Is the sales growth rate of electric vehicles related to the rate of growth of charging infrastructure?

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Introduction

A vehicle that can travel at least partly on electricity is termed an electric vehicle (EV). This type of vehicle includes plug-in hybrids, battery electric vehicles, and hybrid electric vehicles (Xing et al., 2019). Electric vehicles have been around for quite a while but were in their dark era with almost no technological development until Toyota Prius was released in 1999; this was the first ever hybrid electric vehicle to be sold. Even though the concept was heard of here and there, electric vehicles had their fame shot up since the early 2010s, when Chevrolet and Nissan released their plug-in hybrids. In recent times, different companies, especially Tesla, have popularized electric vehicles and given gasoline cars competition for market share (Matulka, 2014).

After ten years of explosive development, the number of electric cars sold worldwide reached ten million in 2020, which was a gain of 43% since 2019. In 2020, battery electric vehicles (BEVs) made up two-thirds of the stock and all new electric car registrations. China has the largest fleet with 4.5 million electric vehicles, but in 2020, Europe saw the largest annual rise to reach 3.2 million. The global market for all types of automobiles was significantly impacted by the economic impacts of the COVID-19 outbreak. In the first quarter of 2020, compared to the same period in 2019, fewer new cars were registered. Stronger activity in the second half helped to counterbalance this to some extent, but altogether there was a 16% decline year over year. Notably, global electric car sales share increased to 70% by a record high growth rate of 4.6% in 2020, despite conventional and overall new car registrations declining. The number of electric vehicle registrations rose in 2020 due to several causes. Notably, the total cost of ownership for electric cars is gradually improving in various nations. Several countries offered or extended tax advantages that protected the purchase of electric vehicles from the slump in the auto industry (International Energy Agency [IEA], 2021).

Prior studies generally suggest that, to increase consumer interest in EVs, charging options need to be made widely available, quick, and affordable (Zou et al., 2020). This model examines if there exists a very strong relationship between them or not. The model makes use of data available for the state of California and tries and predicts the sales patterns and charging infrastructure growth while calculating the interrelationship between them, utilizing correlation.

Existing Models and Research

Zou et al. (2020) carried out a research where the results of different features of charging infrastructures were analyzed to ascertain if it affected the preference for an electric vehicle both for new-car buyers and used-car drivers. The research highlighted that the used-car drivers were more concerned with the distance of the charging infra, as well as preferred faster-charging rates. The new-car buyers were more affected by the possibility of the EV being charged within their premises and safe parking spaces. My model here discusses the importance of the charging infrastructure and how it affects the sales growth of electric vehicles but does not include the features like distance or the speed of charging.

Another research was carried out in Korea by Kim et al. (2019) to assimilate the importance of consumers' intentions and desired time in buying battery electric vehicles (BEV) in Korea. Multiple factors were analyzed, and it was concluded that prior experience with BEV or simply knowing information about BEV was the major factor for buying an EV, followed by age and gender. Furthermore, older and female consumers were more inclined to buy the BEVs. Other factors that inclined people towards the BEVs were the government incentives and public parking allowance.

A research was carried out by Cecere et al. (2018) with data from six different European countries on what features or improvements in an electric vehicle would increase the probability of buying the electric vehicle. The research concluded that price was the major factor in opting for an EV, followed by the driving range (the battery/charging capacity of the vehicle) and availability of charging infrastructure at homes. The top speed of the vehicle and recharging time of the vehicle was found to have a nominal effect on the purchase decision. My model is based on analyzing the importance of charging infrastructure available in the U.S. publicly instead of the private charging infrastructure, and the results obtained were significantly different.

The Model

This model has been developed to simulate the importance of the availability of charging infrastructure for the sales growth of electric cars in the U.S. state of California. Initially, the cost of an electric vehicle and its range was also considered being included in the scope of the model but were chosen to be omitted as the market price of cars was vague for different capacities with ambiguous after-sales benefits. Additionally, the lack of proper data on the actual requirement of range to be driven by average customers resulted in the exclusion of electric vehicles' range from this model.

