The demand and proliferation for electric vehicle charging stations

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Abstract. Because of the renewable nature of electric energy, many countries have begun to develop the electric vehicle industry and achieved remarkable results. After conducting an investigation into the field of EVs (Electric Vehicles), we analyzed the basic situation, quantity, development status and government policies of the EVs nowadays. Based on the analysis of the charging stations and EVs, a model was set up for the corresponding charging station construction programs and promotion methods, for the purpose of predicting future trends. Based on the knowledge of complex networks, we discovered that the overall development of EVs resembles the global spread of viruses. We use the model to give a time forecast of the complete conversion from gasoline vehicles and diesel vehicles into EVs in each country.

1. Introduction
The deterioration of the global environment makes people begin to reduce the use of fossil fuels. Therefore, more and more consumers start focusing on EVs. Referring to [1], [2] and [3], we researched the future adoption of electric vehicles in different countries roughly.

First of all, we applied the Monte Carlo Simulation to simulate the regular behavior of users, calculating the required quantity of charging stations by stochastic simulation, and increase the accuracy of the predicted value by increasing the simulation.

Next, we referred to [4], [5] and [6], based on the knowledge of complex networks, found that the overall development of EVs resembles the global spread of viruses. The process of converting the entire network from gasoline and diesel to EVs is similar to that of healthy human infection. Among them, combining the diffusion model for alternative markets with economic and demographic factors, we found the probability of the individual accepting electric cars to replace gasoline and diesel vehicles.

Then, by referring to the marketing model in developed countries, we considered the development plans of different countries, and the promotion of specific charging stations and EVs based on the situation in different countries. Forecasting was made by considering factors such as total EVs in a thousand vehicles, economic level, and population density.

Finally, we used the model to give a time forecast of the complete conversion of gasoline vehicles and diesel vehicles into EVs in each country.
2. Monte Carlo simulation

Monte Carlo simulation belongs to a branch of computational mathematics and developed in the mid-1940s to adapt to atomic energy. The traditional empirical methods cannot get satisfactory results because they cannot simulate the real physical processes. The MONTE-CARLO SIMULATION method can truly simulate the actual physical processes. It solves the problem in good agreement with the actual situation and gets satisfactory results. In a certain area, people in the process of charging EVs showed a regular distribution, due to the restriction of various social factors, such as individual travel time preferences. We can simulate this regular behavior using MONTE-CARLO SIMULATION, work to out the approximations of the problem through stochastic simulations, and increase the accuracy of the estimates using a number of simulations.

Tesla currently offers two types of charging stations:

1) destination charging designed for charging for several hours at a time or even overnight
2) supercharging designed for longer road trips to provide up to 170 miles of range in as little as 30 minutes of charging [7].

2.1 Destination charging stations

2.1.1 Charging start time. Destination charging power is low and the charging time is longer. EVs are often used for traveling in the daytime, and the destination charging takes a long time. Therefore, the charging time may be assumed that the electric vehicle user starts charging when he/she returns to the parking spot from the last trip of a day in this search. According to the 2009 U.S. Department of Transportation Survey of National Household Travel Survey (NHTS) [8], the probability distribution of vehicles return to their dwellings from the last trip is as follows (figure 1). From the figure, the last time the user of the traveling vehicle returns to the parking space are quite consistent. The time the vehicle return to the parking space is mainly between 8:00 and 21:00. Assuming that the user returns to the car park to begin charging the electric vehicle, and the charging start time of the electric vehicle will also be distributed according to the regularity shown in the figure 1. In order to get the probability distribution of EVs charging, we use the Gaussian function method to fit the histogram to get the curve of continuous EVs charging probability density and the probability density:

\[ f_{t_{dc}}(x) = a_1 e^{-\frac{(x-b_1)^2}{2c_1}} \]

Where: 
- \( a_1 = 0.0853 \)
- \( b_1 = 14.08 \)
- \( c_1 = 6.948 \)

![Figure 1. vehicles return time and probability density](image)

