For office use only
T1 _____
T2 _____
T3 _____
T4 _____

Team Control Number
76315

Problem Chosen
D

For office use only
F1 _____
F2 _____
F3 _____
F4 _____

2018
MCM/ICM
Summary Sheet

IMAGE-BASED MODELLING FOR CONSTRUCTION OF EV CHARGING NETWORKS

Abstracts

Introducing EVs (Electric Vehicles) to our daily life can significantly alleviate the worsening environmental conditions and give a feasible solution to global energy crisis, bringing us a more sustainable earth.

However, one of the inextricable problem of promoting EVs is the construction of charging network due to their longer charging time and higher charging frequency. So optimizing the charging station system would be crucial, especially in congested areas.

The properties of charging stations under determination are their quantity, placement and intra-station configurations and those could dramatically change in different regions. To diversify our model, we chose the US, Ireland and Singapore. For each country selected, we build more than one model to accomplish the scheme.

Basically, our team started from determining the car population density. For the sake of unreachable data, we applied night-light map to find a correlation of its brightness and car population density. Once the correlation established, the pixel-wise brightness data of night-light map were conducted for the hierarchy of lands and further calculation of EV charging demand in a certain area of land. The lands of a country are divided into 4 categories: urban, suburban, rural and unpopulated by its brightness. Simultaneously, because of the convenience for both designers and builders, a fixed configuration (about superchargers/normal destination chargers) in stations of each category of land is suggested. Consequently, the quantity of stations can be determined by the demand and station capacity.

Afterwards, the placement of stations was achieved with SLIC superpixel clustering, which aims to cluster colored points with higher similarity of color and proximity. We logically converted a part of traffic congestion map of each category to an image with color nodes. Then by SLIC clustering, the estimated service area and placement of station will be reachable.

In case of Ireland, chronological factors have to be considered. So gray forecasting model GM (1,1) and species competition growth model were utilized respectively for predicting the car population growth and the proportion of EVs in the coming years, with static analysis while 10,30,50 percent of cars become EVs.

Additionally, we involved the factors of government interventions and innovations that will promote or replace EVs in the future, which also showed obvious effects.

Finally, a handout for leaders of countries who are attending an international energy summit to refer was extracted from our consequences and expected to make a difference on global energy-saving.

Keywords: EVs Charging stations network; Clustering; Image analysis; Energy-saving

Part I Introduction

1.1 Background

Due to the increasing effect of air pollution and fossil fuel shortage on the everyday life, people have to compromise on their ways of transportation. Strictly speaking, the major attempt is to swap their fuel vehicles to electric vehicles (EVs). As EVs mostly run on electricity, the emission and fuel consumption would be significantly reduced, which will be an obvious compensation to our environment.

Driving EVs (not hybrids) seems rare nowadays, but when it becomes a policy of multiple countries with a ban of conventional fuel cars in less than 30 years, everyone would be compelled to do a swap on his/her cars.

Therefore, the downside of EVs should be considered then: for recharging them is a noticeably prolonged process and for their fuel (battery) capacity seem less than conventional fuel tanks, finding convenient charging stations will certainly be mandatory for all drivers. In turn, construction of the infrastructure---charging stations and networks could be massive and complicated.

Consequently, as a team of ICM, we are supposed to do some work of modelling towards determining the distribution scheme---intra-station configuration, quantity, and placement of charging stations.

1.2 Problem Restatement

In order to make an appropriate and robust scheme of station distribution, our team is assigned to predict the situations of diversified countries/areas and build multiple models that fit all of them.

Among the applicable countries in the problem, the US, Ireland and Saudi Arabia are chosen for each task.

The first and largest country to handle is the US, where complex and diverse situation lies and whose car population is the largest in the world; and then, Ireland, a small and highly-urbanized western European country (including North Ireland), which represents an almost totally-developed and more anarchistic area, as the increase of population and cars are steadily low or even negative; followed by Saudi Arabia, a developing country with an abundance of fossil fuel but a rather totalitarian government, and only several main settlements.

Furthermore, the chronological situations are different as well. In the US, the swap of EVs is barely "overnight"---consider only EVs are on the road. In contrast, for Ireland, situation of 10%, 30%, 50% and all cars are changed should be discussed respectively and also the time to achieve the change should be predicted.

Additionally, the analysis towards the impact of other factors such as technology, new marketing methods and even unknown factors (may be recognized here) on our prediction should be carried out as well.

To be practical, the consequence of our models would come with a 1-page handout for officials of states to read.

1.3 Assumptions

- All "cars" mentioned are private household cars.
- All models predicting the growth of EVs are based on **a complete halt** of conventional fuel vehicles and the **productivity** of EV makers is **infinite**.
- As mentioned in the problem, only TESLA EVs will be on the road, which are mostly the currently in-stock sedan MODEL S and the unreleased new sedan MODEL 3, an economical range is 250 to 300 miles. But due to the complex traffic conditions and accessory consumptions (A/C, lights, speakers…), the typical range could be around 200 miles. Meanwhile, our team supposed an average daily mileage of 50mi (including long distance trips may be made on holidays), and common drivers may start a charge when the battery percent goes down to 50%. This is deliberately over-estimated for the over-construction or the redundancy of charging station, which would be a better-guaranteed choice for both charging-network carriers and drivers. In this case, all drivers do a recharge of their EVs every other day (**2 days**).
- For convenience of station designers and constructors, intra-station **configurations** in certain categories

of area (urban, suburb, rural and highway) are **fixed**, such as the SN ratio of all rural stations in the US are 1:9, namely consisting of 2 supercharger and 18 normal destination chargers.

- The **car population density (D_c)** is positive correlated to the **population density** in all areas, which could be manifested in the brightness of night-light map (would be further proved, see **3.1**).
- For countries with large territories, long-distance trips with EVs cannot be neglected. For the maximum range of EVs does not surpass 350 mi (560km), charging stations along highways (especially Interstates) should be placed Meanwhile, **Interstate Highways** can be assumed as **linear linkages** between major cities.

1.4 Notations

Model3.2			
R_i	**category number**	P_i	**proportion of R_i area**
V_i	pixel quantity of R_i	B_i	average brightness
C_i	capacity of stations in R_i	Q_i	station quantity in R_i
Model3.5			
e_r	relative error	b_{gp}	proportional bias
t	Time/year	A(t)	Total demand of cars
E(t)	Demand of EVs	α(t)	Government intervention factor
r_e	growth rate of EVs	r_d	growth rate of the demand for EVs
Model3.6			
E(t)	Yearly demand of EVs	R(t)	Alternatives of EVs
P(t)	Promoters	r_e	growth rate of EVs
r_r	Growth rate of alternatives	N_E	Max demand of the EVs
N_r	Max growth rate of alternatives of EVs	N_p	Max growth rate of promoters
S_1	The stress of competition by alternatives	S_2	The stress of competition by EVs
β_1	The promotion of EVs	β_2	The promotion of alternatives

PART II Model

2.1 Skewed Distribution of Population

This model basically determines the distribution of cars in pixel-based areas. The original data does not from any census or statistics, but from a night-light map (**figure 2.1a**), the map could be rather monochrome (black…gray…white only, **figure 2.1b**) than color for only the brightness value (dark to bright: 0…255) is valid for analysis. This easy-found image data was first applied for the sake of unattainable numerical census

data, however, then our team unexpectedly found that such method has widely utilized on analysis for population and economy conditions of certain regions.

Then, formed on that strong correlation of night-light brightness value and population density, linked to the positive correlation between population density and car population density (quantity of cars in certain area) as a well-proved fact, the conclusion of that a correlation between night-light brightness and car population density do exist can be decently proposed.

