A Report from the University of Vermont Transportation Research Center

Multi-Scale Model of the U.S. Transportation Energy Market for Policy Assessment

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Table of Contents

List of Figures

1. Introduction

Across the globe, issues related to energy, its sources, uses, and impacts on climate change are at the forefront of political and environmental debates (e.g., the 2012 United Nations Climate Change Conference at Doha, http://unfccc.int). Currently, transportation accounts for approximately one third of greenhouse gas (GHG) emissions in the U.S., and is its fastest growing source [1]. Plug-in hybrid electric vehicles (PHEVs) offer advantages to both the environment and the consumer. By powering more transportation through the electric grid, PHEVs may significantly reduce GHG emissions [2-4]. The degree to which this can occur depends on current regional sources of electric power generation [5, 6], the ability of Smart Grid technologies to improve grid efficiency and reduce peak demands[7-9], and shifts in power generation from coal to cleaner sources, including natural gas and renewables (e.g., wind, solar)[10,11]. Potential vehicle-to-grid technologies could further reduce peak demands [12, 13] and therefore have a positive feedback on the grid efficiency. In addition, PHEVs and all-electric vehicles (EVs) have projected lifecycle costs that are much lower than either hydrogen fuel-cell or internal combustion engines [14]. From the consumer perspective, PHEVs can provide large savings in fuel costs without the range limitations of EVs; the EPA/DOT sticker data for the 2013 Chevy Volt states that the vehicle "will save $6850 in fuel costs over 5 years compared to the average new vehicle".

Despite the potential benefits of PHEVs, realization of these benefits ultimately falls on the consumers' willingness to purchase the new technology. In a 2008 survey, 69% of U.S. consumers surveyed had little or no familiarity with PHEV technology [15] and there are a wide range of concerns related to the batteries of electric drive vehicles (including EVs, PHEVs, and hybrid-electric vehicles), and the potential inconvenience of recharging [16-22]. While previous work indicates consumers are willing to pay a premium for greater fuel efficiency [19, 23], initial Volt sales have fallen short of projections [24], and are outcompeted by the otherwise similar gas-powered Cruze [25].

A wide variety of governmental regulations and incentives have been proposed or implemented to accelerate market penetration of PHEVs (www.afdc.energy.gov/afdc). Morrow et al. [26] discuss the effects of fuel taxes, increases in fuel economy standards, and purchase tax credits for fuel-efficient vehicles. They examine the sensitivity of fuel-efficient vehicle purchases using these approaches and predictions of the U.S. Energy Information Administration's National Energy Modeling System. They find that, in general, purchase tax credits are expensive and ineffective at reducing emissions, whereas the most effective approach for increasing fuel efficiency is to increase gasoline costs. Skerlos and Winebrake [27] examined the impact of tax credits for PHEV purchase, which were introduced in 2009 by the U.S. government and are available to all consumers equally in all parts of the country. The authors argue these tax credits would be more effective if targeted in certain geographic locations where PHEV technology offers maximum benefit, and if they were dependent on consumer income. Diamond [28] examined the relationship between hybrid adoption rates and governmental incentive policies in different U.S. states. His findings similarly indicate a strong relationship between hybrid adoption and gasoline price, but a much weaker relationship between hybrid adoption and government incentives.

While studies based on past data trends for HEVs and other fuel-efficient vehicles provide relevant insight, they are of limited applicability for estimating consumer response to the very different conditions associated with current-day adoption of PHEV technology. The plug-in technology offers new challenges to market penetration, and environmental attitudes and awareness are also very different than in past decades. While awareness of the role of vehicle emissions in global climate change is high in many parts of the world, it is not clear how consumers will weigh a vehicle's heuristically perceived benefits against rational financial considerations when making a vehicle purchasing decision. Consumer choices are not necessarily based on financially accurate assessments of alternatives [23], and values that affect consumer choices are often influenced by media and social networks [29-31]. Traditional discrete choice models assume a static distribution of decision strategies and do not support consumer behavior changes in response to social or other external pressures. However, recent variations of discrete-choice models have been proposed that demonstrate the importance of social or psychological factors [32] and 'neighbor effects' on consumer attitudes as the market share of a given vehicle type grows [33].

With this background in mind, the research goals of this project were as follows:

(i) To create a model to study potential PHEV market penetration in the personal transportation sector;
(ii) To assemble data to properly inform the model;
(iii) To develop methods for efficient up-scaling of model behavior;
(iv) To use the model to assess the sensitivities of system behavior to various policies and market conditions; and
(v) To understand the regulatory regime necessary to support widespread adoption of PHEVs.

We used various complex systems modeling approaches to tackle these goals. An agent-based model (ABM) of vehicle consumer choice was developed and used to explore sensitivities and nonlinear interactions between various potential influences on PHEV market penetration. By modeling individual vehicle consumers as agents, the model was able to account for a variety of internal feedbacks and spatial and social effects, including decision threshold effects, homophily, conformity, and media influences. Several different types of artificial neural networks (ANNs) were developed and employed for this project. We developed and compared a spiking neural network, with weights trained using an Evolution Strategies approach, to a generalized regression neural network for efficient up-scaling of model behavior. We also modified an ANN for visualization of clusters in high-dimensional data by adding a new cluster reinforcement phase to Kohonen self-organizing maps (SOMs) and applied this to a database we assembled regarding fuel efficiency in the Vermont passenger fleet. These new ANN methods have since proved useful in other engineering applications. To inform the ABM, we assembled data from the U.S. Census, the NHTS Travel survey, EPA, and many other sources and also developed and applied automated methods for scraping relevant data from websites including the New York Times, Cars.com, and a variety of other locations. Despite this massive search for data, we found that we were still lacking critical data regarding consumer attitudes towards PHEVs and underlying correlations and cross-correlations between consumer attributes and attitudes. To address this, we leveraged additional funds afforded by a UVM-Sandia National Laboratories collaboration and designed and conducted a large consumer survey on PHEVs through the Amazon Mechanical Turk crowd-sourcing platform, and are currently updating the ABM to incorporate this new information. We also partnered with the Vermont Law School (via subcontract) to explore ways in which governmental policies and electricity regulation may impact PHEV adoption.