2.1.2 Charging duration. The EVs charging duration is directly related to the state of charge(SOC) of the battery. According to the above assumptions the user last time to return to the parking place to start charging, then the EVs charging time only related to the daily mileage. According to the NHTS survey of daily driving distances of private vehicles, the daily mileage of electric vehicles is mainly distributed within 100 miles. From the figure the daily driving mileage of EV is mainly distributed...
between 20 and 80 miles, rarely more than 140 miles. If the EVs power consumption per hundred miles \( W \) is constant, and the electric car charging power \( P \) is also a fixed value. Considering the charging efficiency of the charger. If \( W = 35 \text{ kWh} \), \( P = 8 \text{ kW} \) and the charging efficiency = 0.9 [9]. In order to obtain the charging duration distribution of EVs, the probability density curve of charging duration \( T_c \) is obtained by fitting the above histogram with Gaussian function and the probability density:

\[
f_{T_c}(x) = a_1 e^{-\frac{(x-b_1)^2}{c_1^2}}
\]

Where: \( a_1 = 0.3994 \quad b_1 = 1.203 \quad c_1 = 1.566 \)

2.1.3 Simulation. We analyzed the probability distribution characteristics of the initial charging time \( T_s \) and the charging duration \( T_c \) of EV in the out-of-order charging state, the expected charging value of an electric vehicle in one day can be obtained by the Monte Carlo Simulation method.

2.2 Supercharging stations
Supercharging of EVs often occurs when the electric battery capacity cannot suffice the traveling demand. During a journey, the electric vehicle will use supercharging station when the battery power reaches the warning level or the remaining battery power is insufficient to follow-up mileage [10]. The user travel start time \( T_s \) uses the typical day statistics provided by the U.S. National Cooperative Highway Research Program (NCHRP 187). Specific distribution as shown in the figure.

In order to obtain a continuous distribution of the starting times, we fit the histogram using Gaussian function obtain the probability density curve of the EVs user's travel starting time \( T_s \) and the probability density:

\[
f_{T_s}(x) = a_1 e^{-\frac{(x-b_1)^2}{c_1^2}} + a_2 e^{-\frac{(x-b_2)^2}{c_2^2}}
\]

Where: \( a_1 = 0.389 \quad b_1 = 7.046 \quad c_1 = 1.086 \quad a_2 = 0.016 \quad b_2 = 10.610 \quad c_2 = 9.667 \)

The charging station load in one day can be obtained. Taking into account the rational utilization of energy and avoiding the charging station idle for a long time. Introduce a coefficient \( \alpha = 0.0265 \) to make the charging station fully utilized.

2.3 Demand forecast
Tesla is on the track of switching completely to all-electric. As people's environmental awareness and the economy improve, more and more people tend to use the new energy vehicles. Therefore, people will buy TESLA cars Preferentially. From the figure, the general trend of sales of TESLA cars is enhance, and the sales amount will also have a faster development later. The increase in EVs will cause the number of supercharging and destination charging stations to increase. Charging will be more convenient, and it will prompt people to buy TESLA electric cars. This positive feedback system will prompt the United States into an all-electric country.
If everyone switched to all-electric personal passenger vehicles in the US and there are about 254 million cars in the United States at present, we can predict from the charging station demand model that there will be about 164900 supercharging stations and 836490 destination charging stations after this transition is completed.

3. spread of virus in complex network
The network is around us. As individuals, we ourselves are the units of a network of social relationships of different kinds. As biological systems, we are the subtle result of biochemical reaction networks. Networks can be tangible objects in the Euclidean space, such as electric power grids, the Internet, highways or subway systems, and neural networks. Or they can be entities defined in an abstract space, such as networks of acquaintances or collaborations between individuals. [11] Users and charging stations, users and users, charging stations and charging stations can be combined in a network. [12]

The overall development of EVs in the country resembles the global spread of the virus. People who use gasoline and diesel cars are similar to healthy people, and people who use electric cars are similar to those who are infected. The process of converting the entire network from gasoline and diesel to EVs is similar to the process of transforming a healthy population into a diseased population.

