Simulating Population Behavior: Transportation Mode, Green Technology, and Climate Change

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Abstract. This paper presents a decision tool intended to help achieve the goal of reduction in Green House Gas (GHG) emissions in the greater Philadelphia region by the year 2050. The goal is to explore and build a pre-prototype to evaluate the value of the role for agents, alternative data sources (Census, energy reports, surveys, etc.), GIS modeling, and various social science theories of human behavior. Section 2 explains our initial research on an Agent Based Model (ABM) built upon the Theory of Planned Behavior (TPB) and the Discrete Decision Choice model (DDC) to model consumer technology adoption. The users can utilize the proposed ABM to investigate the role of attitude, social networks, and economics upon consumer choice of vehicle and transportation mode. Finally, we conclude with results on agent decisions for which transit mode to use and whether to adopt greener technologies.

Keywords: Agent Based Models (ABM); decision-making process; climate change; energy use in transportation; technology adoption

1 Introduction

The purpose of this research is to build a tool to help the greater Philadelphia region establish carbon emission reduction goals by 2050. Following a standard complex adaptive systems approach, we propose to research, design, construct, and validate an agent based model (ABM) as this tool. In an earlier paper, we discussed the types of policy issues such a tool should help decision makers to evaluate, and we return to that topic at the end of this article in the wrap up [1]. We posit that individual people and their micro-decision making are going to determine the macro-behaviors that emerge in terms of technology adoption and usage to impact the GHG problem. So this paper focuses on the agent model rather than policy choices.

ABM has emerged as a powerful analytical and computational method for studying complex adaptive systems and understanding of micro processes and their emergent consequences at the macro level. This new method offers a flexible architecture that allows for a detailed representation of complex agent systems, including the behavior

adfa, p. 1, 2011.

of agents, their social interactions and the physical and economic environments surrounding them. Agents represent discrete decision-makers as individual people and aggregates of individuals. These agents are simulated by autonomous entities with individual characteristics and independent internal decision making processes. Modeling this behavior provides better understanding and predicting of real world agents' decision making processes. In sum, ABM is an experimentation tool to study and demonstrate diffusion patterns resulting from simple decision rules followed by different agents in the system [2-8].

This paper describes our progress to date in prototyping and studying how ABM can work to accomplish the goals of the tool for supporting Delaware Valley Regional Planning Commission (DVRPC). We are just at the beginning of this research, and we are still experimenting with alternative ABM ideas and formulations, some of which we report here. We then present the baseline model of DVRPC transportation and forecast CO_2 emissions to 2050 in the case of business-as usual. This reveals how much CO_2 needs to be reduced to achieve 80% target. We then turn to some experiments with modeling of agents and present a couple of approaches we have investigated to date. Lastly, we conclude with lessons learned and ideas for the desired tool.

2 Theoretical Background

The Theory of Planned Behavior (TPB) states that "human behavior is the result of the intention to perform the behavior. In turn, the intention itself is driven by the individual's attitude toward the behavior, subjective norms, i.e., perceptions about social expectations and pressure, and perceived behavioral control (PBC), i.e., the individual's perception of her ability to actually perform the behavior. Thus, as a general rule, the more favorable the attitude and subjective norm, and the greater the perceived control, the stronger should be the person's intention to perform the behavior in question". In sum, considering control as an economic attribute, then human actions are led by three variables including attitudinal, social, and economic variables [9].

However, TPB is usually considered as a static model of behavior. Although TPB considers the effect of attitude, social norms, and control in intention, and in turn the effect of intention in actual behavior, it ignores the change of these factors over time and the related change of intention accordingly. Therefore, to compensate this ignorance of changes, we should consider evolving agent variables while integrating TPB in the ABM [5].

To investigate the process of individuals' behavior change over time, we use Dynamic Discrete Choice (DDC) model. In practice, DDC models are among the most sophisticated approaches for analyzing consumer choice. Benefiting from a time component, DDC considers intertemporal tradeoffs. DDC models can be utilized to study the impact of individual decision-making processes on system outcomes due to considering individual as the unit of analysis in these models [9].

In practice, social networks play an important role in leveraging individuals' awareness level. In fact, networks provide individuals with information about the state-of-the-art technologies including energy technologies, the cost and benefits of such technologies and the tendencies to adapt new technologies and accordingly new pattern of behaviors. Previous studies show the importance of peer influences on individuals' behavior, e.g., adoption of hybrid-electric vehicles. In the TPB theory, decision making process is highly affected by economic aspects. However, along with economic aspects, the awareness regarding affordability or lack of affordability to adopt a technology is also highly important in the decision making process. In practice, payback can be considered as a key factor in adopting a new technology as does perceived adoption obstacles [5].

