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2018
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Summary Sheet

Summary

The aim of this paper is to explore the effect of the proportion of electric vehicles and the rural-urban distribution. We first determine the essential factors to the distribution of charging stations, then we create corresponding functions and, finally, optimize the fitting functions.

The US can switch to all-electric in the near future owing to the continuing increase of charging stations and the enhancement of power supply. Since the demand of electric vehicles and the macro index are the two most vital factors affecting the amount of regional charging stations, we then borrow the idea of BASS model and the utility function of investments to simulate the vehicle distribution, and use the cooperative algorithm to determine the comparatively heaviest weights of all variables. Due to the nonlinear relation between factors, the total number of charging stations (19.3 thousand), the ratio of urban, suburban, and rural distribution (58.03%, 22.12%, 19.85%) were calculated by RBF neural network algorithm.

Though regional indicators are different, weights of factors are constant even in varied areas. Hence, our plan could be applied to other countries. Based on the LSTM algorithm, we obtain the data of prediction of the amount of charging stations by regional indicators in South Korea. After uploading the data into the Power Map, the simulation of network of distribution of the charging station has been realized. To lower the construction cost and raise the traffic flow, we improved our model, especially in using LOF algorithm (Local Outlier Factor) to find the progressive solution. Then optimal solutions of the previous step showed how to accelerate the development of both the electric vehicles and the charging stations simultaneously: We do trials in the city first; in the next stage, the ratio of the number of rural and urban charging stations is 3/7. After the optimization of this model, considering the fact that South Korea is more densely distributed than the US, we intentionally select the Bernstein basis function to design an algorithm, of which gave us the timeline for South Korea to reach all-electric. Using the CAPM model (borrowed from finance), then we get timelines of other countries. The key factors coming from the above analysis are electric vehicle demand, urban-suburban proportion, average regional income, and population.

In conclusion, this method, relying on the subdivision region index, can predict and analyze the distribution of the charging stations in different countries. Though the regional indicators are different, the weights of factors are constant even in varied areas. The key factor is electric vehicle demand, then comes the urban-suburban proportion, the average income, the population and the environmental factors.

Keywords: Utility Function; Bernstein Basic Function; CAPM ;Bass Model

Contents

Optimal Model Analysis of Charging Stations

1 Restatement of The Problem

Electric vehicles would be a future trend of transportation.In this paper, we need to propose a growth plan of charging station which will offer an insight for Tesla, Inc. The proposed solution need to be pointed out some key factors which will significantly impact the direction of our plan. Then we need to create a classification system that could apply our growth plan model to other countries, and to state the impact of some other transportation options to our plan.

2 Assumptions

- The greatest distances of Tesla Models, 300 miles, are constant throughout any given year, no matter what kind of models of Tesla that we would like to choose.
- Each Tesla owner fully understood entire circumstances, such as locations, road networks, road conditions and so on, of each charging station, and he or she would always choose the shortest path to reach the destination.
- Because the long-distance travel midway charging can be solved by fast charging. When we choose chargers, we analyze short trips.
- Power outage, damages and other particular conditions of charging stations are excluded.The number of chargers of every type of charging stations is twenty.
- No large-scale migration of the population would happen in any given region, such as rural, suburban and urban areas which will have a separately constant distribution of the population.
- Each country has been divided into a limited number of regions, in which of each indicator had significant differences.
- No supply constraints. Every person is a Rational Economic Man and can buy electric vehicles based on their own desire.

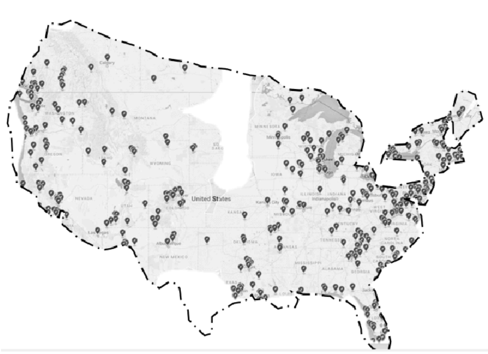
3 How to Distribute EV Stations in America

our research shows that some indicators, such as Total Amount of Tesla Models, Macroeconomic Index (AMI), are key factors to the increase of charging stations. We use cooperative expression algorithm, selecting several most important variables of macroeconomic index; We combine Utility Function and BASS model to describe the number of electric vehicles in different regions. Taking into account the non-linear relationship between the various relationships we use RBF neural network to predict the distribution of charging stations in urban, suburban and rural areas.

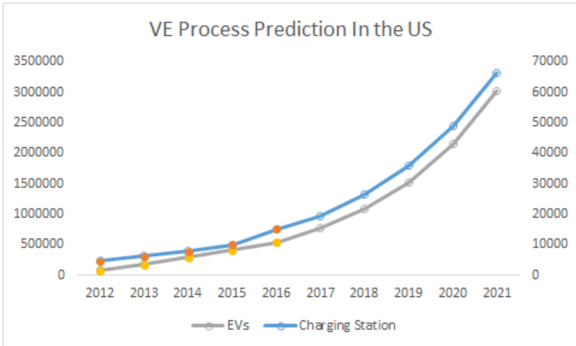
3.1 Achieve Vehicle Fully Electric Or Not?

In this paper, the definition of all-electric is as follows: Tesla Models, with the help of the network of existing charging stations and supercharging stations, are able to reach every corner of the U.S territory.