3.1 SI Virus transmission model
In a typical propagation model, the system of individuals is divided into several categories, each category is a state. The basic dissemination includes: S (Susceptible) - Easily infected status (petrol and diesel car users). Such individuals are healthy individuals, but can be infected with the virus. I (Infected) - Infected status (EVs user). Such individuals have been infected with the virus.

In the early stages of a virus outbreak, a few individuals are infected with the virus in the network and transmit the virus to their neighbors with a certain probability. Once S-type individuals become infected, they become I-type individuals, who then become new sources of infection that infect other individuals in the system. Individual interactions are not homogeneous, dictated by the structure of the network. Models of spreading processes should take the network topology into account. [13]

Let $S(t)$ and $I(t)$ denote the density of individuals in state S and state I at time t respectively. $\lambda$ is the probability of S-type individuals being infected as class I individuals (probability of diesel and petrol users being converted to electric vehicle users) and N is the total number of individuals in the system, then each infected individual will make three individuals infected, and the number of infected individuals in the network is $N_i(t)$. All individuals in the system have only two states, S and I. the dynamics of virus transmission can be described by the following differential equations: the rate of change of infected individuals’ density over time and the rate of change of individuals susceptible to infection over time:
Since all individuals in the system have only two states, \( s(t) + i(t) = 1 \). Suppose at the initial moment, the initial density of infected individuals is \( I(0) = i_0 \). Then the solution of equation (4) can be transformed into the following differential equation solving the problem:

\[
\begin{align*}
\frac{di(t)}{dt} &= \lambda i(t)s(t) = \lambda i(t)(1 - i(t)), \\
i(0) &= i_0
\end{align*}
\]

To get the initial value, we solve the differential equation:

\[
i(t) = \frac{1}{1 + (1/i_0 - 1)e^{-\lambda t}}
\]

From the solution (6), we can see that when the time is sufficiently long, the final state of the SI model is that all the individuals in the system are infected as class I nodes, that is to say, all the users become electric vehicle users.

3.2 EVs diffusion probability model based on the complex network

The probability of infection mentioned in the above SI model is not a fixed value in the EV development model and we present the following EVP model.

The proliferation of new products (EVs) in the market is mainly divided into two types, namely, innovative markets and alternative markets. For the alternative market, consumers have already had similar products. The purpose of adopting new products is to take advantage of the high performance of new products to get more benefits [14].

Let the potential market size of EVs be \( N \), and the number of individual neighbor \( k \) is called the degree of subjects. The degree distribution \( P(k) \) indicates that the probability that the degree of an arbitrary individual in the network is \( k \) is \( P(k) \). Social networks have a small world and scale-free features, degree distribution to meet \( P(k) \sim K^{-\gamma} \) [15].

For individuals with degree \( k \), if a neighbor uses EVs, the probability of the individual being transformed into an electric vehicle user under the influence of neighbors is \( F(k, a) \).

For alternative markets, the probability of an individual using a new product to pay is \( C_i \). Suppose \( C_i = k c_i' \), \( c_i' \) represents the unit payment costs, \( c_i' \) obey uniform distribution \( U(x) \), \( x \in [0, CR] \), \( b' \) represents incremental network value. So, alternative market decision transfer function:

\[
F'_i(k, a) = P(k_a < ab') = P(\frac{ab'}{k} < C_x) = \begin{cases} 
\frac{ab'}{k} \leq C_x & \frac{ab'}{k} > C_x \\
abla
\end{cases}
\]

\( b' = 1 \), we have a simplified form of (7).