The dataset used in this model consists of the rate of sales growth of the different types of electric vehicles and the rate of charging infrastructure available in the U.S. state of California between 2016 and 2021 (U.S. Department of Energy, 2021). By looking at the sales data trends, it was assumed that the sales followed a stochastic approach and were therefore implemented using a normal distribution. The charging infrastructure does seem to have an increasing trend from the data, but it has been assumed to fall after some time as the supply becomes scarce as time progresses. Therefore, the charging infrastructure growth rate has been modeled using a logistic function.

Coming to the different entities used in this model, charging infrastructure is one of them, as it is the initial number of the charging infrastructure that the state starts with and is represented as a green patch in the environment. Then, there is the use of a 'growth-rates' variable that accounts for the sales growth percentage over the years, and its mean and standard deviation are computed. Another variable used in this model is the 'infra-rates', which stores the rate of growth of the charging infrastructures over the years. It initializes the maximum growth rate stored as P1 and the minimum growth rate as P2, which is a random number between 0.01 and the minimum growth rate. This approach has been used such that the minimum infrastructure growth rate can be a small number instead of the higher minimum rate that has been supplied by the data. Then 'number-of-months' has been used to keep a record of the number of model's runs. The geographical state of California will be treated as the environment, with multiple charging stations as patches and output intended as plots on the interface. Each tick in the model represents a month passed and the sales and infrastructure growth rates are predicted at the end of 12 months. The model also makes use of the variable 'number-of-years', which tracks the years run in simulation. The model is currently chosen to predict the correlation between the two factors over five years, which is equivalent to 60 ticks. Apart from that, multiple lists namely, 'probabilities', 'sales-probabilities', and 'correlations' have been used in the model to capture the growth rate of charging infrastructure, the growth rate of electric vehicle sales, and the correlation coefficient between the sales and charging infra being calculated over the model run, respectively.

Method

The model can be initialized with the ‘setup’ button, which imports the dataset and then initializes values for sales growth median and standard deviation to calculate the normal distribution of the sales growth in the sub-model ‘update-sales-rate’. Then, it initializes the minimum and maximum charging infrastructure growth rates for the logistic function. For the same, initially, the ‘setup-growth-logistic’ sub-model is run to initialize the values of ‘growth-logistic-A’ and ‘growth-logistic-B’. This sub-model works by considering X1 and X2 which are the times when the model is assumed to have its highest and the lowest rate of infrastructure growth. As the current model run is 5 years (60 ticks), they have been initialized as 18 months as the infrastructure growth rate is assumed to start on the higher side and 42 months as infra development is expected to go lower after 3.5 years. After all this, the initialization is completed, then as the ‘go’ button is pressed, the model starts to simulate runs wherein it checks if a year has passed in the simulation, which is equivalent to the execution of 12 ticks. If a year has passed, then it calls the increase stations module, which in turn then takes the existing sales growth rate and the charging infra growth rate and calculates the correlation. Then, the sub-model ‘update-growth-prob’ is run to calculate the growth rate concerning the current charging infrastructure for the next iteration. Subsequently, the sub-model ‘update-sales-rate’ is run to update the current EV sales growth rate following the normal distribution. As the different sales growth rates and infrastructure growth rates are calculated after every 12 ticks (passing of a year in the model), the respective lists are populated. After more than two iterations of the model, the correlation starts being calculated and is added to the ‘correlations’ list. The first two-year runs of the model do not have enough relevant data to calculate correlation and therefore are skipped. All the lists are then represented as graphs on the interface, such that each trend can be illustrated and looked upon. In addition, as per the calculated charging infrastructure growth rate, the number of patches is increased in the model using the ‘increase-stations’ sub-model. The BehaviorSpace experiment for the model’s sensitivity analysis is discussed below.