Therefore, we draw circles, of which the radius is Tesla Model's single maximum mileage, 300 miles, each center is the location of Tesla charging stations in the US in 2017, in order to represent the maximum distances that every possible Tesla Model could cover. All the previous steps are powered by MATLAB software. (View analysis of Alaska and Hawaii in appendix)



(a) fig 1



(b) fig 2

In fig 1, the dotted line approximately represents the main extent of the domain territory of the US; the plotted points represent Tesla's charging and supercharging stations. The gray part represents the maximum range that all the Tesla Models could cover, and the white part represent remaining, uncovered territory. In conclusion, All the existed Tesla Models are not able to support all-electric throughout the US.

In fig 2,we can see the increasing trend of charging stations in the US and we take the increasing capacity of power supply for electric vehicles into consideration, so we believe all-electric is possible in the near future.

The macro index in different regions also affects the number of charging stations. In order to better characterize the number of EVs in different regions, we introduce the utility function and BASS model. We use the cooperative expression algorithm to calculate the weight of the variables which have great influence on the charging station in the macro-indicators.

3.2 Predict EV Stations Distribution in The US

Taking into account the relationship between supply and demand, the number of EVs is a major factor affecting the growth of the number of charging stations.

3.2.1 Bass Model Predicts The Number of Electric Cars

Consider the assumptions of the **Bass model**, using Bass to predict the number of cars in the future, getting an indicator of charging stations amount from the supply-demand relationship.

$$\frac{f(t)}{1-F(t)} = p + \frac{q}{m}N(t) \tag{3.1}$$

By using the functionwe can get the equation

$$f(t) = \frac{dF(t)}{dt} = p + (q-p)N(t) - \frac{q}{m}[N(t)]^2 \tag{3.2}$$

We solve the Differential equation $F(0) = 0$,and get the basic form of the Bass model that applies to this problem:

$$f(t) = \frac{(p+q)^2}{p} \times \frac{e^{-(p+q)t}}{(1+\frac{q}{p}e^{-(p+q)t})^2} \tag{3.3}$$

p : represents the external influence coefficient

q : represents the internal influence coefficient

$f(t)$: the probability density function of the number of Tesla Model buyers at time t

$F(t) = \int_0^t f(t)dt$: the cumulative proportion of Tesla Model buyers by t

$N(t) = \int_0^t n(t) = m\int_0^t f(t)dt$: the number of total electric cars at t

3.2.2 The Utility Function Describe The Distribution

The utility function is usually a function of the quantitative relationship between the utility obtained by the consumer in consumption and the product combination consumed.

According to people in different regions to measure the ability to buy the car is different, we can combine the utility function to build different regions of people's purchasing power distribution.We use the usual utility function as follow

$$U(W) = E(a_i) - \frac{1}{2}A\sigma^2 \tag{3.4}$$

In order to describe the different need in different place. We decide to use the function

$$U(X) = \frac{1-y}{\alpha y}(\frac{\alpha x}{1-y} + \beta)^\gamma \tag{3.5}$$

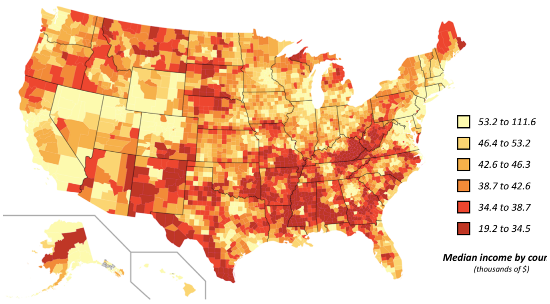
According to the definition of risk aversion degree from the original utility function,we use

$$\gamma(x) = \frac{1}{1-y}x + \frac{\alpha}{\beta} \tag{3.6}$$

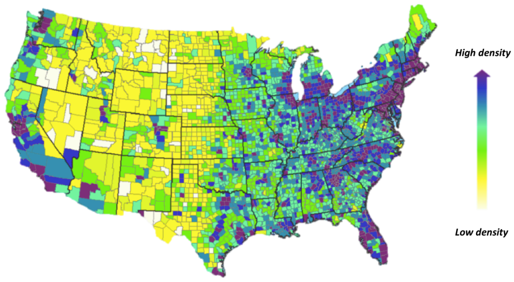
to describe the purchasing power of people. And the bearing capacity coefficient of people in different regions to VE is.

$$A(X) = (\frac{1}{1-y} + \frac{\beta}{\alpha})^{-1} \tag{3.7}$$

Is the meaning of expectation utility function, when people live in some areas face the option of whether to buy a electric car,it can help us to analyze their choice whether it is reasonable and feasible. we need to get a conclusion



(c) 1p2



(d) 1p3

3.3 Coherently Macro Key-factors

we preliminary estimate the similarity between the distribution of map heat distribution and the number distribution of Tesla charging stations may be related to the average regional income and the population density of the area. Using the Grayscale Extraction Function in Matlab to extract Heat Distribution Map of Urban, Rural and Suburb Areas in the United States We obtain urban density and rural density data in various regions of the United States. We use Python reptiles to fetch the electric vehicle inventory of 25 the U.S. states in the Plug In Car website Charge Demand) Data and Super Charger Charging Station with Normal Charging Station Data in PlugShare Website. Getting the following picture.