At time \( t \), the probability of pointing to the vertex (the user using the new product) from any one side in the network is \( \theta(t) \). The degree of \( k \) individuals has a neighbor who has used the new product probability obeys the binomial distribution, the probability value is:

\[
C^a_k (\theta(t))^a (1 - \theta(t))^{(k-a)}
\]

Therefore, the probability of an individual with degree \( k \) changing to a new product user (electric vehicle user) at time \( t \) is:
\[ H_x(\theta(t)) = \sum_{a=0}^{\frac{1}{(1-\theta(t))^{(1-\theta(t))}} F(k,a)C_k^a(\theta(t))^a(1-\theta(t))^{(k-a)} \]  

[16] (9)

\[ \theta(t) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \]  

(10)

**Figure 3. Forecast of the development of electric vehicles in some countries**

Global development model we proposed will vary with different Per capita GDP (PPP) and Number of cars per thousand. Here are some countries' charts about Per capita GDP (PPP) and Number of cars per thousand and Electric vehicle development figure in different countries we draw through the model.

4. **Conclusion**

We used the Monte-Carlo Simulation method to predict the number of charging stations and the virus transmission model was used to forecast and plan the national development of EVs. The analysis showed that the development of EVs is related to many factors, and the most important was Per capita GDP (PPP). However, other factors can also influence the development of EVs. We need to consider a number of factors to make our model more accurately represent the actual situation. Further consideration may include in the study a cost analysis of the energy distribution within the urban energy network. We will also consider the special circumstances encountered during the popularity of electric vehicles and include more parameters that can reflect differences. We can consider the influence of the cultural customs and religious environment of different countries on the development in the model.

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**References**

[1] Yan Yan. Research on the market diffusion of China's new energy vehicles under the background of low-carbon transportation [d]. China University of Geosciences, 2016.

[2] Zhang Zhongyun, Li Chunli, Japan's new energy vehicles related policies and future development path choice [J] *Modern Japanese Economy*, 2015 (05): 71-86.
[3] Yang Fang, Zhang Yibin, Ge Xubo Analysis of the development trend and characteristics of electric vehicles in China, the United States and Japan [J] Energy Technology Economy, 2011, 23 (07): 40-44.

[4] Ganesh, L. Massoulié, and D. Towsley, “The effect of network topology on the spread of epidemics,” in Proc. IEEE INFOCOM 2005, Miami, FL, Mar. 2005, vol. 2, pp. 1455–66.

[5] C. Asavathiratham, “The influence model: A tractable representation for the dynamics of networked Markov chains,” Ph.D. dissertation, Dept. Electr. Eng. Comput. Sci., Mass. Inst. of Technol., Cambridge, MA, Oct. 2000.

[6] D. J. Daley and J. Gani, Epidemic Modelling: An Introduction. Cambridge, U.K.: Cambridge Univ. Press, 1999.

[7] Li Shan. Tesla built a super charging network [J]. Science Grand View Garden, 2013 (22): 71-71.

[8] Taylor M J Alexander A. Evaluation of the impact of plug-in electric vehicle loading on distribution system operations. IEEE Power & Energy Society General Meeting Calgary Canada 2009: 1-6.

[9] Guo Xiaoji. Technical Analysis of Tesla Pure Electric Vehicles[J]. Science & Technology Review, 34(6).

[10] Feng Liang. Electric Vehicle Charging Station Planning and Research [D]. Tianjin University, 2013.

[11] Boccaletti S, Latora V, Moreno Y, et al. Complex networks: Structure and dynamics[J]. Physics reports, 2006, 424(4-5): 175-308.

[12] Goldenberg J, Libai B, Muller E. Talk of the network: A complex systems look at the underlying process of word-of-mouth[J]. Marketing letters, 2001, 12(3): 211-223.

[13] Van Mieghem P, Omic J, Kooij R. Virus spread in networks[J]. IEEE/ACM Transactions on Networking (TON), 2009, 17(1): 1-14.

[14] Clark B H. The evolution of dominant market shares The role of network effects[J]. Journal of Marketing Theory and Practice,1999,7(2):83～96.

[15] Albert R. Barabasi A-L. Statistical mechanics of Complex networks[J]. Rev.Mod.Phys., 2002,74:47～97.

[16] Pastor-Satorras R, Vespignani A. Epidemic spread-Ing in scale-free networks[J]. Phys.Rev. Lett. 2001,86:3200～3203.