Figure 2.1a color night-light map of US

Figure 2.1b monochrome night-light map of US

On behalf of that correlation, a skewed distribution diagram of car population density, which means the demand of charge stations in a scaled area of certain brightness value (the distribution histogram is shown in **figure 2.1c**). As demonstrated, most area of a country is unpopulated or rural area of low car population density, followed by suburb and urban areas. The accurate definition of those 4 sorts (by brightness) would be mentioned latter.

In both night-light map and brightness value diagram, there are significant exclusions of dark (brightness ≈ 0) and bright (brightness $\geqslant 240$) pixel areas, those are respectively: Water surfaces and uncultivable lands which are absolutely unpopulated; and some well-illuminated industrial zones and metropolitan airports that are even brighter than residential areas.

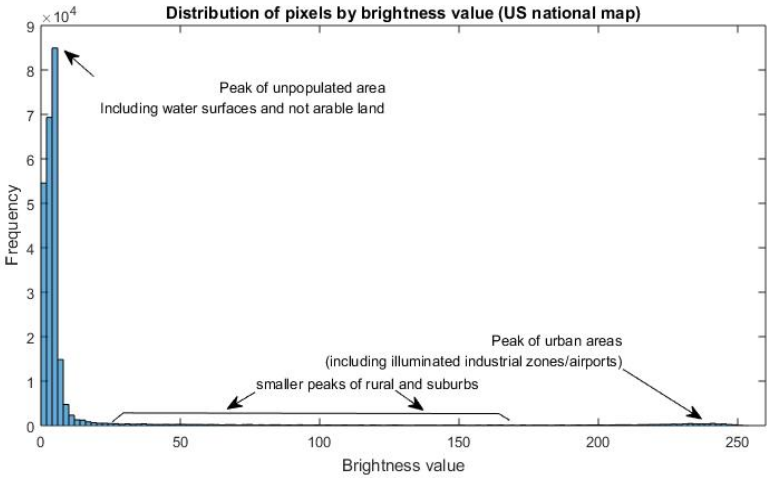


Figure 2.1c see denotes before and in the diagram

2.2 Determination of Demand

2.2.1 Part I

To classify, our team first referred the online statistics about land categories of the US (Texas here). Simultaneously, the monochrome night-light map of Texas (**figure 2.2a**) is analyzed in Matlab® to generate a hierarchical map of those 4 categories of land (**figure 2.2b**).

The four colors represents the brightness value, or the car population density of that pixel. (Blue to yellow means more congested categories)

Figure 2.2a monochrome map of Texas

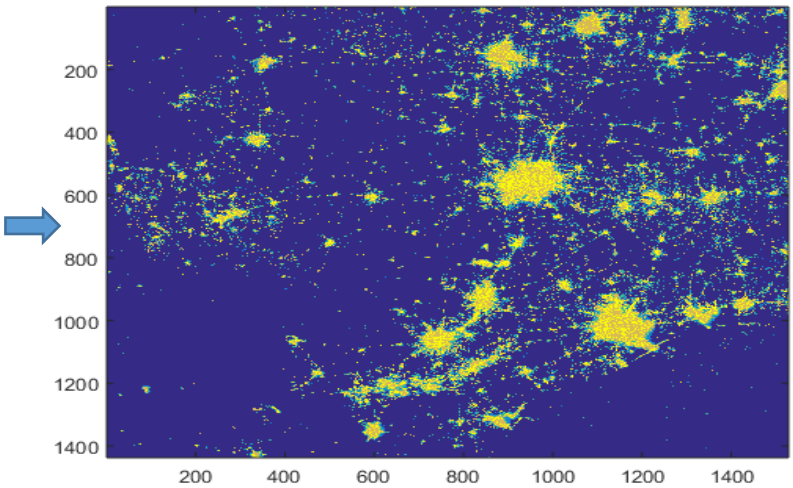


Figure 2.2b hierarchical map of Texas

2.2.2 Part II

To determine the specific average demand of each category, the method of calculating average brightness and deducing it to average charging demand was created then. The chart of average demand is shown below. In the chart, percentage of each category is first multiplied by the total pixel quantity of the image, and then the product is compared to the culmination of frequencies of each brightness value in **figure 2.1a** (shows car population density) to determine points (zones) of hierarchy on axis X. (which was started from the threshold of brightness value=0 or rural) Afterwards, the culmination (sum) of frequencies in a certain category is divided by the total brightness, resulted in a weighted categorical average brightness.

The categorical average brightness will first be multiplied by the total charging demand (in car*day) and divided by the typical station capacity (car*day) of that category, which finally give the quantity of stations.

2.3 Station configurations

2.3.1 Assumptions

For the data of average brightness and brightness range for each category of area are obtained in model 2.2, it can be assumed that the brightness also represents the urgency for superchargers.

Though stations in the rural areas seldom expect supercharger users, for emergency and stall maintenance reasons, a minimum of 2 supercharger stalls in those stations is supposed, consequently a configuration of S:N=1:9 is fixed for rural stations. This ratio will be a reference for other configurations.

Also based on the rule of a supercharger is commonly supposed to be occupied by a car for no more than 30 minutes, it only expects an 18-hour estimated daily usage rather than a full one of normal destination charger.

2.3.2 Description

Formed on the data and assumptions before, the configuration of suburb and urban stations can be made then. In this step, only the quantity of superchargers need to be calculated (20-x for normal ones), by simply divide the average brightness of suburb and urban areas by the reference (brightness of rural areas). The quotient (can be multiplied by 1 for per stall) represents the supercharger demands. (The results will be shown in Model Consequences)

2.3.3 SLIC Superpixel Clustering

Description

The placement of stations, or how to put a finite quantity of stations in certain area as to optimize the efficiency, is basically depend on the urgency of charging demand. Mentioned in the model 2.1, our team supposed that the urgency of demand can be represented by the traffic congestion or the car population density.

As a result, our first trial is to analyze the pixel map of night-light (see the correlation in 2.1) and cluster a bundle of pixels by the compromised relevance of both brightness value and distance. In this case, it means that the higher the similarity of brightness and the closer the pixels are, the more likely are they to be clustered together.

Implementation and Verification

However, most of the normal clustering algorithms, and in whichever software environment, do produce a great sum of temporary data (over 10 GB when process a merely 300*500 pixels image) which surpasses the capacity of ROM in most PCs, which would become a hardware obstacle for conventional users, so a measure with less data-redundancy becomes pretty valuable.

For that sake, an approach called SLIC (simple linear iterative clustering) superpixel clustering is then implemented. The theory generates superpixels by clustering pixels based on their color (a CIELAB color system represents both pixel color and position, rather than RGB) similarity and proximity in the image. The quantity and size of superpixels can be manually specified. The algorithm of SLIC is summarized below (**chart 2.3**) and the SLIC tool our team used is displayed as well **(figure 2.3a).** For this is a theoretical estimation of charging demand, though there are undeniable correlations between the factors in former statements, the accuracy is still under verification.

Algorithm 1 Efficient superpixel segmentation

1: Initialize cluster centers $C_k = [l_k, a_k, b_k, x_k, y_k]^T$ by sampling pixels at regular grid steps S.
2: Perturb cluster centers in an $n \times n$ neighborhood, to the lowest gradient position.
3: **repeat**
4: **for** each cluster center C_k **do**
5: Assign the best matching pixels from a $2S \times 2S$ square neighborhood around the cluster center according to the distance measure (Eq. 1).
6: **end for**
7: Compute new cluster centers and residual error E {$L1$ distance between previous centers and recomputed centers}
8: **until** $E \leq$ threshold
9: Enforce connectivity.