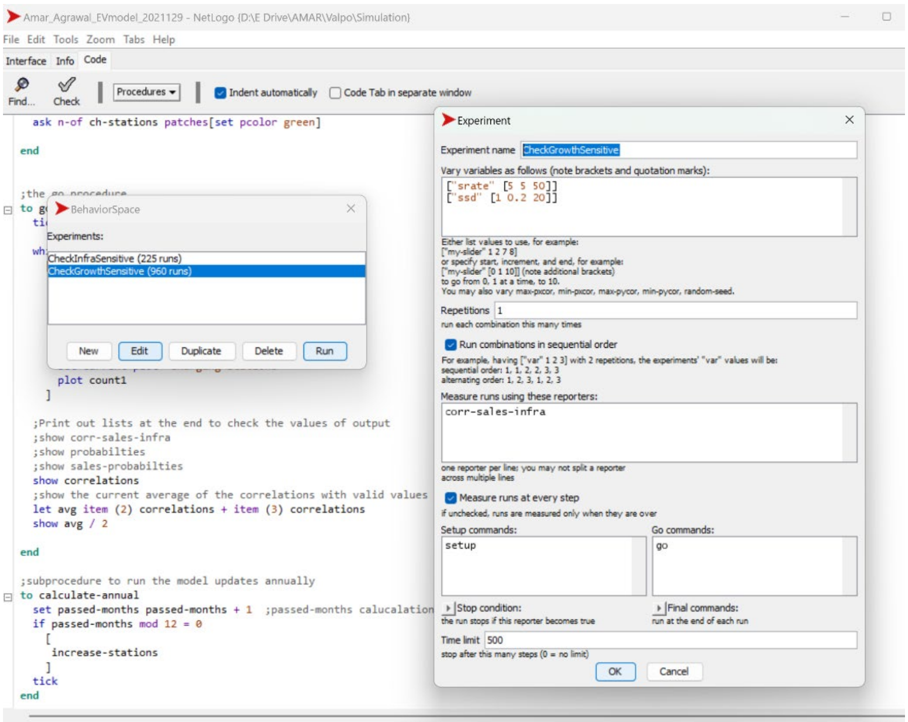

Fig 1: Behavior Space Experiment Setup

The model includes the BehaviorSpace experiments for different values of P1 and P2, which are the infra-growth rates different from the current input. For the infra-growth rates, P1 values between 0.2 and 0.9 are simulated and the P2 values are run with values between 0.1 and 0.8. This is because it is assumed that the growth rate will be decreasing after some period and P1 should never be lower than P2. Additionally, another experiment is included for cycling through the different median and standard deviation values for the sales growth rate's normal distribution. The median sales growth values are kept between 5 and 50, whereas the deviation has been assigned between 1 and 20. Both experiments produce a similar result to the current result for over 1000 runs. The final correlation value remains between 0.12- 0.18 during the different runs.

Results

The model's different runs showed a low value for the correlation between the sales growth rate and the charging infrastructure. The model was first run using a median value of 17 for initial charging stations with 60 ticks and the data file referenced above.

