Summary (Team 85679)

It has become increasingly apparent in modern society that there are environmental risks associated with many of the conventional technologies that we rely on. As a result, there is an urgent need to redesign many of these technologies. One main example of this is the automotive industry, since many people rely on cars as a primary means of transportation and because (conventional) cars use significant amounts of fossil fuels and contribute to pollution in urban areas. There are already several alternatives to conventional vehicles, including biofuel, electric cars, and public transportation. Here, we shall focus on electric vehicles. Though there are still many technological hurdles to overcome, all of the design efforts that led to the development of such vehicles will be fruitless if not enough people adopt these new technologies.

Governments have tried giving incentives to people who buy electric vehicles, but studies have shown that even this will not be very effective unless certain attitudes change. Important factors in this include familiarity with the technology, availability of charging stations, and a sense of environmental urgency. In this paper, we seek to model the effects of such factors in an urban environment over time. Using graph theory and agent-based modeling, we have succeeded in creating a flexible and relatively fast computational model of the ways in which people are influenced by their neighborhoods and cities to buy electric vehicles.

Handout for International Energy Summit

To whom it may concern:

One of the most pressing issues regarding energy consumption is the automotive industry because of how heavily many people rely on cars for transportation and because of the environmental impact that it has. Several alternatives to conventional vehicles are already available. One of the main alternatives available now is electric vehicles. There are still many technological hurdles for electric vehicles to overcome, but one very important factor is social rather than technological: how do we convince people to adopt such technology? One solution is to provide government incentives, but previous work has shown that these alone are not very effective at convincing people who would otherwise not be willing to buy electric vehicles because of other barriers, such as lack of familiarity with the technology.

As a way to answer this question, we propose a computational model that uses agent-based modeling to consider the decisions that go into buying an electric vehicle, such as cost, familiarity, and feasibility of travel. Agent-based modeling is useful for this problem because many of factors that influence the decision to buy an electric vehicle are based on the attitudes and environment of individual agents.

In particular, our model works well for this sort of simulation because is flexible enough to take in data from various communities, and if other factors are shown to have a large impact on this decision, such factors can be added to the agent's decision script. In addition, our model runs relatively fast ($O(a(n \log n))$ time, where a is the number of agents and n is the number of neighborhoods), which means that we can run a simulation on 700 neighborhoods and 7,000 agents in a matter of minutes rather than days. We developed a tool that successfully modeled human behavior in car purchases, and while it may have not yielded significant results in charging station placement function evaluation, it may be useful if we are able to make various improvements.

Sincerely,

ICM Team #85679

Modeling Large-Scale Adoption of Electric Vehicles

ICM Contest Question D

Team # 85679

October 4, 2023

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1 Introduction

As the threats of pollution, climate change, and resource scarcity become ever more imminent, it is becoming apparent that part of the solution must be to redesign the way we go about our lives. In the case of fossil fuel consumption from conventional vehicles, several alternatives already exist, including biofuels, public transportation, and electric vehicles. It is this last alternative that we will address in this paper. In this case, though there are still several disadvantages to having an electric vehicle, such as limited battery life and not enough charging stations, the technology does exist, and using an electric vehicle as a primary mode of transportation is becoming increasingly feasible. Thus, creating alternative technology is only part of the solution; in order for the technology to improve the quality of the environment, it must be used on a wide scale. In this paper, we seek to model how people decide to adopt such technologies

2 Background

There has been a large amount of research concerning factors that influence people's decisions to buy electric vehicles. There are too many factors to include here, but some of the main factors that motivate the adoption of electric vehicles are listed below. Surprisingly, government incentives do not seem to be very effective at convincing people who would not otherwise buy electric vehicles to start driving them, so it is important to figure out what does motivate people to adopt this new technology.