The results of this research have been communicated professionally through a variety of ways, including refereed journal publications in top-tier journals (3 published [34,35,36] and 1 currently in review[37]), 3 refereed conference papers in top-tier conferences (3 published[38,39,40] and 1 in preparation), graduate degrees awarded (1 PhD dissertation[41] and 2 MS theses[42,43]), 3 white papers, and at least 14 additional presentations (including posters, seminars, published abstracts, and invited talks). At least 3 additional projects have been funded, based in part on work completed for this project, including a prestigious NSF IGERT.

The remainder of this report is organized around summaries and major findings of the primary publications resulting from this work. In Chapter 2 we summarize the agent-based model and its use in studying PHEV market penetration. In Chapter 3 we describe the ANN approaches we used for up-scaling the ABM. In Chapter 4 we describe data assembly, curation, and visualization of fuel efficiency of the Vermont passenger fleet and a new method for automated visualization of clusters in high-dimensional data sets using Cluster Reinforcement in SOMs. In Chapter 5 we discuss the regulatory regime surrounding PHEV market penetration. In Chapter 6 we describe the PHEV survey we conducted. Finally, in Chapter 7 we offer some conclusions and briefly discuss ongoing and future work.

2. Agent-Based Model of PHEV Market Penetration

This chapter summarizes work published in the following references:

[35] Eppstein, M.J., Grover, D.K., Marshall, J.S., and Rizzo, D.M. "An agent-based model to study market penetration of plug-in hybrid electric vehicles", *Energy Policy*, Vo. 39 (2011), pp. 3789-3802.

[39] Pellon, M.B, Eppstein, M.J., Besaw, L.E., Grover, D.K., Rizzo, D.M., and Marshall, J.S., "An Agent-Based Model for Estimating Consumer Adoption of PHEV Technology", Transportation Research Board (TRB), Washington, D.C. (2010), 10-3303.

We developed an agent-based model (ABM) to study how the potential market penetration of PHEVs may be influenced by policy and market conditions. It is worth noting that Eppstein et al. [35] has already garnered 24 non-self citations in its first two years since publication. Figure 2-1 illustrates a flowchart of agent decision-making in this ABM.

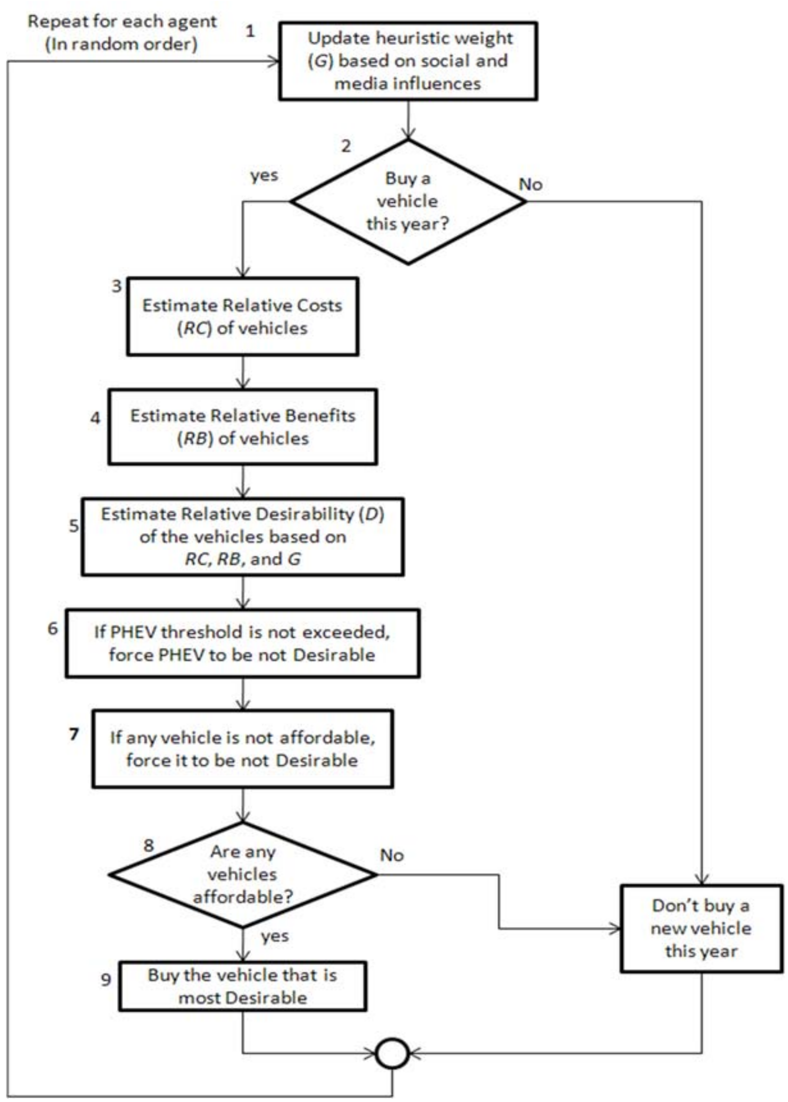

Figure 2-1. Flowchart of annual agent vehicle updates. See [35] for details.