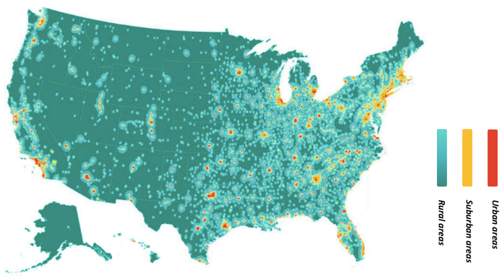


Table 1: Data of Five state provided by software (e.g.)

	Population	E-Car Num	Income	City Density	Rural Density
Alabama	4,830,620	1574	43511	0.08	0.07
Arizona	6,641,928	11396	49928	0.13	0.15
Arkansas	2,958,208	642	41264	0.32	0.37
California	38,421,464	27312	61489	0.85	0.23
Florida	19,645,772	23376	47212	0.54	0.78

We use the collaborative expression algorithm to calculate the key factors to evaluate the distribution between different areas.

it can be reconstructed by a sparse linear combination of an overcomplete normal base $D \in \mathbb{R}^{m \times n}$ as follows:

$$s* = arg \arg\min_{s} ||y - Ds||_2^2 + \lambda ||s||_1 \tag{3.8}$$

s is the representation coefficients.

y is the vector that we want to predict,which contains the number of rural cars and the number of city cars.

D is the Dimension reduction matrix,we use the matrix to reduce the coefficient vector. To quantify the normalness, the standard sparse reconstruction cost (SRC) with l_1 regularization is described as follows:

$$SRC = ||y - Ds^*||_2^2 + \lambda||s^*||_1 \tag{3.9}$$

So the SRC can be exploited as a measurement to identify anomalies.

We define the following objective function:

$$||y_1 - D_1 S||_F^2 + ||y_2 - D_2 S||_F^2 + \lambda||S^*||_1 \tag{3.10}$$

Considering some condition, we need to solve this problem:

$$\min_{D_1, D_2, S, P} ||y_1 - D_1 S||_F^2 + ||y_2 - D_2 S||_F^2 \tag{3.11}$$

$$s.t. ||d_1||_2^2 \leq |1, ||d_2||_2^2 \leq |1 \tag{3.12}$$

$$i = 1, 2, ..., T \tag{3.13}$$

λ is regularization parameters.

By collaborative expression algorithm, we acquired the weight coefficient of supercharging stations and ordinary charging stations, with which in respect to average population, EVs, revenues, intensities and geographical conditions in each region.

Comparatively heaviest Weights (we assumed the value should be larger than 0.6) of the factors are listed as follows:

Table 2: How to design in the U.S.

	Population	VE Num	Income	City Density	Rural Density
Super Charger	0.724	0.7527	0.7246	0.7526	0.744
Normal Charger	0.66	0.7506	0.6544	0.672	0.6271

These three variables are extent of density, population distribution, distribution of electric vehicles. From the weight coefficient table, we know the most critical factor is VE quantity, possibly due to charging demand.

Because of the variances in geographic, traffic, populated and economic situation in different areas, we allocate charging stations separately in urban, suburban and rural areas according to the density distribution of rural, urban and suburban regions. Due to nonlinear relationship within these factors, we use the RBF neural network to get the distribution of the two types of charging stations in rural, urban and suburban regions in the US. Results were shown in the Table.

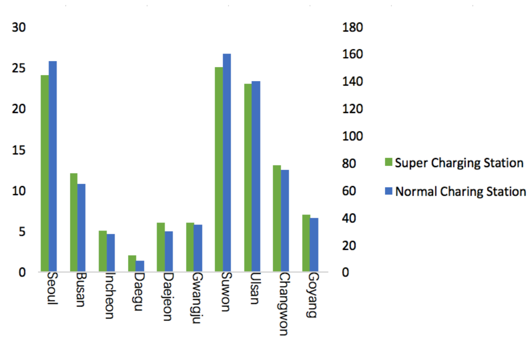
4 How to Design Charging Stations Net in South Korea?

This question considers how to set up a charging station when all of the cars are converted to electric cars. In Question 1, we use the obtained data on EV amount in the

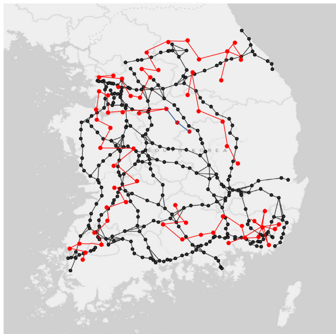
Table 3: How to design in the South Korea

	Rural	Suburb	City	Total
S-Charger	129	143	316	588
N-Charger	547	616	1928	3091
S-Charger(%)	21.98%	24.32%	53.70%	100.00%
N-Charger(%)	17.71%	19.92%	62.37%	100.00%

United States, suburbs and rural areas, the regional density, population density, per capita income density and charging stations Data as a training set, these corresponding data of Korean cities, suburbs, rural areas (10 areas) as a test set. Taking into account the nonlinear factors between the data, we use the RBF neural network algorithm to predict the number of super charging stations and the number of ordinary charging stations in these areas in South Korea.



(e) Blue:S-Charges Red:Charges



(f) Red:S-Charges Black:Charges

Using the function of 3D Map in Power Map, we import the 2D map of South Korea and get the distribution map of charging station amount in South Korea based on the data, then design the simulated map of charging network according to the features of the landscape.

5 How to Build Chargers From Zero?

From scratch to establish a full network system, we need to consider both the driving distance of electric vehicles and charge to ensure maximum traffic flow, but also need to consider the charging station construction costs and site selection conditions. Therefore, based on the previous model, we add these metrics to optimize and construct a multi-objective optimization problem.