2.1 The Agent Based Model

Agent choices to change mode or adopt new technology are made by changing the option that scores highest in all three components. This is Eq. 1 which shows the three terms of the TPB model. In the current prototype, the attitude component (Eq 2) is set based on a function of political party archetype and awareness level, the social component based on the percentage of users in the agent's network (Eq 3), and the economic factor based on the upfront costs, payback period, and obstacles to adoption (Eq 4 and 5). In our model; we have four groups including active, aware (sympathetic towards the environmental movement), unaware, and negative aware. There are negative information centers and information centers on the agent landscape that influence the nearby agents who might happen to come in contact. Agents chose whether to adopt green technologies based on an economic factor and how many of its neighbors have adopted, and overall climate attitude. All of these hold equal weight in the decision to adopt.

To illustrate, we simulate the adoption rates of four vehicle types (VT) including a hybrid-electric vehicle (HEV), a plug-in hybrid-electric vehicle (PHEV), a battery electric vehicle (BEV), and a conventional vehicle (CV). In our model, agents are created based on the number of households in the census tract. Households are given an education level, income, political affiliation, and number of vehicles owned based on census tract data. What follows shows the model for vehicle adoption.

Equation 1 is used to compute the utility of or the intention for each vehicle type. For three type of vehicles (HEV, PHEV and BEV), attitude, social and economic factors are evaluated using equations 2-4. However for CVs, attitude and economic factors are extracted using equations 6-7.

In Equation 4, ticks represents the duration time of simulation (in years) and this term causes obstacle impacts to be reduced over time. Also in this equation, α_{VT} is different for each vehicle type to reflect alternative rates of improvement of the technologies. This value is 1.3, 1.32, and 1.35 for HVs, PHEVs and BEVs, respectively. For these three vehicle types, equation 5 evaluates the payback where β_{VT} is considered as 12 for HEVs and 16 for PHEVs and BEVs to reflect differences in upfront cost for charger and battery.

$$Intention_{VT/MC} = \frac{1}{3}\left(Economic\_Factor_{VT/MC} + Social\_Factor_{VT/MC} + Attitude\_Factor_{VT/MC}\right) \quad (1)$$

$$Attitude_{VT/MC} = \frac{1}{2}(Political\ Party + Awareness\ Level) \quad (2)$$

$$Social_{VT} = \frac{Number\ of\ VT/MC\ in\ network}{Number\ of\ Vehicles/MC\ in\ Network} \quad (3)$$

$$Econimc_{VT} = (0.17 * Financial\ Factor + 0.5 * Payback\ Period + 0.33 * (100 - Obstacles\ To\ Adoption + ticks^{\alpha_{VT}})) \quad (4)$$

$$Payback_{VT} = (-2 * gas.price + \beta_{VT} + Unif\ (0\ ,4)\ ) \quad (5)$$

The literature indicates that liberals favor green technologies [10]. Census data shows political affiliations which are captured in our census tract agents. Political party score is set to Republican (25), Independent (50), and Democrat (75). This causes liberals to care about VTs (HVs, PHEVs and BEVs) in equation 2. We also utilize equation 6 to reflect lower attractiveness of CVs to liberals relative to other VTs.

$$Attitude_{CV} = \frac{1}{2}((100 - Political\ Party) + Awareness\ Level) \quad (6)$$

Political Rating gives a positive affinity for CVs and obstacles to adoption and payback period both are zero for CVs. Also the tick is omitted from equation 4 for CVs. The obstacles to adoption value simulate common reasons a household would avoid buying a different type of vehicle. For example, “range anxiety” and lack of charging infrastructure available are two common reasons listed for not buying BEVs or PHEVs. The tick term in equation 4 tends to reduce these obstacles as the technology matures.

Price strategy also affects mode choice (MC). In practice, short-run fluctuations in gas price may lead to temporary changes in driving behavior (e.g. traveling at more fuel-economical speeds, avoiding rapid accelerations and breaking, making fewer trips or switching to other modes including public transportation, walking, and bicycling). However, consumers might return to old driving patterns when gas prices return to their previous level. On the other hand, long-run changes in gas price have more permanent effects on vehicle miles travelled and gas consumption (e.g. via buying a more efficient car, switching to an alternative fuel or hybrid vehicle, or increase of the tendency of living close to work places). Studies show that higher gas prices decreases GHG emissions from vehicles, improves air quality with benefits for health, and reduces congestion, with benefits for the economy [11].