Each consumer agent in the ABM has several associated attributes including age, annual salary, residential location, typical years of car ownership (*Y*), annual vehicle miles traveled (*VMT*), and vehicle age, fuel type, and fuel economy of their current vehicle, including all-electric range (if any) and miles per gallon (*MPG*) when not in all-electric mode. In addition, each agent has an associated "spatial neighborhood", a "social network", a threshold (*T*) of perceived PHEV market share over which they are willing to consider adopting the PHEV technology, and a level of rationality (*R*) of how (if at all) they estimate projected fuel costs. Surveys indicate that many consumers express a willingness to pay a price premium for a more fuel efficient vehicle [19, 23], may irrationally overestimate potential fuel savings [19], and that non-financial reasons related to the environment, energy, and attraction to new technology can play a large role in consumer willingness to purchase an HEV [23], EV, or PHEV [19]. We model this through an agent attribute (*G*), which indicates how much weight the agent places on heuristically perceived benefits related to saving gasoline that are independent of rationally estimated financial benefits (i.e., *G* can be interpreted to account for a desire to reduce greenhouse gas emissions, oil spills, or dependence foreign oil, as well as irrationally estimated savings in fuel costs). The only agent attributes that can change during a simulation are (a) the heuristic weight *G*, which can change dynamically due to social and media influences (although agent susceptibilities to such influences are heterogeneous) and (b) current vehicle ownership (and associated vehicle attributes, including vehicle age). External forces modeled as dynamic (time-series) data are the intensity of media coverage related to the need to reduce gasoline consumption, gasoline prices, and electricity prices. In this implementation of the model, agents are limited to compact car owners who choose between a gasoline vehicle (GV), a hybrid-electric vehicle (HEV), and a plug-in hybrid electric vehicle (PHEV). These three vehicles are intended to represent realistic similarly sized cars that differ largely in their fuel type, fuel efficiency, and purchase price.

Although we do not currently have sufficiently accurate or complete input data to yield quantitatively accurate predictions, or to warrant a more complex model, the model can still be used to explore potential nonlinear interactions between various influences that will impact PHEV market penetration, provide insight into what combinations of policies and procedures may be the most effective, and inform us as to what additional data may be most useful to gather. The spatially-explicit nature of our model may help policy-makers to explore the combined impacts of regionally variant policies and procedures (e.g., at the city, state, regional, and federal levels) on attaining a more fuel efficient transportation economy.

Assuming there are sufficient potential early adopters, our model results indicate that providing consumers with readily accessible estimates of lifetime vehicle fuel costs, such as on vehicle stickers, could be very important for promoting PHEV market penetration. As vehicle consumers learn to consider the actual financial benefits of fuel savings, increasing gasoline prices (whether through market forces or a gasoline tax) could non-linearly magnify PHEV market penetration and resulting increases in fleet efficiency. Our results also indicated that temporary incentive programs, such as the $2,500 to $7,500 PHEV tax credit currently offered by the U.S. government (see http://www.afdc.energy.gov/afdc), are not likely to have lasting effects on long-term fuel efficiency of the fleet, unless manufacturers are able to lower sticker prices after the rebates are discontinued. Such programs will have virtually no effect if consumer discomfort with the PHEV technology is high. Increasing PHEV battery range is found to be another important leverage point, and longer-range batteries amplify the impacts of PHEV sticker price. Thus, synergistic effects could be achieved, for example, by imposing a gasoline tax and using the proceeds used to fund research into lower-cost, longer-range PHEV batteries.

One conclusion of this study was that further research was needed to understand correlations and cross-correlations in consumer demographics and attitudes that may impact their willingness to consider a PHEV. In particular, we need to determine what proportion of consumers are comfortable enough with the concept of PHEV technology to be willing to consider becoming new adopters, and how far PHEVs would have to penetrate the market to become acceptable to those currently more hesitant. This dearth of available data motivated us to conduct the PHEV consumer survey described in Chapter 6.

3. Up-Scaling the ABM using Artificial Neural Networks

This chapter summarizes work published in the following references:

[40] Besaw, L.E., Rizzo, D.M., Eppstein, M.J., Pellon, M.B., Grover, D.K, Marshall, J.S., "Up-scaling Agent-Based Discrete-Choice Transportation Models using Artificial Neural Networks", Transportation Research Board (TRB), Washington, D.C. (2010), 10-3130.

[41] Besaw, Lance "Advances in Artificial Neural Networks with Applications in Surface and Subsurface Hydrology" *PhD Dissertation, Chapter 5*, (2009), UVM.

The ABM described in Chapter 2 was developed to simulate the consumer discrete-choice decision processes influencing potential PHEV market penetration for a given demographic region, with given socioeconomic characteristics. While ABMs have proven useful for modeling behavior in complex social systems incorporating various feedbacks and social influences, they can require large amounts of computation when implementing complicated decisions with numerous agents. As a result, at large-scales, the application of ABMs may be computationally prohibitive (*e.g.*, for millions of agents). In this portion of our study, our goal was to see if an ANN trained at the regional scale could operate as a "fast function approximator" to estimate nonlinear dynamic response functions (*e.g.*, fleet distribution, environmental attitudes, etc.) based on socio-economic distributions over a much larger scale. To this end, we developed two types of recurrent ANNs (a spiking ANN and a generalized regression ANN) to test as alternative modeling strategies to replicate the behavior of the ABM when considering regulatory policies across larger regions with very heterogeneous demographics.