Chart 2.3 Algorithm of SLIC superpixel clustering

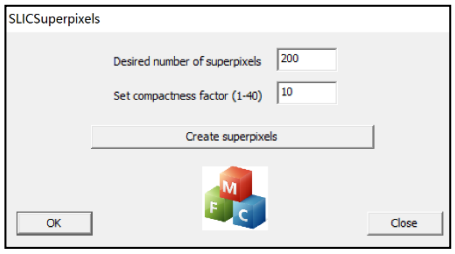


Figure 2.3a SLIC tool our team used

Consequence

The consequence of clustering is still formed on the original image (**figure 2.3b**). For example, a Houston downtown traffic congestion map was first converted to a demand-dot map logically (the darker dots represent a more congested intersect, vice versa) and processed through SLIC then, resulted in a partitioned map. The exact places of stations are finally found in the vicinity of relatively the most congested node, pointed out with a yellow dot, with some excursed points fixed (**figure 2.3c**).

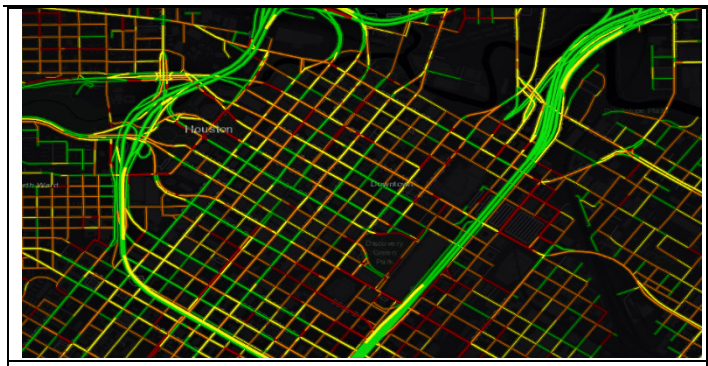


Figure 2.3b Houston downtown traffic congestion map

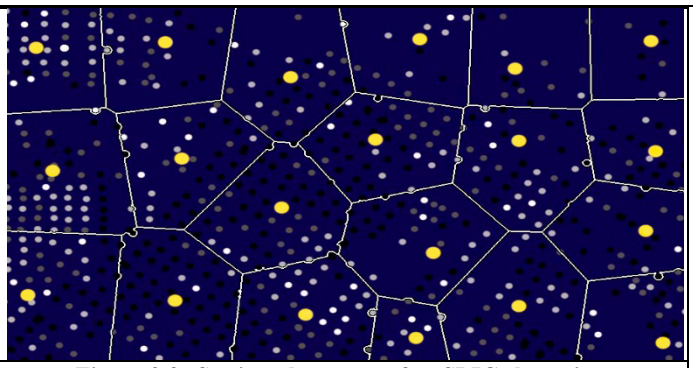


Figure 2.3c Station placement after SLIC clustering

2.4 Gray Forecast Model of Car Population Growth

2.4.1 Description of Gray Forecasting Model

Currently, the most popular gray forecasting model is GM (1, 1), which is applied commonly to predict only one variable by sequences and its first derivative. This theory is based on the original random time sequence, and the characters of the new time sequence subsequent to the culmination of the original one by time can be approached by the solutions to its first derivative equation. As proved, an exponential growth character of the original sequence could be revealed by the solutions to the first derivative equation. Consequently, a successful forecast of GM (1, 1) should be attained when implied exponential growth exists in the original data.

2.4.2 Implementation and Verification of Gray Forecasting Model

The original data of Ireland car population growth (2006…2016) was obtained from an online database of the Ireland officials. Then model GM (1, 1) was applied through Matlab® to predict its future growth towards 2035 (shown in **figure 2.4a**). The function is

$$y = 338583774e^{0.0070828t} - 336336786$$

To verify, both reality data and prediction are shown in the figure, come with a sheet (**chart 2.4a**) of both relative error (e_r) and gradient proportional bias (b_{gp}), which are parameters for fitting: when $e_r \leq 0.1$ and$b_{gp} \leq 0.2$, the forecast is relatively accurate. (Citation)

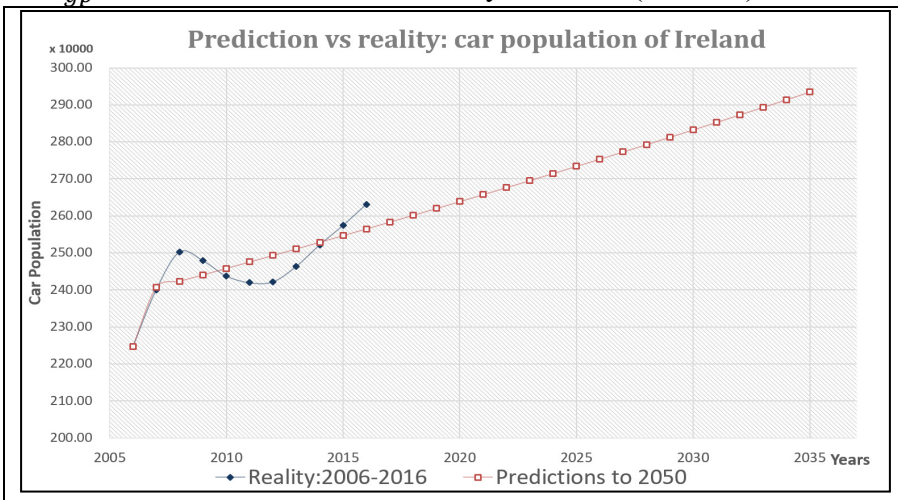


Figure 2.4a Car population growth of Ireland

Year	e_r	b_{gp}
2007	0. 0026	0. 0573
2008	0. 0314	0. 0339
2009	0. 0154	−0. 0166
2010	0. 0085	−0. 0242
2011	0. 0233	−0. 0147
2012	0. 0296	−0. 0062
2013	0. 0192	0. 0100
2014	0. 0030	0. 0160
2015	0. 0105	0. 0134
2016	0. 0251	0. 0148

Chart 2.4a Model verifying data

2.4.3 Description of Species Competition Model

In case of Ireland, the growth of EVs normally depend on time, which was predicted in part 1. However, though Ireland is pretty anarchistic, the government will still make interventions on EV advertising. So in this

case, we suppose the Ireland government make interventions before EVs outweigh 50% of private cars. As assumed, only EVs are in the market, what can be then inferred are that the demand of EVs equals to the demand of conventional fuel cars; and the average growth rate of private cars would not be impacted due to such change, based on that the demands of both types of cars are only dynamic while time evolves.

The growth rate of EVs and the demand of EVs can be calculated in the derivative equations below.

$$\frac{dE}{dt} = r_e\left(1 - \frac{E}{F(t)}\right) + \alpha(t); \quad E_0 = 3500$$

$$\frac{dF}{dt} = r_d F$$

2.4.4 Implementation and Verification of Species Competition Model

The growth of cars and EVs are demonstrated below and another sheet of sensitivity analysis is also shown to prove its robustness. (**figure 2.4b and chart 2.4b**)