Equation 1 is used to compute the utility of or the intention for each mode choice including vehicle (V), bike, walk, or public transportation. For each VT mode choice (MC), attitude and social factors are evaluated using equations 2-3. For three other types of mode choice (walk, bike, and public transit), economic factors are extracted using equation 7. For these three MCs, β is considered as 30 for walk and 27 for bike and 31 for public transit using equation 7. For all vehicle types, economic factor is extracted using equation 8.

$$Econimc_{MC} = \\ 1.5 * (\beta - distance\ to\ work) + Unif\ (0, 2.5) \quad (7)$$

$$Econimc_{VT(MC)} = \\ distance\ to\ work + 10 * \left(\left(1.5 + \left(2.5 - (0.5 * gas.price)\right)\right)\right) \quad (8)$$

3 ABM MODEL EXPERIMENTS

In this section we experiment with ways to extend the baseline model so as to add the agents with the aforementioned preferences for alternative transportation modes and environment quality. A guiding principle in the design of agents is to Keep It Simple, Stupid (KISS). Following KISS, we will look at a few discrete agent differences, mostly linear approximations, and very few choices. At this stage, we are just testing ideas and approaches and can always make things more sophisticated later if we find ideas that are useful.

3.1 Transportation Behavior Model.

A map of the DVRPC region is created and divided into census tracts. As shown in Figure 2, for the current model, initially a map of the DVRPC is split into 5 zones based on the population density data. Zones consist of census tracts with population (1,000s) per acre density; Zone 1 (0-20), Zone 2 (20-40), Zone 3 (40-60), Zone 4 (60-80), and Zone 5 (80+). From these intervals, 1072 tracts are in Zone 1(Purple), 194 are included in Zone 2 (Light Grey), 77 reside in Zone 3 (Yellow), 20 include in Zone 4 (Orange), and finally 6 reside in Zone 5 (Red). Data is not available for the regions shown in black in this figure.

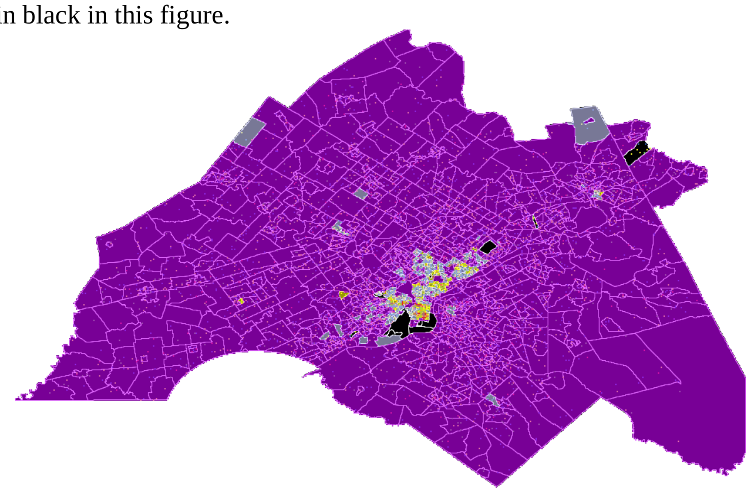

Fig. 1. Zones in DVRPC

As part of this research on agents, we are investigating different archetypes. We have three different political affiliations. Education levels are less than high school, high school graduate, some college or associate's degree, and bachelor's degree or higher. Income are put in five groups including under \$25,000, \$25,000 - \$49,999, \$50,000 – \$74,999, \$75,000 - \$99,999, and over \$100,000. People hold varying views and values about how they personally, and also their community, should manage sustainability tradeoffs. This has been widely researched in the climate change and sustainable development literature. As an example, a useful framework for considering people's values is described in de Vries et al [12] using the two dimensions (or axes) of globalizing versus regionalizing and private/material/market versus public/immaterial/government. The four quadrants have come to be known as: free market-oriented globalizing world (Global Market); the market-oriented protectionist world (Fortress); the government oriented globalizing world (Global Solidarity); and community-oriented regions (Caring Region). We also classify the agents along other factor sets such as, among others, level of being informed (important for informational campaigns) and willingness to change and adopt new technology, products, and behaviors: e.g. see [13].

Agents are created based on the number of total commuters within a census tract. For every 333 commuters, one agent is created due to limitation of personal computer such as memory and CPU. This agent is given an income level, social awareness level, transit mode, and commute time all based on relevant census tract information. Income level and commute time are set according to the median values for that tract. While transit mode is based off the percentage of each mode in that census tract. For example, if the census tract contains 60% public transit commuters, this agent has a 60% chance of choosing public transit as his initial mode of choice. Social awareness level is based on [14] so that the overall number of each type is in line with these numbers. The agent is also given a social network based on a preferential network either within the same social awareness level or solely with others outside of his awareness group. This social network is used to influence decisions on adoption rates and transit mode choices.