Spiking Neural Networks (SNNs) represent a new and more advanced class of ANNs. They attempt to model biological neural networks more accurately in that the individual processing units, or neurons, communicate by sending and receiving pulse or spike trains (more similar to biological brains) [44]. SNNs have been shown to transmit vast amounts of information given only a few spikes [45, 46]. This makes these algorithms advantageous in applications requiring fast and efficient computation (*e.g.,* event detection, reactive control in robotics) and when the timing of input signals contains important information (*e.g.*, signal-processing applications such as speech recognition). In addition, spiking neurons have been shown to be more computationally powerful than perceptions and sigmoidal gates [47]. The ability of SNNs to extract nonlinear relationships from temporal data made them an initially attractive candidate for up-scaling our ABM. Although heralded as more computationally powerful than 1st and 2nd generation ANNs, the SNN algorithm is very challenging to: 1) define the internal states of the neurons, 2) keep track of pre- and post-synaptic firing times and 3) update the weights from all neurons converging to all other neurons. We coded a variation of the SNN algorithm using an evolution strategy (ES) [48] to train the weights. Before applying this to our ABM problem, however, we initially tested it on a simpler problem, that of predicting precipitation-streamflow relationships. Although we were able to show that our SNN-ES had the ability to generalize and make accurate predictions using data on which it was not trained, the accuracy of these predictions was still not quite as high as the more traditional ANNs commonly used to predict precipitation-streamflow patterns [41]. Consequently, we ultimately decided that the SNN was not the most appropriate way to up-scale our ABM of PHEV market penetration.

As an alternative, we implemented a generalized regression neural network (GRNN) [49] to forecast the discrete consumer choices of our ABM under a variety of socioeconomic, social influence, and market conditions. In transportation studies, the GRNN has been used to forecast daily trip flows [50], predict the hazardousness of intersection approaches [51], model travel mode choice [52], predict CO_2 fluxes [53], predict real-time driver fatigue [54] and real-time video traffic modeling [55,56]. Unlike traditional parametric statistical methods, the GRNN does not require assumptions of multivariate normality and allows binary or categorical data. And in contrast to the more commonly used traditional feed-forward backpropagation ANNs, the GRNN has rapid one-pass training and guaranteed convergence. Recurrent connections were added to the GRNN to incorporate feedbacks based on the temporal history of the simulations. For training and validation of the GRNN, we used our ABM to produce a large dataset that exhibited a variety of spatio-temporal dynamics for a variety of population sizes and initial and input conditions.

Our results showed the recurrent GRNN to be capable of learning the spatio-temporal dynamics of the discrete-choice ABM for different agent populations of different sizes, with different demographics, and with different levels of susceptibility to social influence (example results are shown in Figure 3-1). These predictions show that the GRNN was able to predict PHEV-fleet proportion as well as changes in attitudes due to social influence (as represented by the weighting factor *G* described in Chapter 2).

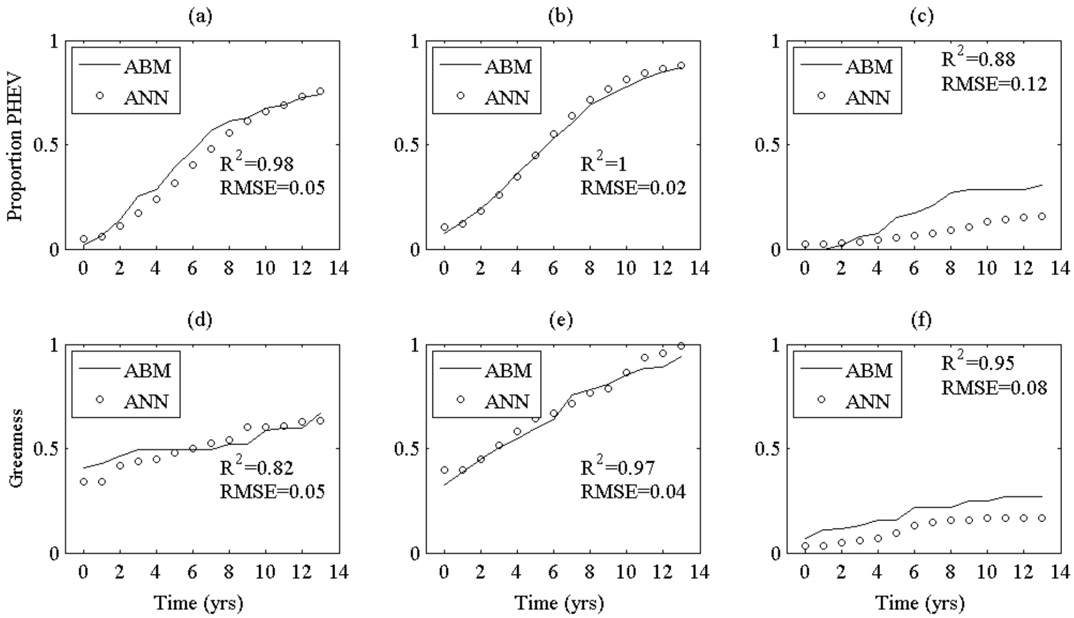

Figure 3-1. Representative GRNN predictions of up-scaled ABM behavior. (a)-(c) GRNN predictions of PHEV fleet proportion versus time for 3 regions; (d)-(f) GRNN predictions of dynamic changes in greenness (*G*) caused by social influences for the same 3 regions.