In a 2015 paper by Haddadian, et al., the authors list several factors that impact the consumer's decision to buy electric vehicles [3]. As one might expect, among the challenges facing the industry, they list the limited range of lithium ion batteries and limited availability of charging stations. Another unsurprising factor that was mentioned was the consideration of cost, particularly the question of whether the significant decreases in fuel and maintenance costs make up for the cost of buying a new vehicle. According to Haddadian, et al., it would take six to eight years to make up for the cost of buying an electric vehicle, which is longer than the three to five years for which the typical owner keeps a given car.

Another barrier to widespread adoption of electric vehicles, studied by Egbue and Long, is the uncertainty in a new technology [2]. This means both uncertainty in the reliability of such technology as a reliable method of transportation but also uncertainty that buying an electric vehicle would be beneficial enough for the environment to be worth the cost. Egbue and Long write that this continues to be a barrier even with the existence of government incentives and increasing gas prices, citing a study that claims that about 50% of Americans are averse to new technology.

In the Netherlands, Bockarjova and Steg use Protection Motivation Theory to explain the increasing adoption of electric vehicles [1]. Protection Motivation Theory is usually used to explain people's responses to more imminent threats, but it can be more widely applied to explain how people adapt when confronted with other risks. As Bockarjova and Steg write:

> A distinctive feature of Protection Motivation Theory is that the model assumes that individuals consider current behavior as well as their expectation of a new behavior in terms of respective costs and benefits when making pro-environmental choices. This way, Protection Motivation Theory allows identifying both barriers and facilitators to adoption of protective behavior.

Bockarjova and Steg were able to use this model to show that an increase in anticipated severity of risks posed by continuing to use conventional vehicles and an increase in people's perceptions of their own vulnerability to these risks both increase the adoption of electric vehicles more than government subsidies do.

3 Model Structure

3.1 Overview

For the structure of our model, we built from the work of O'Sullivan's 2008 paper on agent-based modeling for situations regarding human behavior [6]. We started from a simple, abstract model with a city modeled as a graph of regions connected by roads which take a certain amount of time to traverse. Each region has a set number of agents who live there. Each agent has a randomly - determined workplace and a weekly schedule in which each agent begins and ends each day at home, goes to its randomly-determined workplace every weekday, and has some other randomly - determined set of destinations that it travels to on a given day.

One of the primary factors that influence the agents in our model is the availability of charging stations along the routes that make up their weekly schedules. If an agent encounters many charging stations along its weekly route, it will be more likely to consider electric vehicles as a viable mode of transportation. Likewise, if the distance between charging stations on an agent's route is significantly less than the distance an electric vehicle can drive on a single charge, buying an electric vehicle will seem like less of a risk than if the distance between charging stations is only slightly less than the distance an electric vehicle can drive on a single charge. (If the distance between charging stations along this route is more than the distance an electric vehicle can travel on a single charge, it is infeasible for the agent in question to use an electric vehicle as a primary mode of transportation, so the agent will not buy one.)

There are several factors that might affect an agent's decision to buy an electric car. As was mentioned in the background section, one of these factors is lack of knowledge of the new technology. While it would be very difficult with this model to measure how convinced agents are that electric vehicles are significantly better for the environment than are conventional vehicles, we can measure some aspects of increasing familiarity. As part of our model, if agents in a given neighborhood already own an electric vehicle, the idea of owning one will be less foreign and other agents in the neighborhood will be more willing to buy one of their own. Additionally, if even more agents in the neighborhood buy electric vehicles, their neighbors will be even more likely to start driving them.

3.2 Implementation

The area that we are modeling is represented as a graph, where the nodes represent neighborhoods and the edges between these nodes represent roads between these neighborhoods. Our graph interface was based on Lynn Root's project "Python implementation of Dijkstra's Algorithm" [8]. Cities are represented by clusters of neighborhoods that are near each other, and most agents' activities are confined to that agent's city. Each agent is assigned a home and a workplace within a city. Each agent also has a weekly schedule in which the agent starts at home, travels to work, travels to between one and five other places at random within the city, and returns home for five days out of the week (the work week). For the remaining two days (the weekend), each agent leaves home and travels to between one and ten randomly-assigned locations, and each location has a 90% chance of being insides the city and a 10% chance of being in another city. The agents' routes among nodes in the graph are determined using Dijkstra's algorithm, which is widely considered to be a very efficient method for determining the optimal path between two nodes on a graph. The implementation of Dijkstra's algorithm that we used for this model was taken from Aleksey Kachayev's GitHub Gist [4].

