transportation will begin to gain influence. Hence forth, we would like to discuss how these factors effect the electrification process.

6.1 Why choosing AHP method

Since the absence of accurate quantitative data, we use qualitative analysis to deal with this issue. In order to accurately model the problem, we compared the fuzzy evaluation method, comprehensive evaluation method and AHP method, and eventually chose the AHP method that can better reflect the relative influence degree when solving the problem.

Experiential, we first extracted three hierarchies through the question:

1. Target Hierarchy: The increasing use of electric vehicles.

2. Guideline Hierarchy: Four relevant key factors— Cost, Traffic, Energy and Convenience.

3. Project Hierarchy: Car-share, Ride-share, Self-driving cars, Rapid battery-swap stations, Flying cars and Hyporloop.

6.2 Principle of AHP method

By compiling data from census reports, statistical assessments and available databases, we determine a relative weight of guideline hierarchy at the target hierarchy and of the project hierarchy at each guideline hierarchy (based on a scale of 1 to 9, $\frac{1}{2}$ to $\frac{1}{9}$) to determine a matrix $A(a_{ij})$ which indicates the degree of association between Target Hierarchy and Guideline Hierarchy and also matrices $B_i(b_{ij})$ indicate the degree of association between Guideline Hierarchy and Project Hierarchy.
These matrices are pairwise comparison matrices under conditions as followed:

$$a_{ij} > 0, a_{ij} = \frac{1}{a_{ji}}(i, j = 1, 2, ..., n)$$

After consistency check of each matrix, the total weight of each factor in the project hierarchy to the target hierarchy can be calculated, thereby we can determine the influence degree of each factor.

6.3 Implement AHP method

1. Structure chart and judgment matrices is outlined below.
We assume pairwise comparison matrices as followed:

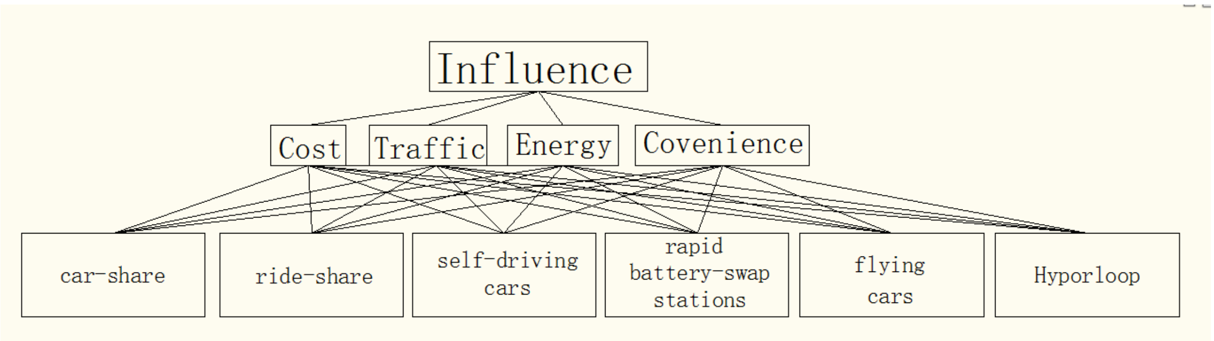


Figure 9: Structure Chart

$$A= \begin{Bmatrix} 1 & 4 & 6 & 2 \\ \frac{1}{4} & 1 & 3 & \frac{1}{3} \\ \frac{1}{6} & \frac{1}{3} & 1 & \frac{1}{5} \\ \frac{1}{2} & 3 & 5 & 1 \end{Bmatrix}$$

$$B_1 = \begin{Bmatrix} 1 & 1 & 3 & 6 & 9 & 9 \\ 1 & 1 & 3 & 5 & 8 & 8 \\ \frac{1}{3} & \frac{1}{3} & 1 & 2 & 4 & 4 \\ \frac{1}{6} & \frac{1}{5} & \frac{1}{2} & 1 & 4 & 1 \\ \frac{1}{9} & \frac{1}{8} & \frac{1}{4} & \frac{1}{4} & 1 & 1 \\ \frac{1}{9} & \frac{1}{8} & \frac{1}{4} & \frac{1}{4} & 1 & 1 \end{Bmatrix} B_2 = \begin{Bmatrix} 1 & \frac{1}{3} & 2 & 5 & \frac{1}{4} & \frac{1}{6} \\ 3 & 1 & 5 & 7 & 2 & 1 \\ \frac{1}{2} & \frac{1}{5} & 1 & 1 & \frac{1}{6} & \frac{1}{4} \\ \frac{1}{5} & \frac{1}{7} & 1 & 1 & \frac{1}{5} & \frac{1}{4} \\ 4 & \frac{1}{2} & 6 & 5 & 1 & 2 \\ 6 & 1 & 4 & 4 & \frac{1}{2} & 1 \end{Bmatrix}$$