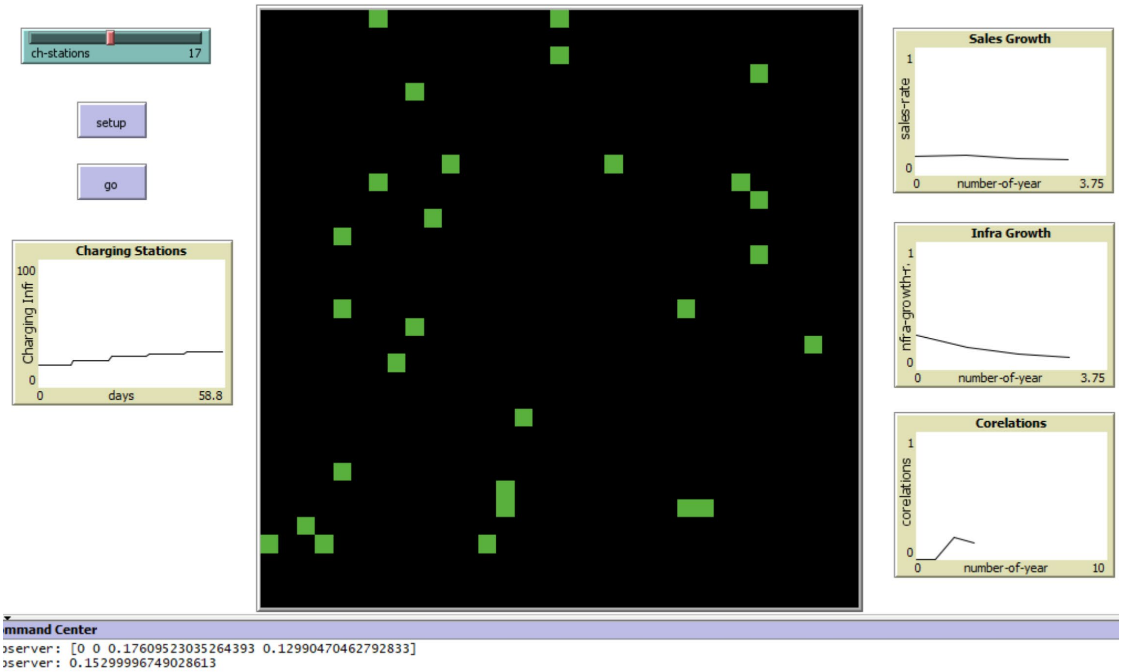

Fig 2: Results of the model using median charging infrastructure value showing average correlation value as 0.15

The model was also run using lower and upper values of 3 and 33 for the charging infrastructure, but the resulting correlation was low in both cases. Figures 1 and 2 show a falling infrastructure growth graph as the growth rate decreases with time and the number of charging infrastructure can be seen rising. On the other hand, Figure 3 shows there is almost no change in the infrastructure growth rate as it starts with a higher value and no significant change can be seen in the charging stations numbers.

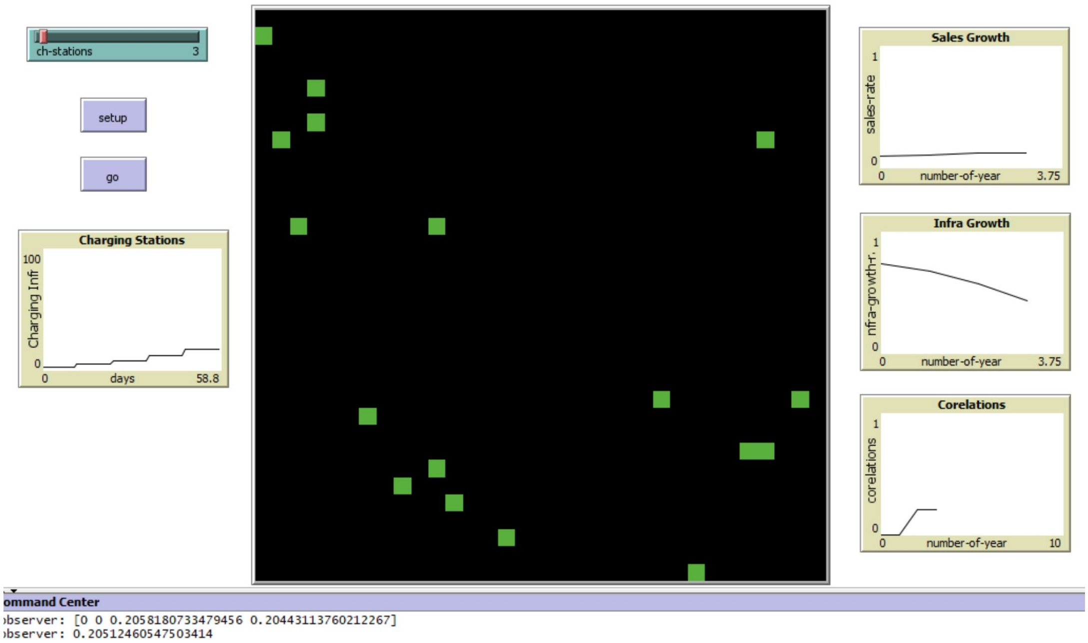

Fig 3: Results of the model using low charging infrastructure value showing average correlation value as 0.20