At the beginning of our simulation, a set number of agents have electric cars, and a set number of neighborhoods contain charging stations. Agents are assigned to their home neighborhood, work neighborhood, and schedule of neighborhoods to visit throughout a theoretical week. Agents are grouped into neighborhoods (based off of their home neighborhood) and work areas (based off of their work neighborhood). At each iteration of the simulation, each agent follows its scheduled path and determines if it is feasible to travel this path with an electric vehicle, i.e., if the distance between charging stations is short enough that the agent can follow the schedule without running out of battery. In any given neighborhood and work area, if enough of the agents have purchased cars (based off a threshold set by the user), then all the agents in that neighborhood and work area will desire cars. In addition, a small proportion of additional agents may spontaneously desire cars based off of random chance. If an agent desires a car and finds buying a car feasible based off of their schedule, then they will buy a car at the beginning of the next week. Over time, more neighborhoods build electric charging stations based off of a station development plan passed into the program, and we measure the effect that this has on the number of agents who own electric cars.

The overall point of our implementation is to test input functions that describe how to place charging stations and when. Currently, our model only supports determining a probability of a neighborhood starting out as a station, as well as a probability a neighborhood will become a station at some point during the simulation. This is implemented by randomly determining whether or not a neighborhood will start out as a charging station or will become a station later on a neighborhood by neighborhood basis. If a neighborhood is set to become one throughout the simulation, it is randomly determined which week that will happen. While this type of charge station placement function is extremely basic, it may lead to general insights about, generally, how many stations to construct immediately, and at what rate to construct them beyond this. In addition, our program could be fairly easily adapted to consider more well-defined schedules given more code development time. Future work could strive to improve our program in this manner.

3.3 Real-Life Data

When running our simulation, we decided to use real data from South Korea to make our model more concrete. Specifically, we looked at data from the nine most populous cities, which contain about 50% of the total population of South Korea. The data we used were from the website City Population [7]. To incorporate these data into our model, we took the area of each of these cities and gave each of our model's cities a number of neighborhoods proportional to the corresponding city's area. We also set the distances between cities to the actual distance in kilometers between the corresponding Korean cities. We make the assumption here that the number of people in a large city who can afford electric vehicles is proportional to the total population of that city. In addition, we set the maximum distance between charges to the actual number of kilometers that a Tesla can currently drive on a fully-charged battery.

3.4 Advantages

One of the advantages of this model is its flexibility. We have set it up to work for South Korea, but we could easily change many of our parameters. Most importantly, we could change the number of cities, the number of nodes for each city, and the distances between each city to fit data on any country.

Another advantage of this model is that it does not take unreasonably long to run, which sometimes happens with simulations such as these. We consider the inputs to the problem to be the number of nodes in the graph, n, the number of edges in the graph, e, the number of iterations in the simulation, i, and the number of agents, a. Construction of the graph simply requires creating every node and edge, which should take $O(n+e)$ time. However, since the number of edges is only a constant factor larger than the number of nodes, this can be simplified to $O(n)$. This graph can be used to run a number of simulations. For every simulation, additional setup is required to set up agents and neighborhoods (which are used to model social influence) as well as schedules for the agents. For every agent, we generate a schedule which consists of seven days (to simulate a week) with some constant number of events per week. Additionally, agent information is stored in a dictionary of neighborhoods. Thus, each agent creation takes constant time. So the entire set up takes $O(a)$ time.