$$B_3 = \begin{Bmatrix} 1 & 2 & 5 & 5 & 4 & \frac{1}{3} \\ \frac{1}{2} & 1 & 4 & 4 & 3 & \frac{1}{3} \\ \frac{1}{5} & \frac{1}{4} & 1 & 1 & 1 & \frac{1}{6} \\ \frac{1}{5} & \frac{1}{4} & 1 & 1 & 2 & \frac{1}{5} \\ \frac{1}{4} & \frac{1}{3} & 1 & \frac{1}{2} & 1 & \frac{1}{7} \\ 3 & 3 & 6 & 5 & 7 & 1 \end{Bmatrix} B_4 = \begin{Bmatrix} 1 & 1 & \frac{1}{6} & 2 & 3 & 1 \\ 1 & 1 & \frac{1}{5} & 2 & 1 & 2 \\ 6 & 5 & 1 & 6 & 3 & 5 \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{6} & 1 & 2 & 3 \\ \frac{1}{3} & 1 & \frac{1}{3} & \frac{1}{2} & 1 & 1 \\ 1 & \frac{1}{2} & \frac{1}{5} & \frac{1}{3} & 1 & 1 \end{Bmatrix}$$

Judgment matrices

2. Consistency check:

from the formula

$$\widehat{\lambda_m} = \frac{1}{n}\sum_{i=1}^{n}\frac{(A\widehat{\omega})i}{\widehat{\omega_i}}$$

we may get the result of

$$\lambda_m = \{6.3073, 6.5918, 6.2561, 6.5945\}$$

use coincidence indicator

$$CI = \frac{\lambda_m - n}{n-1}$$

we can figure out

$$CI = \{0.0615, 0.1184, 0.0512, 0.1189\}$$

For a given n, randomly structured a anti-matrix $\widetilde{A}$. a_{ij} is also randomly chosen from 1 to 9 and$\frac{1}{9}$ to $\frac{1}{2}$.We can conclude that $\widetilde{A}$ is not consistent. Using a large n to calculate the mean.

$$CR = \frac{\widetilde{\lambda_m} - n}{n-1}$$

comparing the given sheet

n	1	2	3	4	5	6	7	8	9	10	11
CR	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Table 1: Random variable CR

$$CI \leqslant 0.1CR$$

Through consistency test

3.Conclusion:

$$\omega_2(x) = \{0.2428, 0.2405, 0.2259, 0.1066, 0.0852, 0.0989\}'$$

Since every factor of project hierarchy may influence the target hierarchy from different direction, we assign these weight with a positive or a negative sign. The final answer as followed:

1. ride-share services, car-share services, self-driving cars, rapid battery-swap stations has a positive influence on the increase use of electric vehicles; flying cars, Hyperloop has a negative influence on the increase use of electric vehicles.

2. ride-share services, car-share services, self-driving cars and rapid battery-swap stations will affect the speed of electrification, while the technique of flying cars, Hyperloop may not be mature before the electrification, therefore will only affect the number of electric cars.

3. Ride-share services and car-share services have a dominant influence, while flying cars and Hyperloop only has little influence on the electrification.

7 Task 5

You honorable leaders:

These years, gas price starts to fluctuate sharply, it seems like there is a downward trend in prices. But as time goes by, the total amount of global gasoline storage decrease sharply, which must cause the increase of the price of gasoline. This is the inevitable trend of the market which cannot be against.Eventually, resources will run out one day. We foresee that in the coming decades without gas and coal, where will your country's fuel from?

If we want to control your energy future and avoid these gas price spikes down the line, then we need a sustained, all-of-the-above strategy that develops every available source of energy all over the world. Technology must go on so that it will allow us to use less oil in our cars, and save more fuels for our future.

Under this circumstances, the popularize of electric vehicles brooks no delay.

There are some key factors must given priority.

GDP as a key point to the growth of national economics is also essential to the distribution of charging stations and quantity of them. GDP, in another word, is a reference point of affluence degree. Areas with higher GDP also have a greater tendency to contact the frontiers of science so that these areas are pioneers to their transitions.