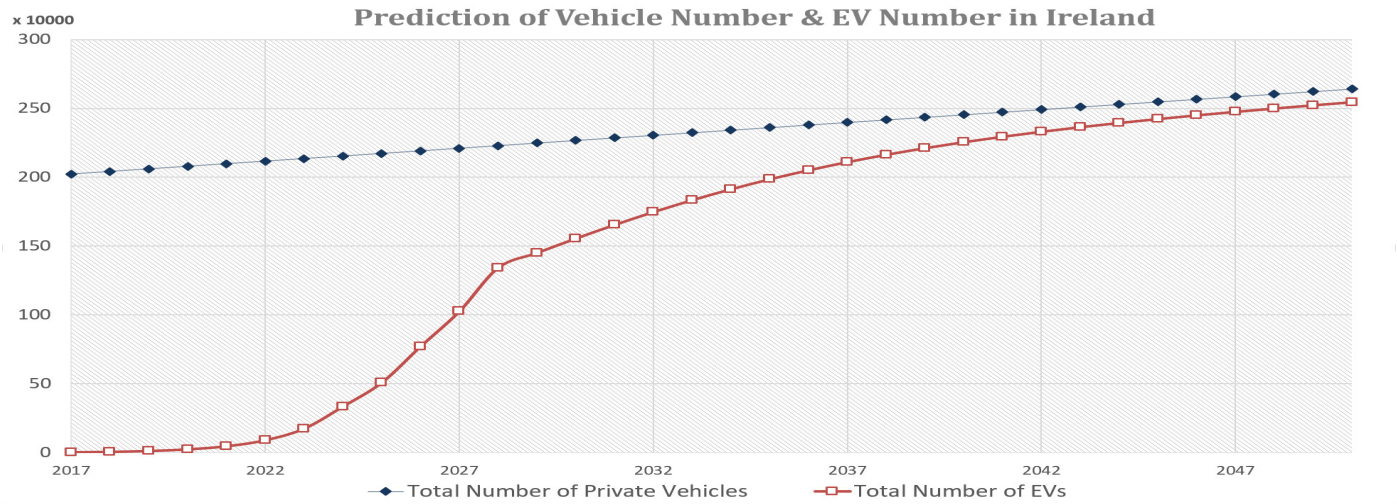


Figure 2.4b the growth of cars and EVs

Accomplishment	original	intervention-0.01	Intervention+0.01
E(t)≤10%	0.9	0.89	0.91
10%<E(t) ≤30%	0.5	0.5	0.5
30%<E(t) ≤50%	0.2	0.2	0.2
Influence (error)		0.014	0.014

Chart 2.4b Sensitivity Analysis to the change of intervention

2.5 Prediction with Technological Factors

2.5.1 Description and Assumptions

Future innovations such as sharing vehicles, autopilots and battery swapping stations that improve the efficiency of future transportation system will concurrently lay a good effect on the existing charging stations, for those can alleviate the congestion of charging stations (including reducing drivers, shortening recharging time and diverting demands).

Majorly, the aforementioned innovations are alternatives of EVs or their promoters. There are different reciprocal or competitive mutual relationships among those three. The promotional effects can be told as stimulating the update of such products and the ultimate convenience for the users.

Assumed that the development of promoters does not affected by EV itself and its alternatives, the model can be built as:

Symbols in the equations: see legend charts before

$$\frac{dE}{dt} = r_e\left(1 - \frac{x}{N_E} - S_1\frac{R}{N_r} + \beta_1\frac{P}{N_p}\right)E$$

$$\frac{dR}{dt} = r_r\left(1 - \frac{R}{N_r} - S_2\frac{x}{N_E} + \beta_2\frac{P}{N_p}\right)R$$

$$\frac{dP}{dt} = r_P(1 - \frac{R}{N_r})P$$

The results of Matlab® simulation are displayed as 4 graphs below (**figure 2.5**).

Different conditions are discussed below.

A---a modest situation, all three are finally stabilized at a moderate level.

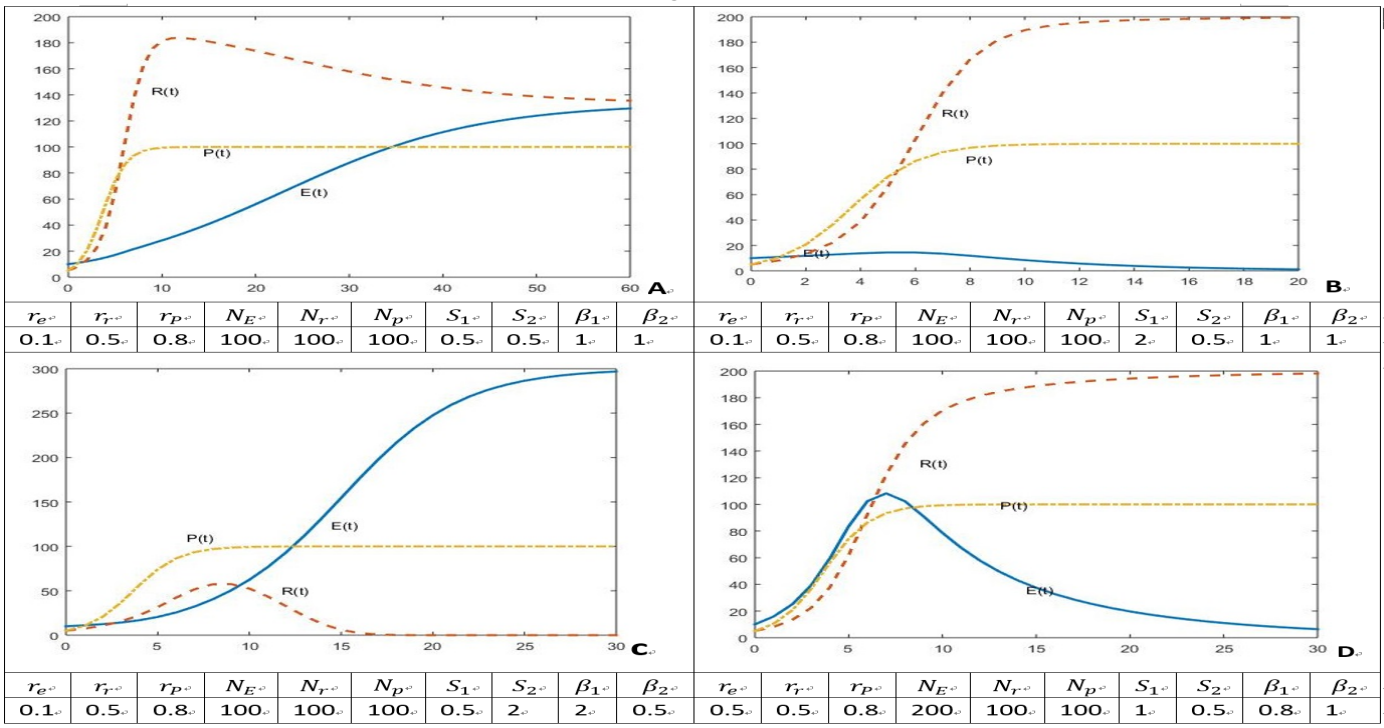
B---a situation of $S_1 \gg S_2$, the growth of the alternative rapidly surpassed EV.

C---a situation of $S_2 \gg S_1$ and $\beta_1 > \beta_2$, the growth of the alternative quickly fades due to both factors, resulted in a rapid increase of EV and a mild one of its promoters.

D---an opposite situation of C but with a higher ***re*** and more benignancy due to smaller differences of both parameters.

Though the influence of technology seems to be complicated and multiple-factorial, the final level of each element and the speed of its growth are basically depend on the inequity and difference of parameters, majorly S and β.