Although it takes significant amounts of time to generate the training and validation datasets and optimize the GRNN's smoothing parameter, once trained, it is capable of operating as a fast function approximator of the ABM behavior. For this proof-of-concept study, it took approximately 24 hours to produce the training and validation dataset (4,320 scenarios). However once these datasets were developed, the GRNN took only 4 hours to fully train. Once trained, it took very little time to actually run a simulation (~1.7 seconds in this work), no matter how large the region being simulated. The combined effects of accurate approximation and dramatic speedup permit GRNN simulation of much larger-scale dynamics than is computationally practical with an ABM.

4. Visualization of VT fleet efficiency and Cluster Reinforcement in SOMs

This chapter summarizes work published in the following references:

[34] Manukyan, N., Eppstein, M.J., and Rizzo, D.M., “Data-Driven Cluster Reinforcement and Visualization in Sparsely-Matched Self-Organizing Maps”, *IEEE Transactions on Neural Networks*, Vol. 23, No. 5, (2012), pp. 846-852.

[42] Manukyan, Narine “Improved methods for cluster identification and visualization in high-dimensional data using self-organizing maps”, *MS Thesis*, (2011), UVM.

We assembled a dataset of the locations and fuel efficiencies of vehicles in the Vermont passenger fleet. This dataset was collected from several sources, starting with the VT Department of Motor Vehicles (DMV) database of vehicles titled in Vermont obtained in summer 2011. This database originally contained *600,000* records of the registered address, make, model and year of each registered vehicle titled in the state of Vermont. After the elimination of large trucks, boats, snowmobiles, vehicles with addresses given as P.O. Boxes, and vehicles that were registered in other states, we were left with *321,487* data records, which is 78.5% of all passenger vehicles currently titled in Vermont. We then converted addresses of the form <street, apt, state, zip code> to the form <latitude, longitude> using a combination the 911 Building data from the Vermont Center for Geographic Information (VCGI), ARC GIS, and Web GPS visualizer (*http://www.gpsvisualizer.com/*), and used the VCGI and TRC to obtain elevations corresponding to each GPS coordinate. Makes and models of vehicles in the database were reported with inconsistent abbreviations (for example, “Toyota” was often reported as “Toyt”, “Toy”), so we used regular expressions to map each of these abbreviations to full names of make and model. We then wrote Ruby code to scrape the website cars.com (with permission) to retrieve mileage information for each make, model and year of vehicle that exists on this web site, and used this data to look up the fuel efficiency of the VT passenger vehicles stored in our database. In Figure 4-1 we show heat maps of the density of registered vehicle locations, the average fuel efficiency (city mpg), and the proportion of hybrid vehicles in VT. This data provides useful guidance regarding spatial correlation in the fuel efficiency of vehicles that can be used to inform the ABM described in Chapter 2.

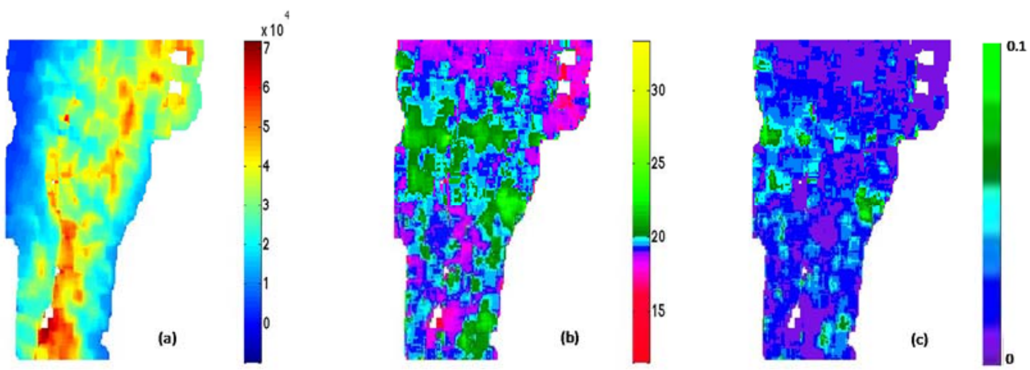

Figure 4-1. Spatial visualization of VT passenger fleet. (a) Density of registered vehicles, (b) city mpg of registered vehicles, and (c) proportion of registered vehicles that are hybrids.

We had hoped to obtain spatially explicit data on other relevant socio-political attributes that may shed some light on consumer vehicle choices, but we have not yet had the time to do this. Given that we were not able to assemble sociopolitical data, it is not surprising that we were not able to find any obvious linear correlations between the limited attributes available (vehicle density, elevation, and fuel efficiency). However, in order to see if there were possible nonlinear correlations between these variables, we developed a method to automatically find clusters in high-dimensional data and used this to visualize the VT fleet data. Unfortunately, due to the limited nature of this dataset, we were not able to find any interesting patterns with this non-linear method, either. However, the method we developed proved to be a valuable contribution in and of itself, and has since been successfully applied in other engineering applications. Below, we briefly describe this new cluster visualization method and one successful engineering application of it.

A Kohonen self-organizing map (SOM) [57] is a self-organized projection of high-dimensional data onto a two-dimensional (2-D) feature grid. Each data vector is associated with exactly one grid-point (the so-called "winning neuron"), such that similarity in the high-dimensional data vectors is translated into topological proximity in the 2-D projection. When there are more grid-points (neurons) than data vectors, the neurons between winning neurons essentially interpolate between the data vectors. However, this interpolation means that boundaries between clusters of similar data vectors become diffuse, making it difficult to identify clusters of data vectors and/or to assess distances between clusters. To address this, we created a new Cluster Reinforcement (CR) phase for sparsely-matched SOMs, described as follows.