Population density is another key factor, but GDP also influence the population density, they have positive correlation,so that they approximately have the same influence tendency of migration from gasoline vehicles to electric vehicles.

Base on our model in task1 and task3, not only you will have a clear impression of the construction strategy but also you will know the development of this migration step by step. Our model already have took all the significant factors mentioned above. Just by using the statics of your country to fit our model, it will generate use result almost instantly.

Best Regards,

Team 88621

8 Strength and Weakness

8.1 Strength

- Using a state as a unit to calculate the complex networks reduce much more effort and time comparing to a direct calculation of the entire network.
- Our model can calculate the specific location of every charging station. You can get a whole view of the distribution of all the charging station and accurate location as well.
- The model is highly coherent with the actual population density, economic index, road density and other indicators, and distinguishes the boundary of urban area, rural areas and rural areas very well.
- The model has good scalability. When you can another type of data, what you only need to do is to modify the weight density function and penalty items, or add the relevant factors.

8.2 Weakness

- To simplify the network of road, we straighten the twists and turns of roads, so the distance between roads might have some deviation.
- Our model is highly relied on the detailed shapefiles with particular geographic information. Sometimes it is very difficult to obtain the data required.
- We merely considered the arterial roads. If we want to take every road into consideration, the network complexity will skyrocket hundreds of times and our computer would not be able to bear.
- We fixed the number of charging stations and the number of charging piles at each charging station. But if the number of charging stations and working hours can be flexibly arranged according to the location, the required number of charging stations could be further reduced.