Figure 2.5



r_e	r_r	r_P	N_E	N_r	N_p	S_1	S_2	β_1	β_2
0.1	0.5	0.8	100	100	100	0.5	0.5	1	1

r_e	r_r	r_P	N_E	N_r	N_p	S_1	S_2	β_1	β_2
0.1	0.5	0.8	100	100	100	2	0.5	1	1

r_e	r_r	r_P	N_E	N_r	N_p	S_1	S_2	β_1	β_2
0.1	0.5	0.8	100	100	100	0.5	2	2	0.5

r_e	r_r	r_P	N_E	N_r	N_p	S_1	S_2	β_1	β_2
0.5	0.5	0.8	200	100	100	1	0.5	0.8	1

Part III Conclusions

3.1 Task I

The solution of Task 1 engaged with the Model 3.1~Model 3.4 mentioned above. Putting the preprocessed monochrome night view of the US into the models we derived before, we can get the some data as follows:

Demand Ratio of Suburb/Rural Area=1.45113
Demand Ratio of Urban/Suburb Area=1.13709
Distribution Ratio of SuperCharger/DestinationCharger in Urban Area=1:3
Distribution Ratio of SuperCharger/DestinationCharger in Suburb Area=3:17
Distribution Ratio of SuperCharger/DestinationCharger in Rural Area=1:9

Total Vehicles in Urban Area: 72485000
Total Vehicles in Suburb Area: 67734500
Total Vehicles in Rural Area: 26269900
Total Station Demand in Urban Area= 515096
Total Station Demand in Suburb Area=434196
Total Station Demand in Rural Area=295871
Total Station Demand on the Highways=2103
Total Stations demanded =1247270

Though this table, we gained the total number of charging stations demanded, which is 1,247,270.Based on the data deprived from Telsa, we assumed that construction expenditure per station similar to the size we designed will be at least $350,000. Hence the total cost building sufficient charging stations to support the entire US vehicle population will be $437 billion. Such astronomical amount will cost Telsa approximate 63 year's revenue (Telsa's annual revenue is $7 billion in 2016). Moreover, the United State is a capitalism country that adores free market and fairness of market power. Such behavior allowing one single company to control the dominant share of energy supply market will be strongly prohibited. Based on analysis above, we believe that Telsa can't hold such a complete switch on its own shoulder.
As for the distribution of stations in different areas, we selected certain typical blocks in US that represent the general conditions of those 3 areas and applied the SILC method in **Model 2.4** to gain results as follows:

Figure 3.1a-Area Selections

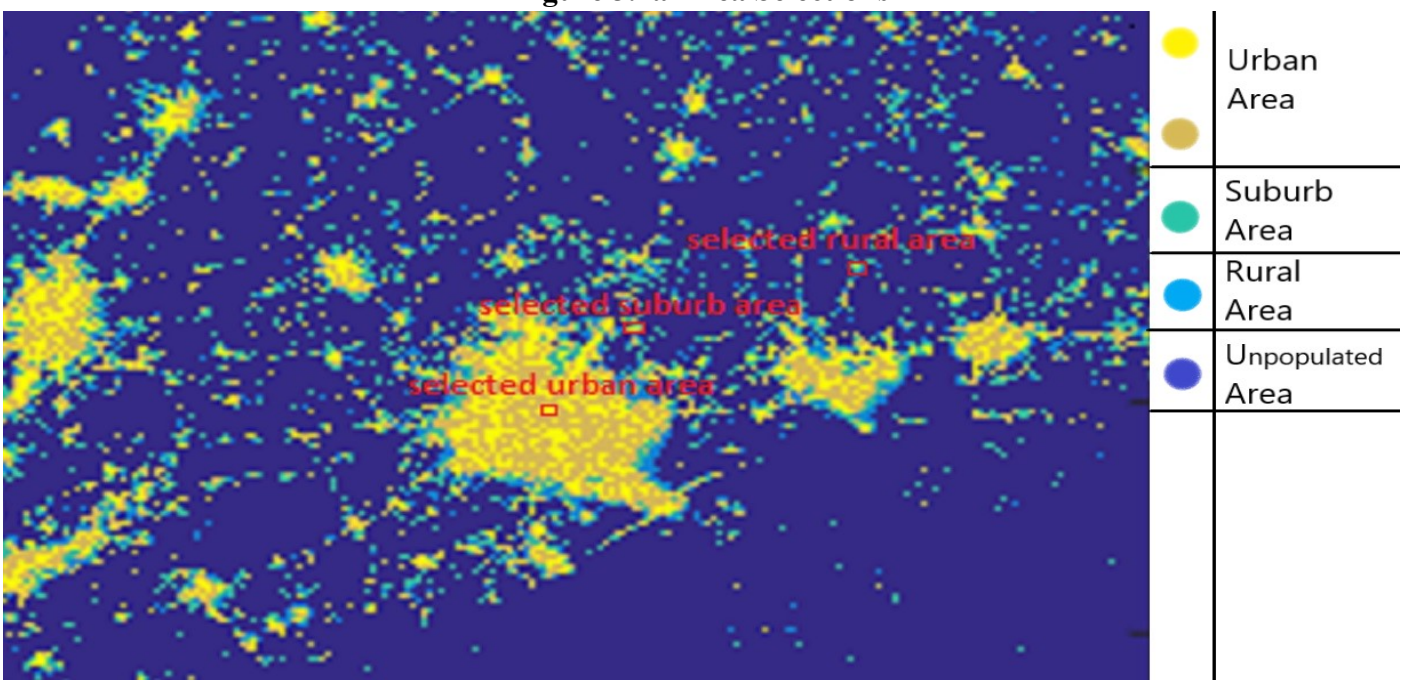
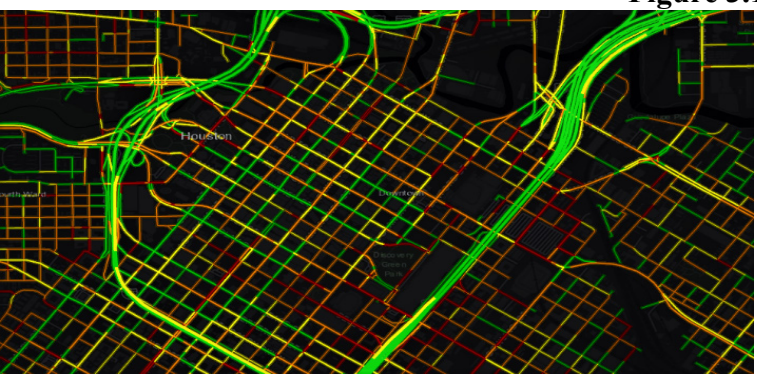


Figure 3.1b-Urban Area



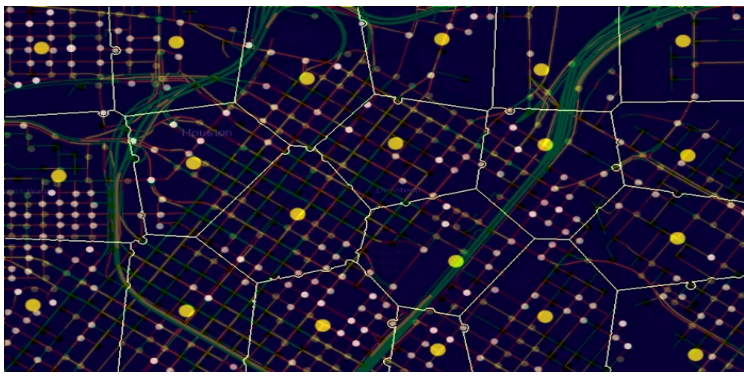
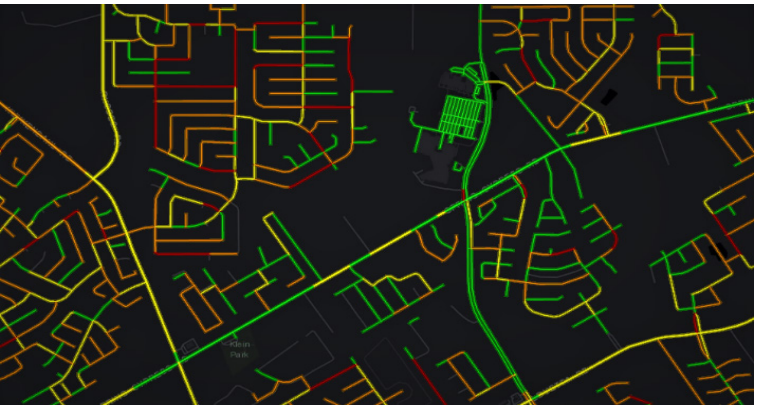