In an SOM, each neuron is randomly initialized to a vector of the same dimension as the data vectors. These neurons are then iteratively updated by looping through for each data vector, finding the winning neuron that most closely matches it, and then updating all of the neurons in the neighborhood of the winning neuron to move closer to the data vector, where the magnitude of the update is strongest for the winning neuron and declines with topological distance from the winning neuron. After all the data vectors have been applied, the size of the neighborhood function is decreased and the process repeated. This continues until the neuron values stabilize. After self-organization has occurred, we apply the new CR phase. In the CR phase, we do a similar iterative updating process, but here the magnitude of the neuron updates is proportional to the Euclidean distance between the data vector and the neuron, rather than the topological distance to the winning neuron. The result is that the map is altered away from one that smoothly interpolates the data vectors into one with stepwise discontinuities between self-organized clusters of similar data vectors. We then visualize the boundaries between clusters as grid lines of varying thicknesses based on the magnitude of the stepwise discontinuities (we store these boundary magnitudes in a so-called B-matrix).

We used the SOM with the new CR phase to visualize a hierarchy of clustering high-dimensional microbial data obtained from 22 monitoring wells around the leaking Schuyler Falls landfill in Clinton, NY. Figure 4-2a shows two clusters that correspond to clean and contaminated wells, Figure 4-2b shows three clusters corresponding to clean, fringe, and highly contaminated wells, and in Figure 4-2c the fringe cluster is shown to be the most heterogeneous as the cluster rapidly breaks apart when lower B-matrix values are shown. The spatial locations of the wells around the landfill are illustrated in Figure 4-2d, where the colors of the dots indicate cluster membership as identified from Figure 4-2b. See Manukyan et al. [34] for more details of the method and this application.

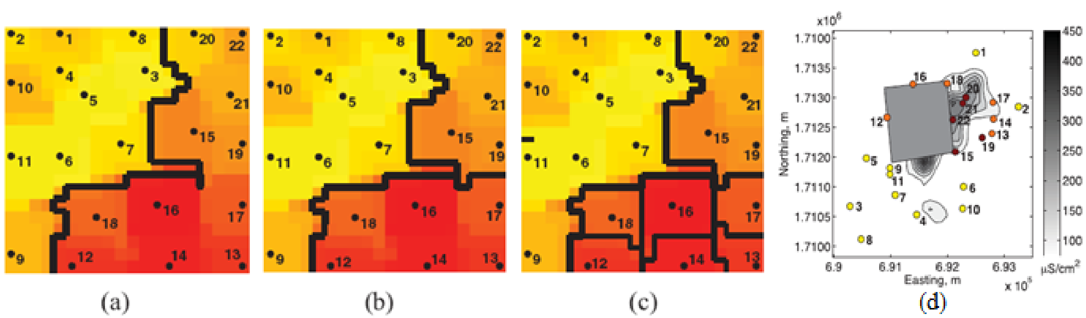

Figure 4-2. Results on SOM + CR on the landfill data. The backgrounds are heatmaps of the first principle component of the neurons in the SOM, the numbered dots show the locations of the winning neurons best matching the values at 22 wells shown in Figure 4-3. Black lines indicate cluster boundary values above (a) 0.92, (b) 0.88, and (c) 0.60. (d) Locations of numbered wells (colored by contamination level) relative to landfill (gray square) and plume of contamination (contour lines). The wells are colored to show the three clusters identified in Figure 4-2b, where yellow is clean, orange in fringe, and dark red is highly contaminated.

5. Legal Regime of Widespread PHEV Market Penetration

This chapter summarizes work published in the following references:

[36] Changala, D. and Foley, P., "The Legal Regime of Widespread Plug-In Hybrid Electric Vehicle Adoption: A Vermont Case Study", *Energy Law Journal*, Vol. 32, No. 1 (2011), pp. 99-124.

Now that PHEVs are in the marketplace (the Chevy Volt was introduced into the market in 2010), there is an urgent need for an on-the-ground legal analysis of how these vehicles can be integrated into the existing legal regimes for the regulation of electricity. Key legal issues need to be resolved for widespread fleet penetration of PHEVs to be achieved. In addition, to maximize the benefits of widespread PHEV market penetration, infrastructure and regulations must be put into place that encourage off-peak charging and vehicle-to-grid technologies that enable the PHEV fleet to provide short-term electric storage capacity to the grid that can facilitate the incorporation of more stochastic renewable power sources, such as wind and solar. Consequently, we subcontracted with collaborators at the Vermont Law School to perform an extensive case study of the how the legal regime would need to change to accommodate widespread PHEV adoption in Vermont. The findings of that study are summarized below.

The relative cleanliness of Vermont's existing energy mix means that PHEVs will reduce greenhouse gas emissions in Vermont at a higher rate than n more carbon-dependent areas of the United States. However, the extent of the role that PHEVs will play in a low-carbon future for Vermont depends in significant part on how this new technology will be integrated into Vermont's pre-existing legal regime for the regulation of electricity. Based on an extensive analysis of the current regulatory regime, the following five key recommendations made below are paraphrased from Changala and Foley [36].