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10 Appendix

Python Code The Python code of our simulation and algorithm.

```python
import shapefile
from math import *
cross_file = shapefile.Reader("/Users/mac/Desktop/US_Road/cross_US.shp")
cross = cross_file.shapes()
road_file = shapefile.Reader("/Users/mac/Desktop/US_Road/road_US.shp")
road = road_file.shapes()
EPS=1e-12
def dist(x,y):
    x=list(x)
    y=list(y)
    return sqrt((x[0]-y[0])**2+(x[1]-y[1])**2)
    line_road_file = []
line_road_file = shapefile.Writer(shapeType=3)
line_road_file.autoBalance = 1
line_road_file.field('FIRST_FLD')
line_road_file.field('SECOND_FLD', 'C', '40')
for i in road:
    st=[]
    en=[]
    st=i.points[0]
    en=i.points[-1]
    line_road_file.record("row","one")
    line_road_file.line(parts=[[ st,en ]])
    line_road_file.save("/Users/mac/Desktop/US_Road/line_road")
```

```
line_road = shapefile.Reader("/Users/mac/Desktop/US_Road/line_road.shp")
line_road = line_road.shapes()
inter_point_file = []
inter_point_file = shapefile.Writer(shapeType=3)
linter_point_file.autoBalance = 1
inter_point_file.field('FIRST_FLD')
inter_point_file.field('SECOND_FLD', 'C', '40')
inter_point=[]
for i in line_road:
    inter_point.append(tuple(i.points[0]))
    inter_point.append(tuple(i.points[1]))
    inter_point=list(set(all_point))
cross_unique_file = []
cross_unique_file = shapefile.Writer(shapefile.POINTM)
cross_unique_file.autoBalance = 1
cross_unique_file.field('State')
cross_unique = []
cross_record = cross_file.records()
for i in range(len(cross)):
    cross_unique.append((tuple(cross[i].points[0]),cross_record[i][0]))
    cross_unique = list(set(cross_unique))
for i in cross_unique:
    cross_unique_file.record(i[1])
    cross_unique_file.point(i[0][0],i[0][1])
    cross_unique_file.save("/Users/mac/Desktop/US_Road/cross_unique_road")
line_road_dist_file = shapefile.Writer(shapeType=3)
line_road_dist_file.field('Distance')
line_road_dist_file.field('State')
for i in line_road:
    st=[]
    en=[]
    st=i.points[0]
    en=i.points[-1]
    line_road_dist_file.record(geo_dist(st,en) , get_point_state(st) )

    line_road_dist_file.line(parts=[[ st,en ]])
    line_road_dist_file.save("/Users/mac/Desktop/US_Road/line_dist_road")
    state_point = []
for i in state_code:
    state_point.append([])
    for i in cross_unique:
    state_point[state_code.index(i[1])].append((i[0][0],i[0][1]))
    for i in range(len(state_code)):
    print(state_code[i],len(state_point[i]))
    for i in state_code:
    state_point_file = []
    state_point_file = shapefile.Writer(shapefile.POINTM)
    state_point_file.autoBalance = 1
    state_point_file.field('State')
    for j in cross_unique:
        if(j[1]==i):
            state_point_file.record(j[1])
            state_point_file.point(j[0][0],j[0][1])
    state_point_file.save("/Users/mac/Desktop/US_Road/%s_point"%i)
    line_dist_road_file = shapefile.Reader("/Users/mac/Desktop/US_Road/line_dist_road.shp")
line_dist_road_record = line_dist_road_file.records()
line_dist_road = line_dist_road_file.shapes()
for i in state_code:
    state_road_file = []
    state_road_file = shapefile.Writer(shapeType=3)
    state_road_file.autoBalance = 1
    state_road_file.field('Distance')
    state_road_file.field('State')
```

```
    for j in range(len(line_dist_road)):
        if(line_dist_road_record[j][1] == i):
            st=[]
            en=[]
            st=line_dist_road[j].points[0]
            en=line_dist_road[j].points[1]
            state_road_file.record( line_dist_road_record[j][0], line_dist_road_record[j][1])

            state_road_file.line(parts=[[ st,en ]])
    state_road_file.save("/Users/mac/Desktop/US_Road/%s_road"%i)
def in_point_set(x,y):
    for i in range(len(x)):
        if(geo_dist(x[i],y)<1e-3):
            return i
    return -1
    def get_n_point_line(st,en,n):
    ret = []
    for i in range(n):
        lam = i*1.0/n
        ret.append([st[0]+lam*(en[0]-st[0]),st[1]+lam*(en[1]-st[1])])
    return ret
    country_urban_station = 0
country_suburban_station = 0
country_rural_station = 0
country_urban_station_point = []
country_suburban_station_point = []
country_rural_station_point = []
for state_code_i in range(int(len(state_code)) ):
    state_name_i = state_code[state_code_i]
    print("********")
    print("state_name:",state_name_i)
    print("state_car_num:",state_car_num[state_code_i])
    print("state_station_num:",state_station_num[state_code_i])
    state_point_file = shapefile.Reader("/Users/mac/Desktop/US_Road/%s_point.shp"%state_name_i)
    state_point = state_point_file.shapes()
    state_road_file = shapefile.Reader("/Users/mac/Desktop/US_Road/%s_road.shp"%state_name_i)
    state_road = state_road_file.shapes()
    state_road_record = state_road_file.records()
    point_set = []
    dense_point = []
    edge_table = []
    print("point_data:",len(state_point))
    print("road_data:",len(state_road))
    for i in state_point:
        point_set.append(i.points[0])
    for i in point_set:
        edge_table.append([])
    for i in range(len(state_road)):
        st=[]
        en=[]
        st=state_road[i].points[0]
        en=state_road[i].points[1]
        st=list(st)
        en=list(en)
        if(in_point_set(point_set,st) != -1):
            edge_table[in_point_set(point_set,st)].append([st,en,float(state_road_record[i][0])])
        if(in_point_set(point_set,en) != -1):