Figure 3.1c-Suburb Area



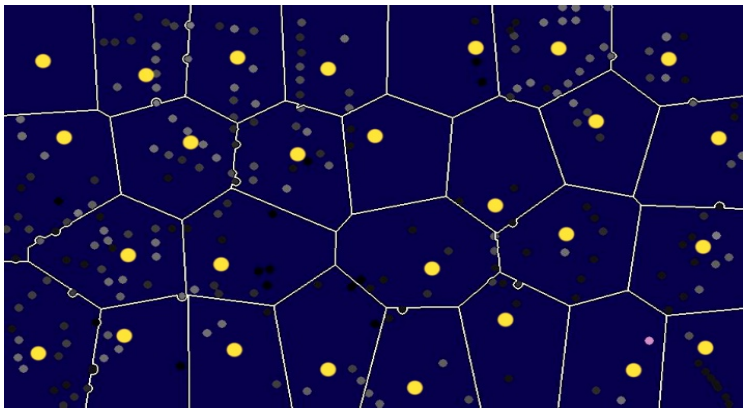


Figure 3.1d-Rural Area

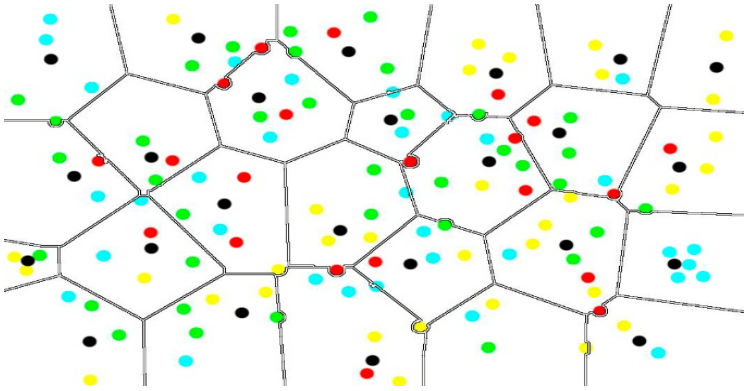
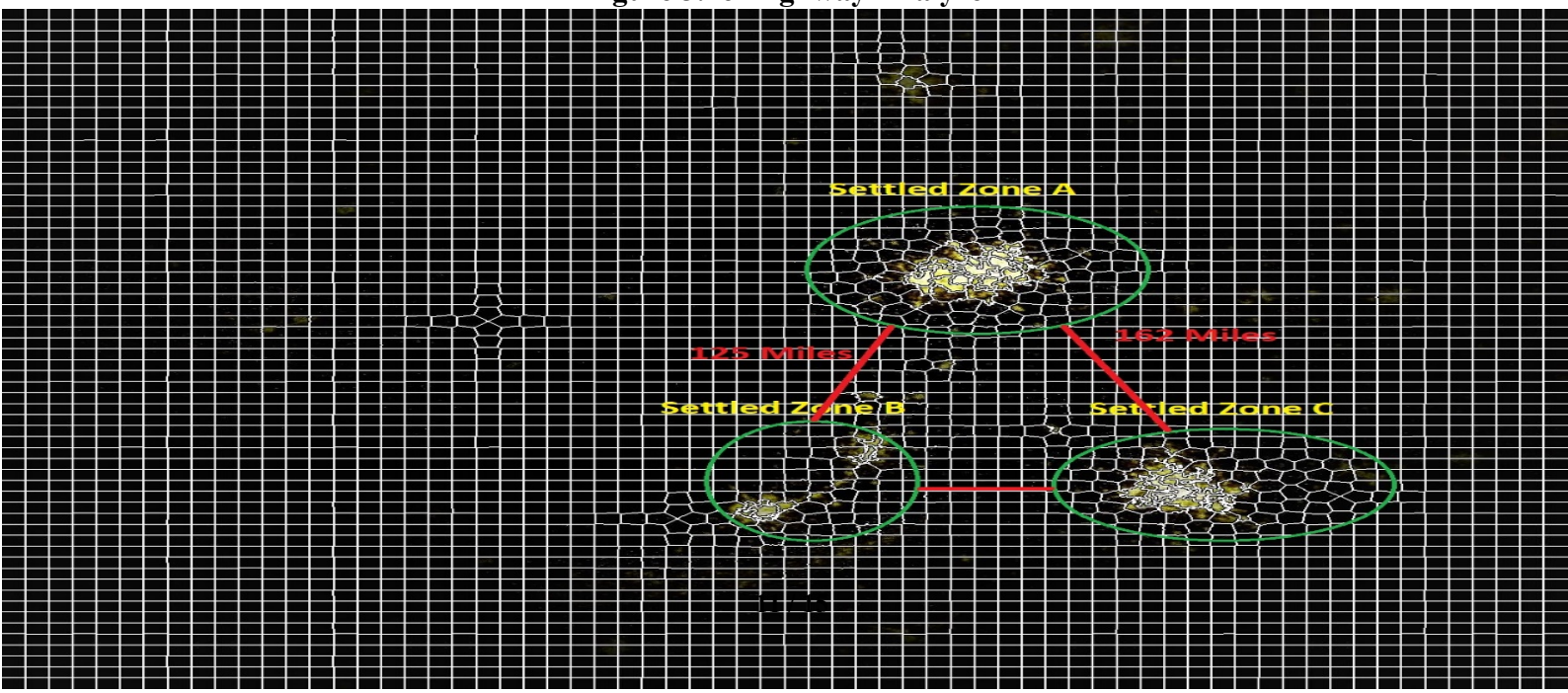


Figure 3.1e-Highway Analyze



3.2 Task II

As for task 2, we chose Ireland as our sample. For Task 2a, we put the preprocessed monochrome night view of Ireland into the models and repeated the process above. Here are the final results:

Total Number of Charging Stations: 31,573

As for the placement and distribution of stations, we decided to repeat the SILC process as above because Ireland has similar government system and area distribution pattern as US. Here are the results:

Figure 3.2a-Urban Area

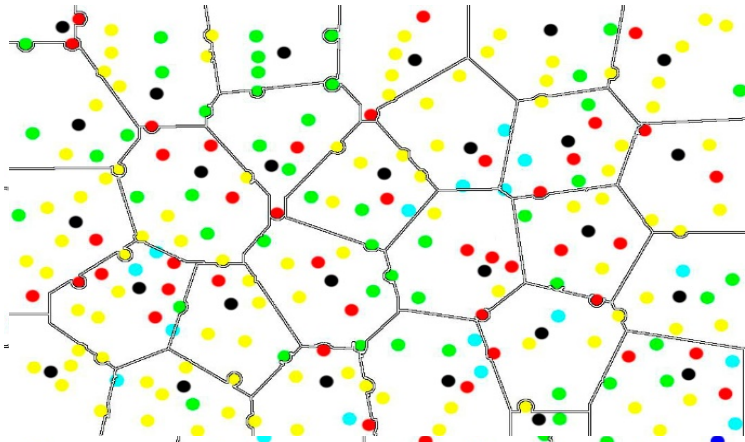


Figure 3.2b-Suburb Area

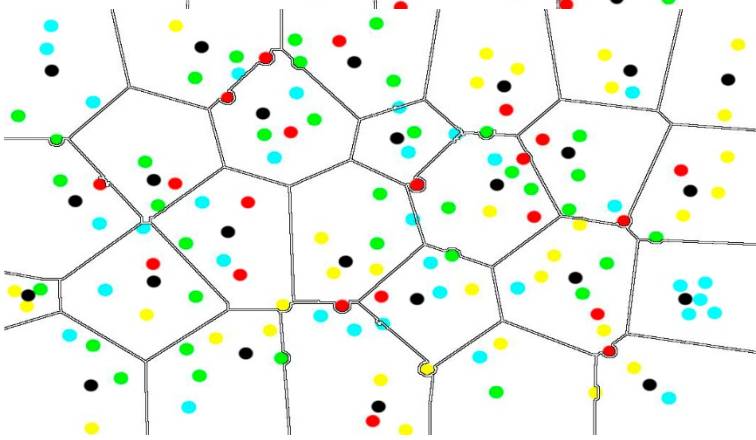
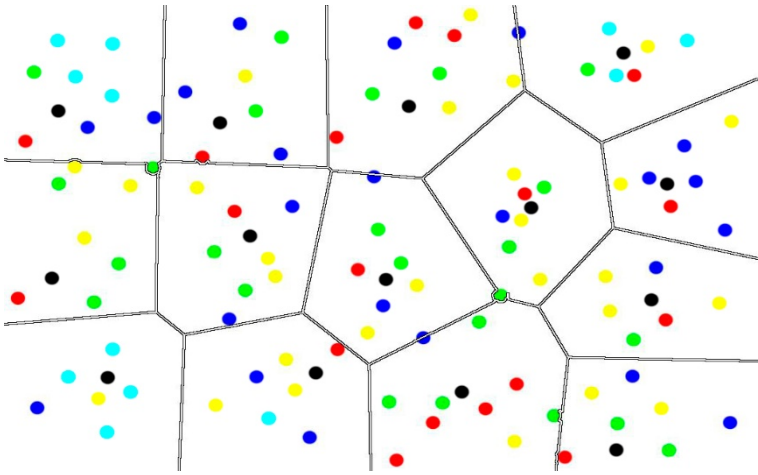


Figure 3.2c-Rural Area

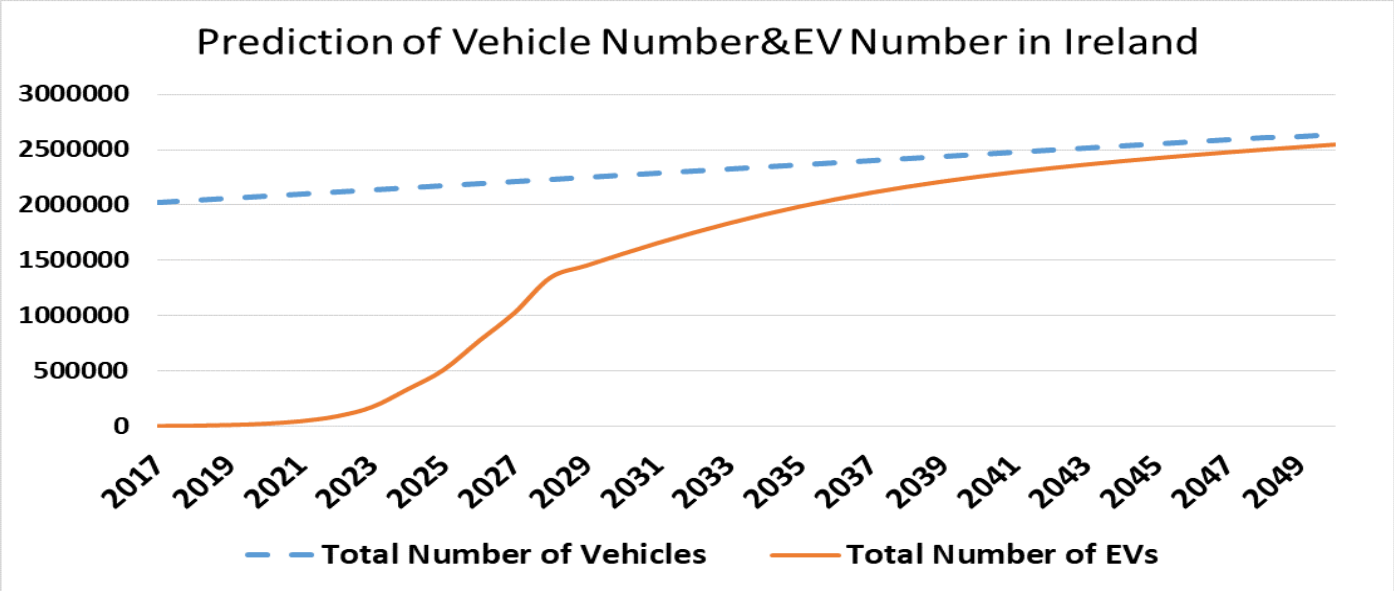


After zoom-in observation and examination, we found that models fit US situations can extended to analyze countries with similar conditions. Furthermore, after comparing the similarity and differences of these two results of the same model sets and filtering irrelevant factors we discovered that the key factors shaped our plan are the urbanized degree, total land area, population density, government architecture and state policy.

For Task2b&2c, we think that it's better for governments to set a deadline because such behavior not only displayed a strong signal of the country's determination that promotes the development of EVs significantly but also awakened the awareness to go green of citizens. Hence we proposed a deadline for the government in 2050 and assumed that the construction of stations is demand-based. Then we focused on this period of time to discover both the best choice of sequences and combinations of investment and the timeline of development.

As we considered, the amount of vehicles in a country will vary with time. So we adopted the Grey Prediction method to anticipate the total number of vehicle in the future years and combined it with our original model sets to predict the evolution of the charging network. As we further considered, the Evs, appearing in the market as both an alternative of traditional cars and a new fancy commodity for consumers, may face the competition with traditional cars and general attitude's swift of its consumers. Such case is similar to the survival competition of two species so we further applied Lotka-Volterra Equation to analyze the growth of EVs.

Chart 3.2a

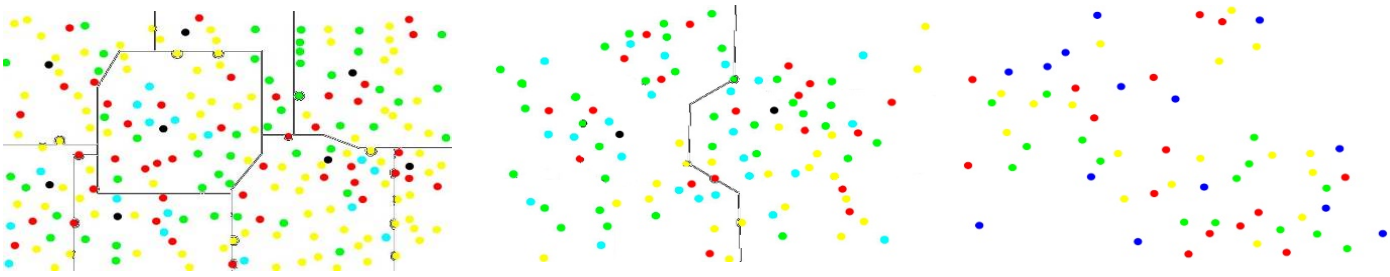


After analyzing and calculating with our new set of models, we got some results as follows:

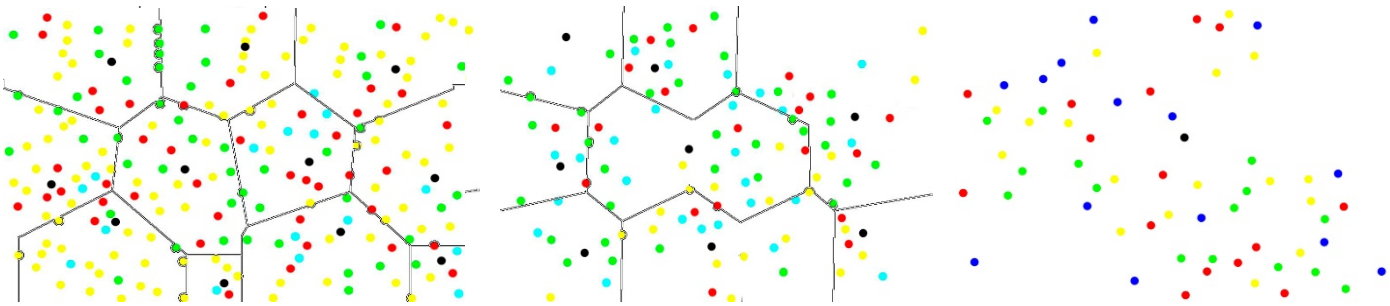
Figure 3.2d

Urban **Suburb** **Rural**

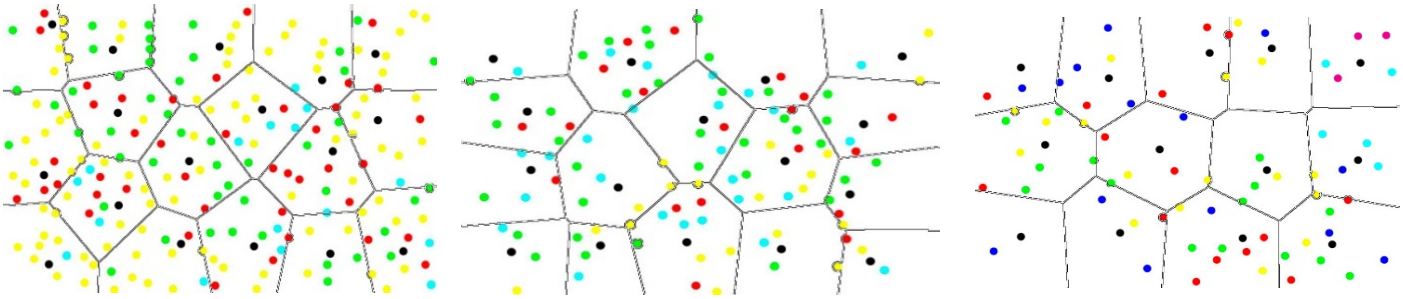
10% Vehicles in Ireland are EVs:



30% Vehicles in Ireland are EVs:



70% Vehicles in Ireland are EVs:



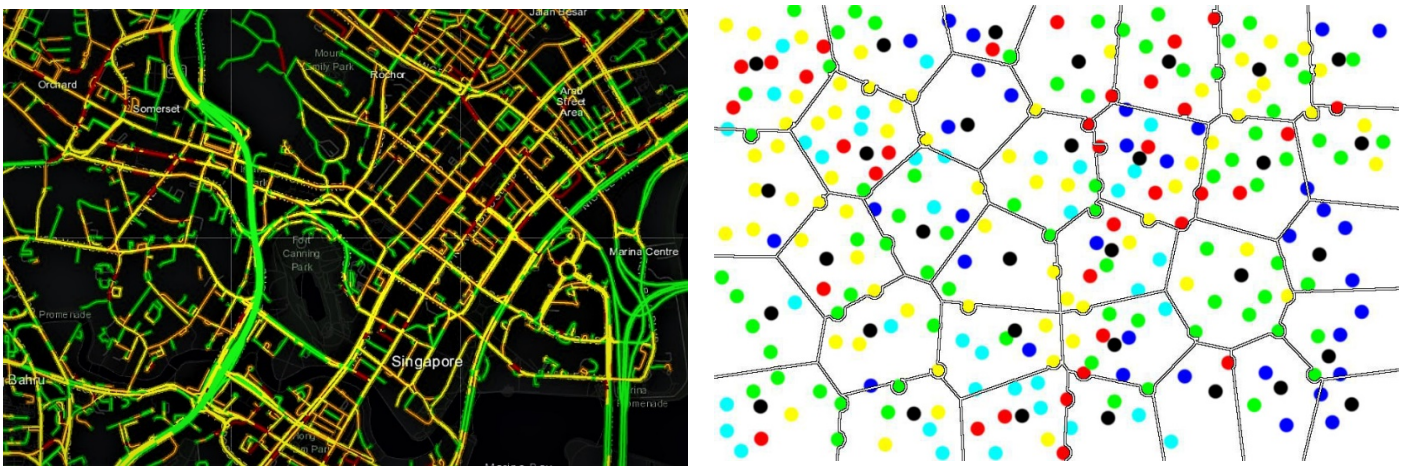
In our timeline, the growth plan starts in 2017 and ends in 2050. At the end of the first decade, the growth speed reaches its peak. At the end of 2042, the evolution of EVs almost finish and the growth rate goes slower year by year till 2050 the entire transition completed. In order to achieve this goal, we suggest the country to invest totally on construction of charging stations in urban areas by the first 10%; invest a mix of both in urban and suburb areas by the 30%; invest a mix of both in suburb and rural areas by the 70% and then invest exclusively in rural areas till the end.

Again, the key factors led to our choices are still the same factors above shaping our previous model sets though our examination and analysis.

3.3 Task III

As we've considered and tested, our model sets with different combinations still apply to many other countries like Australia, China, Indonesia and Saudi Arabia. The only difference exists in picking the approach fits these countries. For example, China is a less urbanized communism country with much larger population density and living area than US or Ireland. So the approach we suggest China to adopt is investing in the urban areas and highways as priority and construct less intensively in suburb especially rural areas. However, one country, Singapore, is exception because there is no rural or highway areas in Singapore. So our classification system didn't work well because it shows no difference of the entire area. And the result shows no divergence, either.

Figure 3.3a- Obstacles on Singapore



But one "Rule Breaker" is never an enough fatal fault to sentence our models to death. Though such many times of practice and analyze, trial and error. We still believe that it is very feasible establishing a classification system to help the decision-makings of EV development wiser

Part IV Strength and Weakness

4.1 Strength

- We analyzed the problem based on image data, and excavated the link between image data to a great extent, which unveiled a correlation among night-light map, population density map and road traffic heat map, making our first model more practical.
- Considered the imbalanced distribution of a country's population, economy and traffic, the demand for charging stations varies from region to region. So we did a hierarchy to the land of chosen countries and defined four categories to simplify the problem, which is worth to do for both designers and constructors.
- We add the factor of the intervention from the government to the species-competition model of Ireland, which showed a significant influence, came with sensitivity analysis.
- We use the Lokta-Vol Terra model to describe the change among the alternative, the promoter, and the EVs.

4.2 Weakness

- We must admit that some invaluable data are unattainable. Part of data used in our modelling was from estimation.
- The accuracy of image-based models may not be satisfactory in case of showing accurate details.
- The service radius of stations belong to each category was considered and initiated to be determined, but didn't realize due to the lack of time.

Part V Reference

[1]Tesla: www.tesla.com/models
[2]Liu, Q., Sutton, P. C., & Elvidge, C. D. (2011). Relationships between nighttime imagery and population density for Hong Kong. Proceedings of the Asia-Pacific Advanced Network, 31, 79-90.
[3]Ghosh, T., Anderson, S. J., Elvidge, C. D., & Sutton, P. C. (2013). Using nighttime satellite imagery as a proxy measure of human well-being. Sustainability, 5(12), 4988-5019.
[4]Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., & Süsstrunk, S. (2010). Slic superpixels (No. EPFL-REPORT-149300).
[5]https://www.lta.gov.sg/content/dam/ltaweb/corp/PublicationsResearch/files/FactsandFigure/MVP01-1_MVP_by_type.pdf
[6]http://www.cso.ie/multiquicktables/quickTables.aspx?id=tha10_1