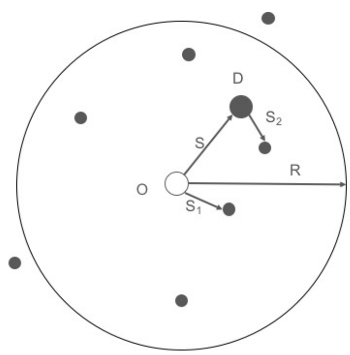
5.1 Meet The Maximum Traffic Flow

From scratch to establish a full network system, we need to consider both the driving distance of electric vehicles and charge to ensure maximum traffic flow

5.1.1 Charging car driving distance

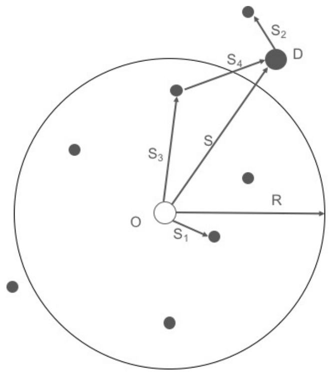
Taking into account the actual travel situation and charging station type is different, we think the electric car owners had three possibly different options based on the remaining power and the greatest mileages the cars could cover under particular circumstances.

- Select a normal charger to reach the destination directly



0refers to the starting point,D is the destination, and the other points represent the charging station. $R$is the cruising range of remaining capacity of the electric car. Starting from $0, R$ is a radius to draw a circle, the charging station in the circle is the charging station to which the electric vehicle can go, and the charging station outside the circle is the charging station that can not be reached. S is the distance from the initial point to the destination, S_i is the distance to the nearest charging station to the initial point, and S_2 is the distance from the nearest charging station to S_2. In this case, $R >> S + S_2$ and $R >> S_i$, electric vehicles will go directly to the destination.

- Choose Fast Charge To Reach Your Destination



In Figure 2, S_3 represents the distance from the initial point to the charging station, and S_4 represents the distance from the charging station to the destination. In this case, $R << S + S_2$, the remaining capacity of the EV can not guarantee that the EV can reach the destination ($R << S$) or can reach but can not reach any of the charging stations ($R << S+S_2$) after arrival. The electric car should go to a charging station to replace the battery, and then travel to the destination, the total distance of driving $S_3 + S_4$.

- The battery is not enough to reach the charging station or destination

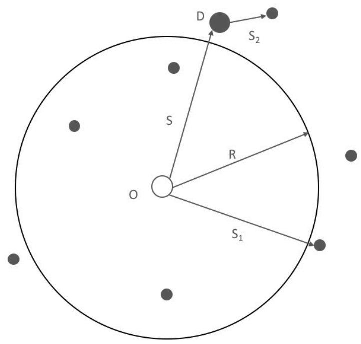


Figure 3 illustrates the third scenario, where $R < S_1$ and $R < S$, the electric car is not enough to travel to the destination and to any charging station.

We assumed that there are n charging stations, represented by $c_1...c_r$ represents the full battery life range of electric vehicles. From the front chapter section, we know:

$$R \geq S + S_2 \tag{5.1}$$

When full battery life range could enable the electric vehicle to leave from the closest charging station near to the destination and reach this location again, we represent such situation as able to arrive. If full battery life range could enable the electric vehicle to reach any destination stated above, and every destination could satisfy this circumstance $S = S2$, then

$$R \geq 2S_2 \tag{5.2}$$

We could use Monte Carlo algorithm to calculate r. The algorithm is as followings:

- We can randomly have n objection,used$d_1, ..., d_m$ to represent.x_{d_i}can represent $X - axisy_{d_i}$can represent $Y - axis$,x_{c_i}can represent $X - axis$ of charging stations y_{c_i}can represent $Y - axis$of charging stations.

- Try to calculate l_k to represent the nearest charging station.

$$l_k = min\sqrt[2]{(x_{d_i} - x_{c_i})^2 + (y_{d_i} - y_{c_i})^2} \tag{5.3}$$

$$S_2 = max\{l_1, ..., l_m\} \tag{5.4}$$

- $R_2 \geq 2S_2$,calculate the minimum

Traffic density and charging demand are closely related to the operation of electric vehicles by the constraints. Charging demand refers to a certain number of electric vehicles in a specific time and place of demand for charging. In general, the greater density of EVs in the region suggests that the greater the number of EVs operating in a region, the greater the need for charging stations. Therefore, the control of the number of charging station outlets should be proportional to the traffic density of EVs in all regions, so the distribution of warranty and charging needs should be as consistent as possible.