Next, we look to execution runtime. Since we are using Dijkstra's algorithm to find the shortest path between two points, this process will take $O(n \log n)$ time, where n is the number of nodes[1] for each agent, so the first iteration of the algorithm will take $O(a(n \log n))$ time, where a is the number of agents. However, instead of recalculating the best path between nodes each time, we store every path that we calculate in a hash table, so we can avoid spending time on repeating calculations. Therefore, every iteration after the first one will take $O(a)$ time. Thus the entire simulation takes $O(a(n \log n) + ai)$.

Evidently, the simulation part of the process takes strictly longer than the set up required. Thus the overall runtime of the program is $O(a(n \log n) + ai)$. Note that this is polynomial in all of our inputs, and in fact, is less

[1] Actually, the runtime of Dijkstra's algorithm is $O(e \log v)$, where e is the number of edges and v is the number of nodes, but in our case, the number of edges is proportional to the number of nodes, so its runtime will be $O(n \log n)$ for n nodes.

than cubic in our input size. Thus, this is an efficient algorithm. However, it is noteworthy that fine resolution inputs to our algorithm require large graphs (a resolution of one square kilometer per node requires 7000 agents, and that is not a very fine resolution) and even more agents. In practice, our algorithm does require minutes to run on smaller inputs, but should not exponentially increase for larger inputs.

4 Results

We ran a number of tests to evaluate the effectiveness of our model. Note that for every test that involved the same probabilities for initial and future charging station placement, the graph was only generated once. Different instances of graph generation with the same input parameters do not vary the structure of the graph, but they do vary in terms of the different placement functions. In other words, different trials then represent different agent placement and agent schedule generation, not different station placement functions, although regeneration of graphs would be able to do this if desired.

As a control group, we started by running some simulations where every node has a charging station. That is, it is feasible for everyone to travel to every destination using only electric vehicles, so the only factors at play are social influence and increasing familiarity. We created a plot to visualize how the number of car owners increase over time in this situation. This was graphed over a 52-iteration timespan across three different trials. The results are plotted in Figure 1. This shows that, if we can guarantee that there are enough charging stations, social influence and increasing familiarity increase agents' willingness to buy electric vehicles. This is seen in the increase in growth rate in the graph over time. Note the three different trials all seem to agree on the results.

We also graphed the increase in car ownership over time in simulations involving more intricate charging station placement functions. Across these trials, the probability that a neighborhood gains a charging station at some point during the simulation is 0.10. The probability that a neighborhood starts with a charging station is set to, 0.01, 0.05, and 0.10 across the three trials. Each trial was run over 10 iterations. Our results can be seen in Figure 2. Results are similar to that of our first test, however we did not allow the simulation enough time to converge to 100% car ownership, if that would even happen under this model.

It is possible, depending on which nodes were randomly selected to

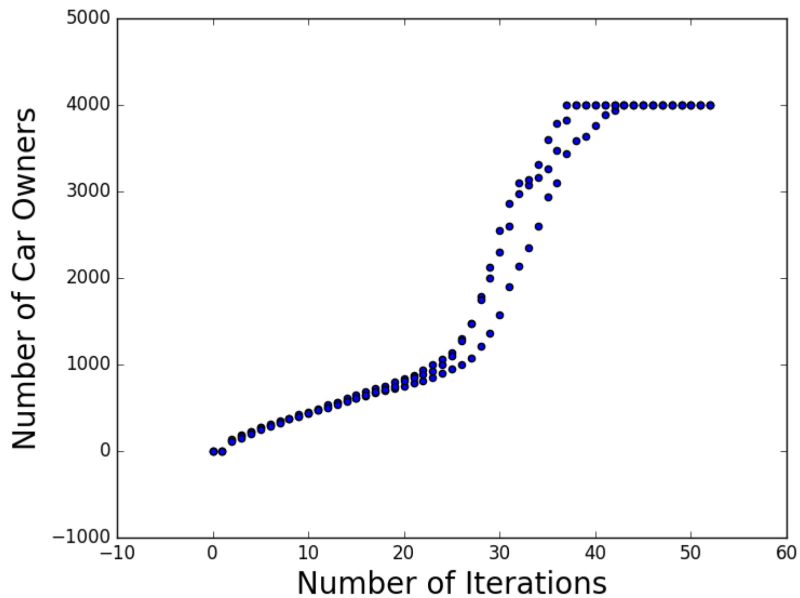

Figure 1: The graph above shows the results for the simulation if every node has a charging station. After running three simulations, the results show that as more people in each neighborhood own cars, the growth rate in number of electric car owners also increases.