Change of Vehicle.

Strategies to promote adoption of BEVs, HEVs and PHEVs reduce air emission and oil dependency impacts from passenger vehicles. Initial vehicle types are set by the current market share of each relevant vehicle type. Each vehicle type is given an up-front cost, payback period, and obstacles to adoption value. Up-front cost is based on the average cost of each vehicle type currently on the market. The length of payback period is created by taking into account any additional costs to adopt, such as installing a home charging unit, and the current gas price, which is an input to the model. As the simulation progresses in years (ticks), the obstacles to adoption are decreased, as to simulate innovation and improvements in each technology that will occur over time (see EQ. 4).

Mode Choice.

To help DVRPC to exceed the goal of 80% reduction in the emission of GHG by 2050, it's vital for people to shift their mode from personal vehicle to walk, bike, or public transit. The decision criterion for transit mode is a function of distance to work, social awareness level, the transit mode of others within that agent's social network, and gas price. The simulation runs for 36 years, during which agents make decisions for which transit mode to use, and whether to adopt greener technologies. Adoption rate is modeled using equation 1.

3.2 Results Analysis and Discussion

As gas price is increased, the number of drivers decreases drastically (see Figure 2a). The number of walkers, transit riders, and bikers all increase at different rates when gas price is increased (Figs 2b-d). An increase of gas price from $3 to $5 results in about 150,000 less people using a car as their primary commuting mode. These 150,000 people convert mostly to transit ridership or walkers. This is 2.39% of DVRPC population (6,261,673 people).

The effects of the different social networks can be seen as the two sets of projections in each plot. There are 2 projections in each plot of Figure 2 – one for each type of network that is influencing the agents (internal vs external). When a person with a low level of social awareness is surrounded by a network of people who are more socially aware than themselves, then the person is more likely to make environmentally conscious decision. For instance, there are more people walking and less people driving when there is an external network type. This outcome can only happen when using the external network type. Networks composed of agents with similar social awareness levels only reinforce the behaviors to which they are already predisposed.

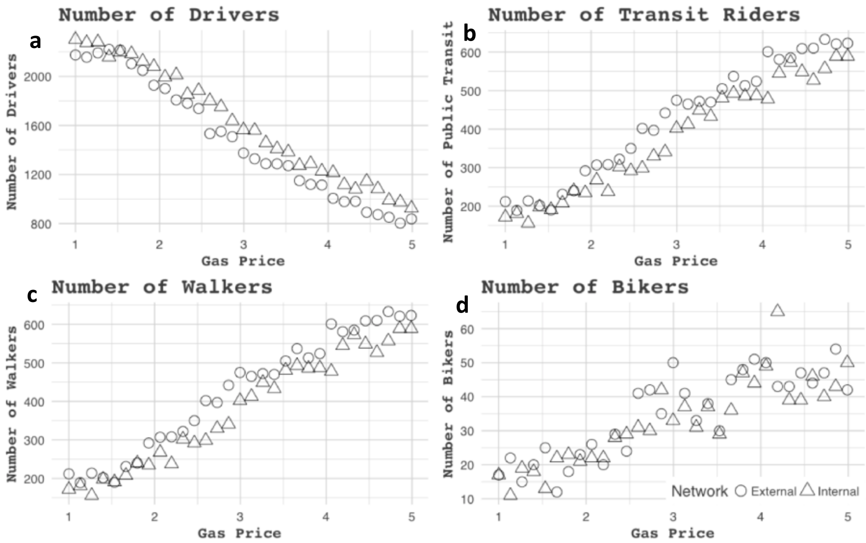

Fig. 2. The Roles of Social Network and Gas Price in Transportation Mode

Using the theory of planned behavior, each household will make decisions on which vehicle type to buy. Equation 1 leads the agents to compute an intention value for each vehicle type, purchasing the one with the largest intention. The decision to replace a vehicle varies according to a triangular distribution over 3 – 11 years. Therefore, each household will not decide on a new vehicle until their current vehicle is adequately used.