5.2 Meet The Minimum Cost Of Building Site

We need to consider the charging station construction costs and site selection conditions. Therefore, based on the previous model

5.2.1 Investment Cost

Initial investment cost

The initial investment cost of new station j G_{b1j} includes the cost of purchasing equipment E_j and purchase cost $A_j.E_j$ including AC charging piles, points box charger and other equipment purchase costs. A_j is determined by the location of the battery charging station.

$$G_{b1j} = \frac{r_0(1+r_0)^m}{(1+r_0)^m - 1}(A_j + E_j) \tag{5.5}$$

The new route cost G_{b3j} refers to the line investment of the new battery charging station j to the nearest substation, which is not only related to the location of the battery charging station but also related to the power load level of the planned area. G_{b3j} is calculated as

$$G_{b3j} = \frac{r_0(1+r_0)^m}{(1+r_0)^m - 1}\lambda_1 l_j \tag{5.6}$$

r_0 is investment recovery rate, indicate the battery charging station operating life.

q : represents the internal influence coefficient

$f(t)$: the probability density function of the number of Tesla Model buyers at time t

$F(t) = \int_0^t f(t)dt$: the cumulative proportion of Tesla Model buyers by t

$N(t) = \int_0^t n(t) = m\int_0^t f(t)dt$: the number of total electric cars at t

Driving cost from electricity

Driving cost of electricity Gb3j is calculated as

$$G_{cj} = \alpha\beta k\omega \sum_{i=1}^{n} D_{ij} \tag{5.7}$$

α denotes the road tortuous coefficient road

β denotes the road flow coefficient

k denotes the average times each vehicle charged

w denotes distance to the price of the conversion factor

D_{ij} denotes i-th electric vehicle to the battery charging station$j$ linear distance

I_j denotes the collection of EVs which charge at charging station$j$

5.3 Constraints Analysis

In order to make the grid power quality meet the needs of users, the battery charging station planning model need to add the following constraints:

Chargers number constraints

$$n_j T_j \leq N_j \tag{5.8}$$

$$r_j \leq e_{soc} L_N \tag{5.9}$$

$$r_j \leq e_{soc} L_N \tag{5.10}$$

n_j is battery number of station$j$

T_j is average daily working hours of battery charging station j

N_j is battery amount of charging station j.

r_j is battery radius of battery charging station j

e_{soc} is the average state of charge of electric vehicles

L_N is single-rated electric vehicle mileage.

5.4 Outlier Detection Algorithm Optimization

Find out the behavior which is different from the expected object of a testing process. Consider the dense population of charging stations in urban areas, charging stations amount in rural areas is sparser. We cluster the number of charging stations in urban areas, because the number of charging stations in rural areas is relatively small and relatively dispersed, charging stations in rural areas can be considered as abnormal points and retrieved, which is significantly different from that of urban areas Data object. In order to ensure the accuracy of the division, we run the program for 10 times, and get averaged result.

It is advisable to extend the charging station and the car at the same time because it costs a lot to maintain and repair the charging station. It is best to ensure that the

Table 4: Result

	Rural	City
S-Charger	17.87%	82.13%
N-Charger	37.63%	62.37%

number of surrounding users can match the number of charging stations (where the car has a local charge and the charging station will not be idle).

We recommend to set up a charging station and purchasing a car at the same time. However, considering the high degree of urban density, charging station should first be set up in an urban densely populated city. Rural areas and cities should set up charge stations according to the above ratio.

6 Basis Function Fitting to Forecast

On the basis of the above-mentioned function, Monte Carlo simulates the time and the number of charging stations needed to establish a charging station when the ratio of electric vehicles is from 10% -30% -50% to 100%. Each index is more densely distributed, and the time required for the charging station to change with the ratio of electric vehicles is predicted by Bernstein function and CAPM model, used as the construction plan of the charging station, to realize the full electrification of Korean cars. The key factor in achieving full electrification is electric vehicles amount.

Compared to the United States, South Korea is relatively small size of the land, with more developed economy, a larger population and more densely distribution of various indicators. And compared with than the Lagrange , the Bernstein function can better satisfy the dense condition and smoothness.

Bernstein basis function fitting modeling and prediction

Let m-order Bernstein polynomials of time series $X_i(i = 1...n)$ be the basis function,

$$B_{j,m}(t) = C_m^j(1 - t)^{m-j}t^j \tag{6.1}$$

the construction curve is:

$$X(t) = \sum_{j=0}^{m} b_j B_{j,m}(t), 0 \leq 1; m \leq n \tag{6.2}$$

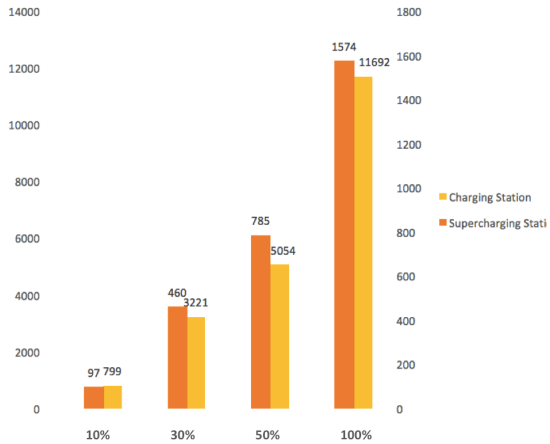
Fitting a few points of this time-series, the model was established from Bernstein's basis function

$$X(t) = \sum_{j=0}^{m} b_j B_{j,m}(t) + \varepsilon(t) \tag{6.3}$$

$b_j(j = 0, 1, ...n)$is the control point to be determined

$B_j,m(t)$ is a Bernstein basis function then predicts the future development of social phenomena using the properties of the constructed curve

Taking the different numbers of electric vehicles in Korea and other influencing factors as the training set, we select the appropriate Bernstein function to predict the dense set.



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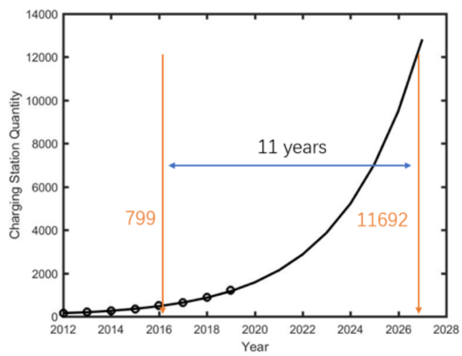


(h) Red:S-Charges Black:Charges

Determine how much time is needed to make Korean cars fully electric step by step. The key factor in achieving full electrification is electric vehicles amount.