            edge_table[in_point_set(point_set,en)].append([st,en,float(state_road_record[i][0])])
    print("Edge_table:",len(edge_table))

    for i in edge_table:
        sum_w = 0
        for j in i:
```

```
            sum_w += j[2]
        if(sum_w!=0):
            dense_point.append(1.0/sum_w )
        else:
            dense_point.append(0)
    Kstate = 0
    sum_dense_w = 0
    for i in range(len(state_road)):
        st=[]
        en=[]
        st=state_road[i].points[0]
        en=state_road[i].points[1]
        st=list(st)
        en=list(en)
        equal_dense = 0
        if(in_point_set(point_set,st) != -1):
            equal_dense += dense_point[in_point_set(point_set,st)]
        if(in_point_set(point_set,en) != -1):
            equal_dense += dense_point[in_point_set(point_set,en)]
        equal_dense /= 2
        wij = float(state_road_record[i][0])
        denseij = equal_dense
        sum_dense_w += wij * denseij
    Kstate = state_car_num[state_code_i]/sum_dense_w
    print("sum_dense_w:",sum_dense_w)
    print("Kstate:",Kstate)
    print("dense_point_set:",len(dense_point_set))
    state_dense_point_file = []
    state_dense_point_file = shapefile.Writer(shapefile.POINTM)
    state_dense_point_file.field('State')
    state_dense_point_file.field('Car_Number')
    for i in dense_point_set:
        state_dense_point_file.record(state_name_i, i[1] )
        state_dense_point_file.point(i[0][0],i[0][1])
    state_dense_point_file.save("/Users/mac/Desktop/US_Road/%s_dense_point"%state_name_i)
    state_station_point_file = []
    state_station_point_file = shapefile.Writer(shapefile.POINTM)
    state_station_point_file.field('State')
    state_station_point_file.field('Station_Number')
    Kless = int(len(dense_point_set)/state_station_num[state_code_i])
    for i in range(len(dense_point_set)):
        if(i%Kless == 0):
            state_station_point_file.record(state_name_i,dense_point_set[i][1]/
                                            state_station_num[state_code_i])
            state_station_point_file.point(dense_point_set[i][0][0],dense_point_set[i][0][1])
    state_station_point_file.save("/Users/mac/Desktop/US_Road/%s_station_point"%state_name_i)
    state_urban_station = 0
    state_suburban_station = 0
    state_rural_station = 0
    Avg_road_dense = 0
    Avg_road_dense /= len(state_road)
    print("Avg road dense:",Avg_road_dense)
    for i in range(len(state_road)):
        st=[]
        en=[]
        st=state_road[i].points[0]
        en=state_road[i].points[1]
        st=list(st)
        en=list(en)
        equal_dense = 0
        if(in_point_set(point_set,st) != -1):
            equal_dense += dense_point[in_point_set(point_set,st)]
        if(in_point_set(point_set,en) != -1):
```

```
            equal_dense += dense_point[in_point_set(point_set,en)]
        equal_dense /= 2
        wij = float(state_road_record[i][0])
        denseij = equal_dense
        road_point_num = int(Kstate * denseij * wij)
        if(road_point_num==0):
            continue
        dense_now_road = road_point_num/ Kless / float(state_road_record[i][0])

        relative_dense = dense_now_road/Avg_road_dense
        n_point = []
        n_point = get_n_point_line(st,en,int(road_point_num/Kless))
        if( relative_dense> 0.478 ) :
            state_urban_station += road_point_num / Kless
            country_urban_station_point.append(n_point)
        if( relative_dense >= 0.250 and relative_dense <= 0.478):
            state_suburban_station += road_point_num / Kless
            country_suburban_station_point.append(n_point)
        if( relative_dense < 0.250):
            state_rural_station += road_point_num / Kless
            country_rural_station_point.append(n_point)
print("Country_urban_station Ration:",country_urban_station/sum(state_station_num))
print("Country_suburban_station Ration:",country_suburban_station/sum(state_station_num))
print("Country_rural_station Ration:",country_rural_station/sum(state_station_num))
urban_set=[]
suburban_set=[]
rural_set=[]
for i in country_urban_station_point:
    if(i!=[]):
        urban_set.append(i)
        for i in country_suburban_station_point:
    if(i!=[]):
        suburban_set.append(i)
        for i in country_rural_station_point:
    if(i!=[]):
        rural_set.append(i)
        urban_point=[]
suburban_point=[]
rural_point=[]
for i in urban_set:
    for j in i:
        urban_point.append(j)
        for i in suburban_set:
    for j in i:
        suburban_point.append(j)
        for i in rural_set:
    for j in i:
        rural_point.append(j)
        urban_file = []
    urban_file = shapefile.Writer(shapefile.POINTM)
    urban_file.field('Area')
    for i in urban_point:
        urban_file.record("Urban")
        urban_file.point(i[0],i[1])
        urban_file.save("/Users/mac/Desktop/US_Road/Urban_station_point")
    suburban_file = []
    suburban_file = shapefile.Writer(shapefile.POINTM)
    suburban_file.field('Area')
    for i in suburban_point:
        suburban_file.record("Suburban")
        suburban_file.point(i[0],i[1])
        suburban_file.save("/Users/mac/Desktop/US_Road/Suburban_station_point")
    rural_file = []
```

```
rural_file = shapefile.Writer(shapefile.POINTM)
rural_file.field('Area')
for i in rural_point:
    rural_file.record("Rural")
    rural_file.point(i[0],i[1])
    rural_file.save("/Users/mac/Desktop/US_Road/Rural_station_point")
```