1. The Legislature should enact PHEV tax incentives. Currently, PHEVs qualify for up to $7500 in U.S. federal tax credits and many U.S. states offer additional financial (as well as other) incentives for plug-in vehicles, ranging from sales tax exemptions to an additional $7500 tax credit (www.pluginamerica.org/incentives). However, Vermont currently offers no additional incentives for PHEV purchase. At present, PHEVs are not cost-competitive with conventional automobiles, even after the $7500 federal tax credit. This does not imply that the subsidy offered can or should make PHEVs equal in price to conventional automobiles, but it does imply that an additional incentive may be necessary to encourage a viable commercial market for PHEVs in Vermont.
2. The Vermont Public Service Board (PSB) should initiate a proceeding on PHEV local infrastructure requirements and proactively addresses some of the legal questions that public PHEV recharging facilities will invariably raise. While many PHEV owners may do the majority of charging at home, widespread public recharging facilities will be needed to accommodate PHEV owners who live in multi-family dwellings or otherwise do not have a private parking space with charging capabilities, to recharge PHEVs of those with long commutes, or to capitalize on incorporation of PHEVs into the Smart Grid using vehicle-to-grid technologies. Some of the issues that must be resolved are whether public charging providers must be legally regulated by the PSB; whether approvals for new charging stations should be streamlined; whether electric vehicles should be separately metered; and whether utilities should be allowed to make infrastructure improvements for PHEVs which are recoverable by ratepayers.
3. The PSB should require utility Integrated Resource Plans (IRPs) to address PHEVs. All regulated utilities in Vermont are required to implement IRPs for efficiently meeting projected energy demands. However, PHEVs have yet to be incorporated into Vermont Utility IRPs. As PHEVs penetrate the Vermont market, IRPs will have to quantify PHEV costs and benefits, including potential benefits to the grid from bi-directional flows. PHEVs should thus not be examined in isolation, but should be assessed in relation to their impact on other renewable technologies and methods of demand side management, including energy efficiency programs.
4. The PSB should initiate a smart grid proceeding. PHEVs can serve as an integral component of smart grid deployment by providing storage capacity to the grid, which can be utilized during times of high-peak demand, assuming the vehicles can be plugged in during these times. Moreover, since most PHEVs will likely be charged at night during off-peak hours, generators will have an incentive to shift nighttime production from lower efficiency to higher efficiency combined-cycle base load units, thereby producing more electricity with less fuel. Furthermore, the addition of nighttime charging demand decreases the

amount of times that generation units must be turned off at night and restarted in the morning; this levels out the plant's generation and reduces the need for additional energy needed for restarting [58].

5. The PSB should adopt uniform rates to incentivize off-peak PHEV charging. Rate design structures present a powerful tool that the PSB should utilize to regulate PHEV charging and storage on the grid. In particular, for each regulated utility, the PSB should approve rates that incentivize off-peak charging by charging higher rates during daytime and peak use hours. The PSB should also modify block tariffs so that the increase in electricity use from residential customers charging vehicles at home, or at public charging facilities, reflects both the marginal cost of the electricity used and the social and economic benefits of electric vehicles. Finally, the PSB should adopt a statewide rate design infrastructure; this would prevent a particular utility service area from receiving a favorable rate structure and thereby attracting a disproportionate number of PHEV charging customers.

Vermont now has the opportunity to affirmatively address the legal issues that PHEVs will precipitate. PHEV technology should not be allowed to merely stumble into Vermont's regulatory framework, but should be allowed to succeed or fail based on its own merits, without first encountering unnecessary obstacles to its integration into the State's legal and regulatory regimes.

6. PHEV Consumer Survey

This chapter summarizes work published or in review in the following references:

[37] Krupa, J.S., Rizzo, D.M., Eppstein, M.J., Lanute, D.B., Gaalema, D.E., Lakkaraju, K., and Warrender, C.E., "Analysis of a consumer survey on plug-in hybrid electric vehicles", *Transportation Research Part A: Policy and Practice*, (2013), in review.

[38] Krupa, J.S., Chatterjee, S., Eldridge, E., Rizzo, D.M., and Eppstein, M.J**.** "Evolutionary Feature Selection for Classification: A Plug-In Hybrid Vehicle Adoption Application", Proceedings of the 2012 Genetic and Evolutionary Computation Conference (GECCO), Philadelphia, PA (2012), pp. 1111-1118.

[43] Krupa, Jo "Plug-in Hybrid Electric Vehicle Consumer Survey Analysis", *MS Thesis*, (2013), UVM.

In developing the ABM described in Chapter 2, the need for additional data to properly inform both the decision-making model and agent initialization became apparent. To address this, a joint collaboration between the University of Vermont and Sandia National Laboratories initiated an extensive online survey of 1000 stated adult U.S. residents using the Amazon Mechanical Turk (AMT) crowd-sourcing platform (https://www.mturk.com). Our goals were to gather data to (i) identify consumer characteristics (if any) that differentiate between those willing and those not willing to consider adopting PHEV technology, (ii) identify possible factors that could positively influence consumers' willingness to consider adopting the new PHEV technology, (iii) assess how much extra consumers might be willing to pay up front to purchase a vehicle with the expectation of fuel savings in the future, and (iv) construct and analyze distributions and correlations between consumer demographics and attitudes. In short, this AMT consumer survey was designed to better understand the attributes associated with, and the influences that might affect a person's decision to buy a PHEV, and how consumers weigh the tradeoffs between short and long-term financial, convenience, and environmental priorities and concerns.

AMT is a crowd-sourcing service provided by Amazon where users may either post or complete tasks for compensation. Interest in AMT as a tool for inexpensive data collection has grown considerably in recent years, and its potential as a survey tool has been assessed across a variety of domains [59-63]. These studies show AMT data to be reliable and comparatively less expensive than more traditional survey collection methods (e.g., college surveys, on-site store surveys, or phone surveys). Research in psychology and the social sciences [59,60] shows that, although the level of "Turker" participation is affected by compensation and the time required to complete tasks, the data quality remains relatively unaffected.