Table 5: Full Electric Corresponding Time

	10%VE	30%VE	50%VE	100%VE
Year	2022	2025	2027	2029

7 Generally Applicable Method for Different Country

Our network design of charging station based on the region (states, cities, rather than the entire country) which can be viewed as a unit. We select each separate region for analysis. The number of independent variable, electric vehicles, urban density, suburban density, population density, and per capita income are different, but the correlation coefficient is constant. We design the charging network based on the region, not the country. So this method of designing the network of charging stations by small areas is universally applicable for each country.

- Choose a specific region in one country. (State, City, or other regions)
- Based on the electric vehicles, regional urban density, suburban density, population and regional average income in all regions of the country could be viewed as independent variables. Taking the number of super-charging stations of and charging stations the US as the training set, we calculate the number of charging stations in each region, and then design the charging network in every region.
- From the correlation matrix above, one primarily key factor is regional EV amount which will influence the amount of charging stations in the region. In addition,

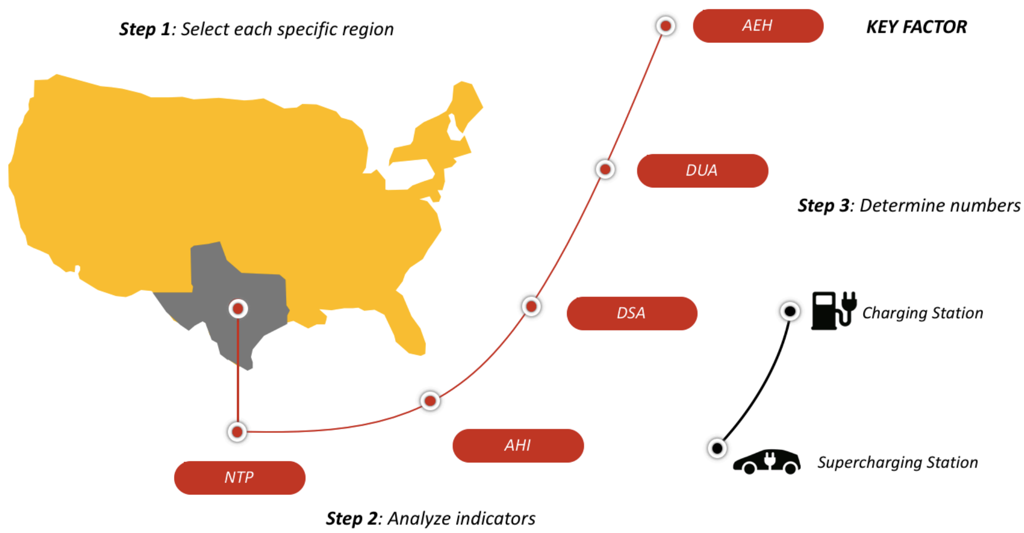
the intensity of urban areas and suburban areas are also important factors affecting the number of charging stations. The weight is as high as 0.71 and 0.68. Also, the regional population and the average income, although are not key factors, the weight is as high as 0.6 and should also be taken into consideration, whereas the geographical characteristics of the area based on the correlation index are not the key factors affecting the number of charging stations.

Table 6: Factors influence the model

	AEA	DUA	DSA	AHI	NTP
S-Charger	0.7527	0.7526	0.744	0.7246	0.724
N-Charger	0.7506	0.672	0.6271	0.6544	0.66

- **AEA** :the Amount of Electric Automotives.
- **DUA** :the Density of Ubran Areas
- **DSA** :the Density of Sububran Areas
- **AHI** : Average Household Income
- **NTP**: the Number of Total Population

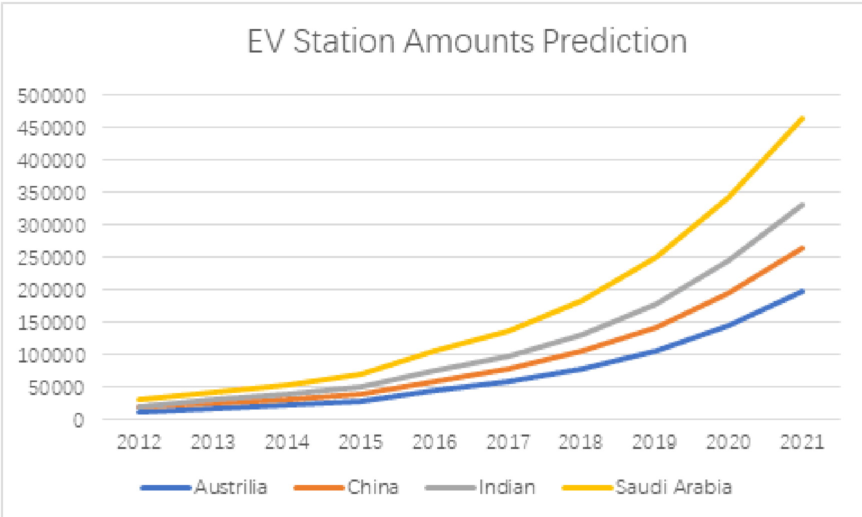
National charging network design conception:



We believe that building a classification system in order to help a nation to determine the general growth model of charging stations is feasible. Every country can follow the steps of South Korea, viewing the following indicators: the urban density, the suburban density, the population density, the per capita income, and the number of charging stations, as a training set.