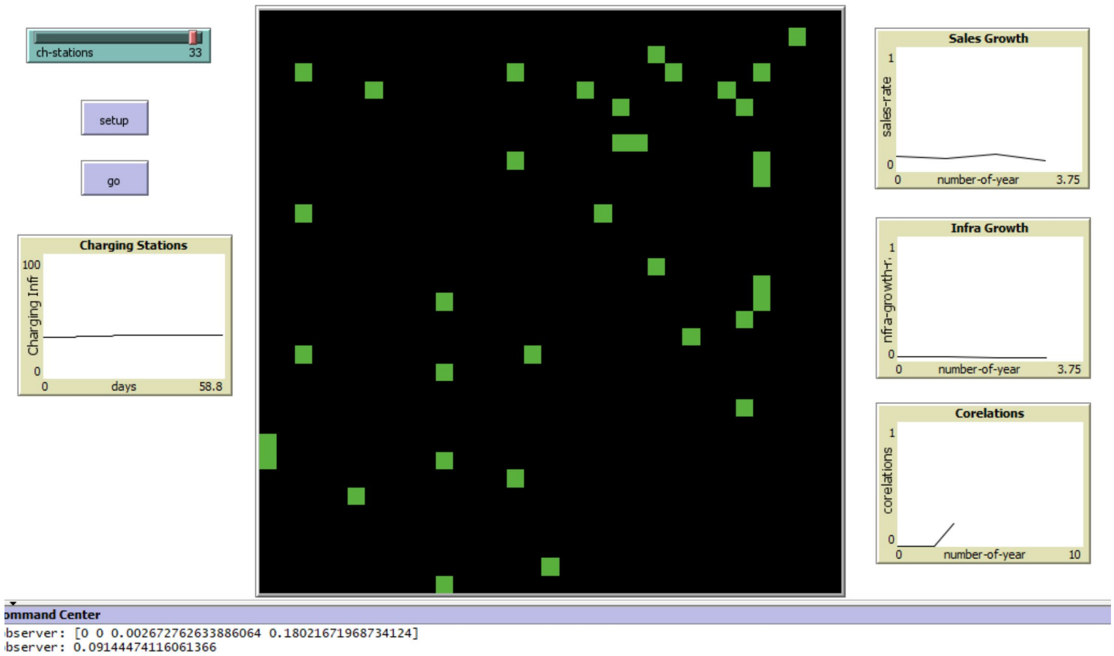

Fig 4: Results of the model using higher charging infrastructure value showing average correlation value as 0.09

Discussion

The model's output shows that there is not a significant relationship between sales growth and the rate of charging infrastructure growth, as the final correlation values are significantly lower and below 0.2 in the majority of runs.

One of the reasons for this might be the stochastic approach used for sales growth prediction. The sales growth rate in the input data has also been majorly affected due to COVID-19 wherein the rates are not as high as it was expected and it also impacts some of the growth of charging infrastructure.

Another important factor is the exclusion of the existing personal or workplace charging stations due to which the number of charging infrastructures currently being recorded is not as realistic. The data used in the model currently includes all types of public alternative power stations in California, but it does not account for the charging stations that people might have at their homes, workplaces, or any other property that is not deemed public. Due to this, the number of charging stations in the model is significantly lower than in reality due to the absence of records of the private charging infrastructure, which might have led to a lower correlation than expected.

One of the limitations of the model is the number of charging infrastructures that can be chosen to initialize the model. The model currently has a slider that allows values from 1 to 35 but produces output for values between 2 and 34. This is due to the logistic function used in the model, which restricts the charging infrastructure values. In the first case, when the charging infrastructure value is initialized as the exponential of the logistic variables results in a value higher than 0.5, which in turn makes it difficult for correlation to be calculated in the model. When a value like 35 is applied to the model, the exponential goes below 0.02, which obstructs the model from giving out its desired output.

The model can be extended firstly by using a comprehensive number of charging infrastructures that include all the charging infrastructure available in the environment being considered. The data file can also be changed to add multiple years for past data along with different data from various locations. Another improvement in the model can be made in sorts of predicting the sales growth rate. In the above model, a simple normal distribution has been used for the sales growth with the basis of the input data files, but a better approach can be used for ascertaining accurate sales growth rates.

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