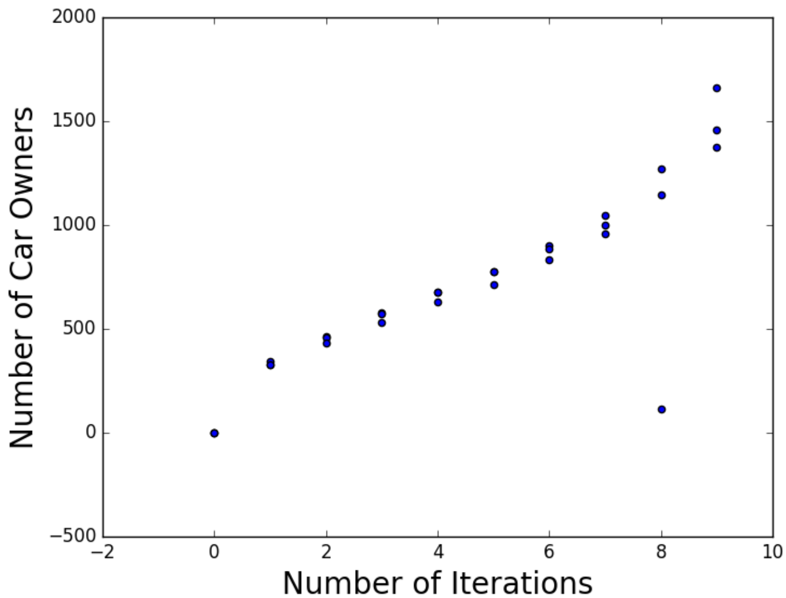

Figure 2: The graph above shows the results for the simulation if every node has a 10% chance of gaining a charging station during the simulation, and varying probabilities of starting with a charging station. Like Figure 1, after running three simulations, the results show that as more people in each neighborhood own cars, the growth rate in number of electric car owners also increases.

start with or at some point have a starting station, that it is impossible for some agents to be able to buy a car, given their schedule. Thus for the given graph set up, it is possible the car ownership would never converge to complete ownership. However, continued randomized graph generation would develop many different station placement functions, some of which may converge to complete ownership eventually. But not all will.

In addition, we ran some tests to determine how varying charging placement schedules affect car ownership over time. We ran 10 iterations per trial. First, we tested how varying the probability of a neighborhood starting with a station affects the number of agents with cars. To simply isolate this element of the station placement function, we set the probability that a neighborhood would eventually gain a station to zero. Therefore, our neighborhoods either start with a charging station or never have one.

In this trial, we found no correlation between charging placement schedules and proportion of car ownership in the overall population or among those who wanted electric vehicles. This may be because there was too much randomness and noise in our model. In the future, we could run more tests with a greater degree of control over this randomness or run longer tests in order to reduce the amount that noise contributes to our final results.

5 Limitations

Because our model is so simplified and focuses on factors that are easily visible from the outside, such as availability of charging stations, it ignores some other, more internal factors that might also be important. For example, our model does not take into consideration the sense of environmental urgency that an agent might have, even though this was mentioned as an important factor in the background section. Also, in our model, agents never stray from a path from one destination to another in order to visit a charging station. While it may be less convenient to actively seek out a charging station, a model that allowed agents to stray from their paths to go to a charging station would likely result in more people buying electric cars.