We view the VE amount in each area, the regional urban density, the suburban density, the population density and the per capita income density as the test set. According to the neural network algorithm, the number of charging stations indicates the maximum power supply capacity of the VEs, using the LSTM algorithm to predict the number of charging station over time. Then we gain the corresponding year of which the ratio of electric vehicles to gas vehicles is $10\%, 30\%, 50\%, 100\%$ respectively. This insight could assist other authorities in different nations to determine the timeline of enacting policies regarding to the application of electric vehicles.

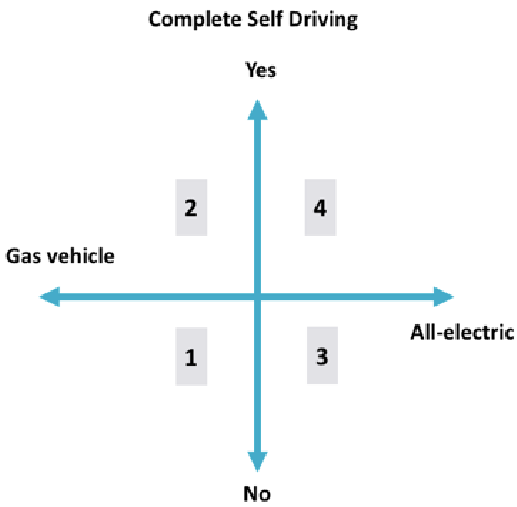
According to this method, we can draw the conclusions of the forecast results of charging stations in 4 different countries:



8 The Influence of New Technology to EV

The continuing advancement of technology, the emergence of self-driving, car-share and ride share services, will absolutely have an impact on our options of transportation mode, which will change the development of electric vehicles, let alone our plan. we select one technology, self-driving, which is in the most vigorous debate among countless people, to determine possible influence it might have to our plan.

Impact Analysis: Self-driving technology also has an impact on the growth of electric vehicles. There are four possibly varied patterns due to different combinations of self-driving and electric vehicles.



- Technologies of electric vehicles and self-driving automobiles are both premature; technology of self-driving will not have a significant impact on the volume of electric vehicles.
- Self-driving technology is gaining ground when there is no rapid growth in the initial stage of charging vehicles. Therefore, self-driving technology will significantly dampen the growth of penetration of electric vehicles.
- Self-driving technology is still premature, but policy environment and consumption conception already embraced electric automotives. Therefore, self-driving technology will not affect the penetration of electric vehicles.
- Self-driving cars have become mainstream vehicles; the market has been dominated by both providers of electric automobiles and self-driving vehicles; self-driving technology has promoted the increase of penetration of electric vehicles.

Analysis other technologies in the same way

Table 7: Residual

	Car-Share	Ride-Share	Rapid Battery	Flying Cars	Hyperloop
EV undeveloped	↑	↓	↑	↑	↑
EV developed	↑	×	↑	↑	↑

In this table, EV underdeveloped means the EV technology is premature. EV developed means the EV technology is quite mature. These 3 different signals indicate how this new technology will influence the increasing amount of the EV.

9 Letter

Dear sir or madam:

Greetings! It's our pleasure to have this opportunity to meet you in the energy summit! Recently our research focuses on the possible path of a complete switch to all-electric in certain regions. We sincerely hope our research results could offer you some insights to identify important factors of development of electric transportation in your great commonwealth.

First and foremost, in an extremely small area, the probability of intention of charging of an electric vehicles owner tended toward a constant value. Measured by the similarities within typical indicators, certain areas could be classified and grouped into a new region, in which we are able to calculate the total amount number of charging stations. Therefore, by adding all these numbers, we could easily put forward a precise number for every new region.

Questions may occur in your mind; how did we select typical indicators? Could these indicators depict the reality? Proposed and testified by our research, adequacy of household electric vehicles and macroeconomic environment are two main factors that will shape the basic demands for charging stations. Then we further assumed and proved that household income per capita, average population, per capita GDP and some other elements could represent macroeconomic indicators. Hence, your nation could follow the similar steps to determine the total number of charging stations.

In the statement above, any nation, if had the accurate number of these typical indicators, could measure the total number of charging stations based on a freezing time dimension. But, the thing is, the wheel of the god of time is moving forward all the time. We need to consider a new dimension, time.

By adding time to each variable in our models, the growing trend of charging stations could be obtained. Our research applied our detailed model into North Korea, predicting that in 2029, Korea could enter into a stage of all-electric. Similarly, your nation could determine the timeline of all-electric. Afterwards, authorities can set a gas vehicle-ban date.

Last but not the least, we suggest there should be a flexibility in enacting policies. For instance, set a buffer zone to establish mental preparation of citizens for embracing electric automotives; set a growing zone to ban typical automobiles from driving on the road, etc. Progressive policies could somewhat accelerate the pace of the promotion of electric vehicles.

Thank you for taking time to read our letter. We look very much forward to offering a considerate plan for your nation! If you have any problem, do not hesitate to contact us.

Sincerely, ICM Team 83665.