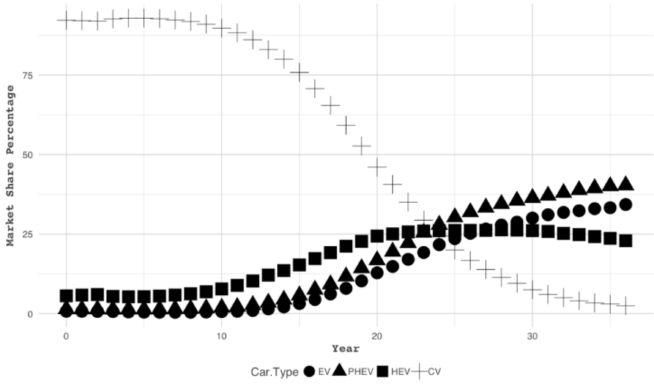

Fig. 3. Market Share of Vehicle Types

Figure 3 shows, the crossover point where CV is no longer the dominant vehicle type occurs around year 23, which corresponds to the year 2037. Initially, HEV is the main competition as the obstacles to adopt HEV right now are relatively low, and since the market share is currently highest. Thus, the social component is the strongest among all the other choices. However, as the simulation progresses both PHEV and BEV overtake HEV. This is mainly due to the simulated decrease in the obstacles to adoption. As the range of electric car batteries continues to improve and charging infrastructure is constructed, more households will gravitate towards PHEV or BEV. Assuming this technological innovation for PHEV and BEV continue, CV sees a significant drop in market share by 2050.

Based on these market share results, we can now estimate the GHG impact of agent mode choice and adoption decisions. The GHGs are estimated from three VTs (CV, HEV, and PHEV). The GHG or CO_2 emissions are calculated using equation 9 (Where VT_1, VT_2, and VT_3, represents CV, HEV, and PHEV respectively). Recalling that, each agent represents 333 households. Figure 4 shows the outcome. The horizontal line across the top is DVRPC's 2010 estimate of GHGs from vehicles. The predicted line shows a reduction of just over 50% by 2050.

CO2 Emissions =

$$\left(\sum_{i=1}^{n=3} \text{Number of } VT_i \, * \, \text{Average Annual } VT_i \text{ Emissions} \, * \, 333\right) \tag{9}$$

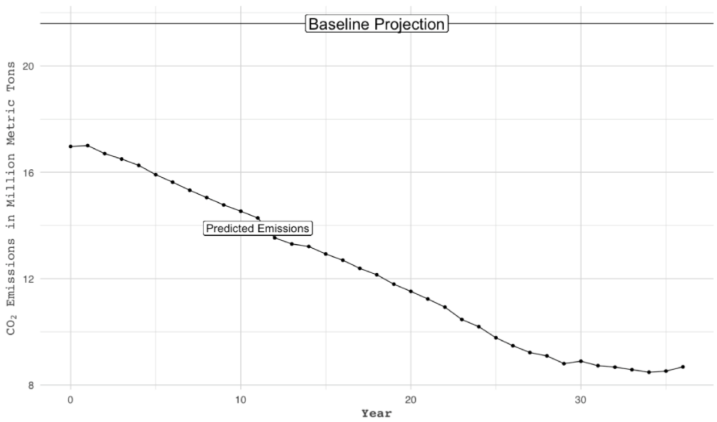

Fig. 4. Predicted CO_2 Vehicle Emission vs Baseline

4 Conclusion

As systems engineers, it is tempting to think that as better technologies become available for conserving energy and reducing GHGs, they will naturally lead to a better outcome. In Section 1 we reviewed a number of innovations for the transportation sector producing GHGs. But cities and regions are complex sociotechnical systems filled with people with divergent objectives.

Using a flat line forecast from DVPRC's 2010 Vehicle Emissions Report, we expect to be pumping 21.6 million metric tons of CO_2/year into the atmosphere from vehicles alone in the business as usual scenario. Using TBP and DDC discussed in Section 2, we have begun the effort to look how people will react to large social challenges. Section 3 then delved into the equations used to model the adopters of these innovations. The goal is to incorporate such theories within an ABM that can in turn help policymakers seeking to bring new technologies and approaches into the marketplace.

In section 4, we applied our agent model for transportation system to see if CO_2 emissions decrease relative to the baseline. We simulated our model and presented the simulation results. In transportation sector, the 51.17% CO_2 reduction that actually occurred relative to the baseline.

Pushing gas prices higher than $5/gallon and providing education and economic incentives for alternative transportation options appears to be needed to get closer to the 80 by 50 goal. Our future research will explore these issues further. Future work will also focus on the residential and commercial building sector to model households' energy behavior aiming at reducing CO_2 emissions through applying strategies such as moving towards green buildings, smart grid, and renewable energies. Finally, there were innumerable assumptions, significations, and guesstimates that needed to be utilized to get this prototype built. We need to go back and ground our equations more thoroughly by conducting surveys and more fully utilizing available data sets.

5 Acknowledgements

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