There are also more concrete factors that are heavily simplified in our model. For example, our model doesn't concern people who live in rural areas, the suburbs, or even small cities, and people who live in less densely-populated areas probably rely on cars more heavily and have to drive longer distances than people who live in large cities. We also assume that everyone has a set weekly routine, so we are overlooking the cases where people want the option of leaving the city occasionally but do not want to do so every week. We also did not take into consideration at-home chargers, although this could probably be implemented without much more difficulty. Finally, we assume that people who are wealthy enough to afford electric vehicles are evenly spread within a city and among cities. To remedy this last oversight, we could probably find data on wealth distribution in South Korea or whichever other country we are modeling and use them to determine the number of people in each neighborhood individually, instead of giving every neighborhood the same number of people.

In addition, our model assumes that cars are the only method of transportation between nodes. Further work might be done to determine how our results would change if we included the option of public transportation or other modes of transportation. It seems likely that this would depend on the infrastructure of the city or country in question. For example, in Seoul, which is relevant to our location-specific model, has one of the best public transportation systems in the world [5]. Hence, if our model took this into consideration, there would probably be less widespread adoption of electric vehicles because Tesla and similar companies would have to compete with the public transportation system.

Finally, our model allows people to stop at every possible charging station with no cost or disadvantage associated with it, when in reality, it would take at least 30 minutes for even the fastest charging stations to refuel an empty battery. Stopping at every station, then, is inconvenient and time-consuming. Thus, this model could be improved on by having the agents evaluate the cost both in money and time of stopping at a charging station, especially compared with a conventional vehicle.

6 Conclusion

We have successfully developed a model that allows people to input station placement functions in a simplified map of South Korea. Our model contains a fair amount of variability that can affect the results of running trials, so a large number of trials are required to gain significant results. It also requires a large graph in order to get a decent resolution over the map of South Korea. However, as we showed in the runtime analysis section, our solution actually runs pretty quickly. Therefore tool is efficient and would be a viable option for use in industry to verify station placement functions.

Theoretically, our tool is useful because it models the interactions and desires of individual agents. Many mathematical models fail to consider this dynamic. It takes into account the influence of individuals on other individuals by having agents automatically desire to buy a car if enough other agents in their neighborhood or work area already have a car. Some additional randomness is incorporated at each iteration of the simulation in that each agent has a small chance of spontaneously desiring a car.

But the most important insight of our model is that agents keep track of the feasibility of buying a car based off of their ”weekly routine” (modeled by their schedule per iteration) and charging station locations. This is vital in terms of evaluating a charging station placement function. It ensures that, in order to have a good placement function, there must be enough charging stations placed on agents' scheduled routes as they begin to desire cars. This is how our program attempts to model the importance of dispersing placement functions. In addition, the fact that agents mostly travel within their own city, but some occasionally visit other cities, attempts to model the requirement that charging stations need to be placed on the roads between cities, but that this may be less necessary than having such stations inside of cities.

In our results section, most of our success comes from how the development of car ownership over time seems to reasonably model how demand for cars increases. For a plan that places all charging stations at every neighborhood, whether or not people buy cars is entirely based upon social factors. Our model depicts what looks more or less like logistic growth, starting with zero car ownership after the first week, and eventually converging to complete car ownership. This result seems like a reasonable model of social influence in communities.

Unfortunately, we failed to get significant results when evaluating placement functions that vary in how fast they place charging statements. As stated in the Results section, this is likely due to too much randomness in the scenario development. If we run this on a larger number of trials or reduce the impact of randomness in our program, both of which are doable, we may find significant results.

Ultimately, the program with the current evaluation in its current state, has not shown to produce a good measure of placement function effectiveness. However, given more time, further evaluation on more trials could exhibit that this model can, in fact, evaluate placement functions correctly. In addition, there are a number of improvements that could be made to the program. This could include the reduction of the impact of randomness in the algorithm, the application of social models to represent the spread of car desirability in a community, a more intelligent function for agent placement function (ie, have some nodes represent denser populations in a city and place more agents there), and so on. But even as is, there are a number of parameters, input country statistics, granularity of graph representation, charging station placement function parameters, neighborhood car desirability threshold, and more, that make our model robust and able to represent a vast range of situations.

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