10 Model Verification

10.1 Sensibility Analysis

We use the fitting function to optimize the stochastic differential equation, and the optimization results as initial value optimization based on Bornstein basic function's result of the next step. Finally we get the optimization results. First, we take all VE stations as a whole and optimize the objective function of the whole country. In iteration, the optimal solution descending speed is as follows (odd cuckoo algorithm, even number is the inexact linear search algorithm), furthermore, we optimize the model, the rate of decline is as follows (space limit, we only show one of the results):

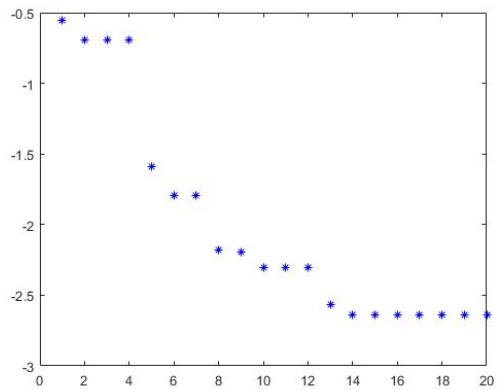


Table 8: Final result

	Normal	Function value	Special lane	Function value
Ignore cost	0.6723	0.8356	0.9296	0.9653
Consider cost	0.6541	0.7542	0.9026	0.7258

This paper mainly discusses the mapping relationship between the VE stations and the multiple factors. We have discussed the sensitivity of this variable in detail, and then we do sensitivity analysis to the macro factors and VE amounts. It can be seen that with

Table 9: Optimum proportion

	3-3	3-4	4-4	average
70000	0.510104	0.581644	0.678539	0.590096
80000	0.624679	0.718282	0.745100	0.696020
90000	0.680063	0.55139	0.615434	0.615626
100000	0.615452	0.528745	0.541388	0.561862
110000	0.895057	0.647490	0.903681	0.81540
120000	0.951235	0.831297	0.815681	0.866070
average	0.742268	0.692786	0.724434	0.570558

the increase of macro factor rate, the optimal proportion of the final solution in different situations is increasing. However, with the increase VE amount, the optimum proportion of the final solutions in different situations is not too obvious.

10.2 Stability Analysis

Many models are used in this paper, so we will analyze the stability of different models separately.

The first is to analyze the stability of the stochastic differential equation. Our stochastic differential equation can be seen as a composite of the previous two equations, so the stability is based on the stability of the previous two equations. The stability of this equation has been described in detail above, through some specific perturbation test to see if the equation is stable. (The horizontal axis of the table is the initial value adding perturbation, the vertical axis is the boundary value adding the perturbation, and the content of the table is the numerical solution of the L1 norm of the two solutions.)

Table 10: Norm variation

	0.0001	0.00001	0.000001	0.0000001
0.0001	0.044602	0.011347	0.021053	0.042664
0.00001	0.074897	0.020272	0.007463	0.017085
0.000001	0.04367	0.012566	0.014252	0.002203
0.0000001	0.011677	0.021444	0.00743	0.001279

We then performed a stability analysis of the different fitting methods. The results are shown in the following table. It can be seen that the accuracy of the fitting after the addition of perturbation (10^{-4} order) did not change much.(The table is the amount of change in the error).

Table 11: Residual

	RBF	LOF	LSTM	BS
Peak traffic	0.008083	0.001948	0.003282	0.003058
macro factors	0.009769	0.006289	0.00657	0.004512
VE amount	0.00650	0.001858	0.006416	0.002146

10.3 Robustness Test

We use a variety of non-linear function fitting methods in the process of fitting the function. The robustness of the following models is tested as follows:

Table 12: Residual

	RBF	Test set	LOF	Test set
Peak traffic	0.042657	0.290921	0.050583	0.061032
macro factors	0.017008	0.061012	0.238124	0.331451
VE amount	0.029993	0.04246	0.030293	0.095688
	LSTM	Test set	BS	Test set
Peak traffic	0.043313	0.103117	0.042688	0.140682
macro factors	0.027907	0.096188	0.018886	0.05912
VE amount	0.05308	0.064049	0.032927	0.072931

It can be seen that several models have good robustness, so the fitting model has a strong generalization ability.

11 Summary

Strength

- Consider population, economy, urban density and other indicators as factors to establish charging stations, the model can be widely applied to many countries.
- Using Excel Power Map software, import the national map and data to get the charging station distribution network Intuitively.
- The creative using of investment utility function combined with EV numbers to meet the regional purchasing power of the VEs distribution
- Taking full account of site selection factors in charging station construction, in the least economy conditions, consider the maximum traffic flow, consider the micro-car charging behavior.
- Using LOF algorithm and progressive optimization algorithm to solve nonlinear optimization problems
- Using Bernstein function as a solution to these dense indexes area to forecast the stations distribution.

Weaknesse

- No modeling cases for EVs with different driving distance.
- In the process of solving a progressive problem, there may be multiple optimal results.
- The data we fetched from the Internet may be inaccurate.

Conclusion

From the existing distribution of two charging stations and the furthest mileage of car, the United States cannot achieve full electrification at this time. However, with the increasing number of charging stations and enhancement of power supply capacity, the United States can reach full electrification in the future. Our method, relying on the subdivision region index, can predict and analyze the distribution of the charging stations in different countries. Though the regional indicators are different, the weights of factors are constant even in varied areas. The key factor is electric vehicle demand, then comes the urban-suburban proportion, the average income, the population and the environmental factors. In the process of establishing the classification system, we have used the imprecise linear search and the cuckoo algorithm to iteratively make up for each defect.

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