The survey was posted to AMT in July 2011, and was terminated when 1000 participants, all of whom stated U.S. residency and a minimum age of 18 years, had completed the survey. To encourage completion, the survey was administered in four parts, with a bonus provided as an incentive for completion of the entire survey, for a total of $2 per participant. The AMT survey comprised 105 questions divided into six sections, 77 of which were Likert-scale (i.e., ordinal, interval-based, multiple-choice style). The six sections were as follows:

I. Participant Demographics: age, income, gender, education, state of residence, region of residence (i.e., urban, suburban, rural), location on political spectrum, home ownership, estimated average daily drive, frequency of recycling, and whether they consider themselves an early adopter of technology in general;

II. Purchasing Decisions: stated influence of advertising and social factors on purchasing decisions, such as the importance of whether others like their chosen products and brands;

III. Vehicle Acquisition: number of cars owned and the importance of certain factors influencing their most recent and future vehicle purchases (e.g., vehicle price, class, financing);

IV. Environment and Energy: attitudes/concerns toward climate change and U.S. energy independence;

V. PHEV Technology: importance of concerns or incentives influencing their willingness to consider purchasing a PHEV; and

VI. Discounting Questions: assessed how much a participant might be willing to pay upfront for a vehicle (not necessarily a PHEV) that provides future benefits, framed in terms of gallons of gasoline saved, dollars on fuel saved, and degree of locality of reduced impacts of climate change;

It is important to note that participants were not aware the survey was about PHEVs until Section V, to ensure this did not bias early responses, and that PHEV-related questions were phrased so as to deliberately disentangle concerns about sticker price from other attributes of PHEV technology.

In general, the stated demographics of participants were fairly representative of U.S. demographics; that, and other internal quality control checks, gave us some confidence that survey respondents were providing honest answers. We performed extensive analysis of the survey results, including using a genetic algorithm to identify sets of non-linearly interacting features that can be used to predict stated willingness to consider purchasing a PHEV, using single and multiple ordinal logistic regression to build predictive models of stated willingness to consider a PHEV, and identifying and exploring cross-correlations in the data. While the results of the survey are far too extensive to reproduce here, some highlights are listed below.

In the ABM described in Chapter 2, we assumed that consumer agents would not even consider purchasing a PHEV unless they saw more than a certain percentage of PHEVs in the fleet around them (their "threshold"), independent of financial considerations. Heterogeneous agent thresholds were drawn from a truncated Gaussian distribution. Our survey results validated that a truncated Gaussian distribution reasonably approximates the distributions of such thresholds in our AMT participants (Figure 6-1). However, in Eppstein et al. [35], with no data to guide the parameterization of this Gaussian, a standard deviation of only 20% was assumed. In our AMT survey population, the standard deviation was observed to be much higher (48%). This is an important finding, because a higher standard deviation results in a greater proportion of early adopters, rendering ultimate PHEV market penetration less sensitive to the mean of this distribution.

In general, environmental benefits of PHEV adoption were less often rated important than were financial or battery-related factors. However, respondents who felt most strongly about reducing U.S. transportation energy consumption and cutting greenhouse gas emissions had, respectively, 71 and 44 times greater odds of saying they would consider purchasing a compact PHEV than those who felt least strongly about these issues. Another interesting finding was that consumers stated a willingness to pay more for a vehicle that would save them in fuel costs when the savings were framed in terms of gallons saved rather than dollars saved. Unfortunately, we found that the relatively high sticker price premium of current PHEVs is outside the amount that most survey participants state they would be willing to spend for a more fuel efficient vehicle, regardless of how strong their environmental attitudes were. However, we also found that the combination of currently available financial incentives combined with savings in fuel and other operating costs could be sufficient to incentivize consumers to purchase PHEVs, if manufacturers and dealerships were to make personalized life-cycle cost estimates more readily available.

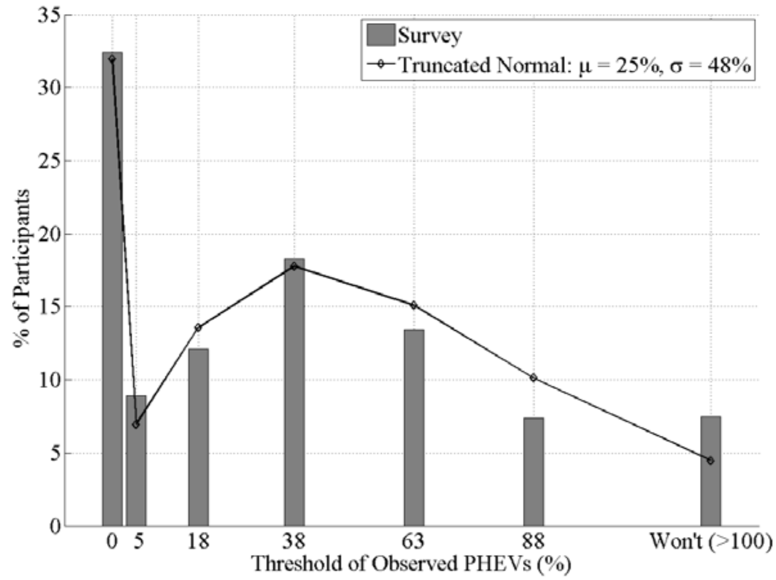

Figure 6-1. Histogram of AMT participants' stated thresholds. These indicate the percentage of PHEVs they would need to see on the road before they would consider adopting one, shown along with a truncated Gaussian distribution mean and standard deviation of 25% and 48%, respectively.

The most predictive model we have found to date is an ordinal multiple logistic regression model using the top questions (i.e., those with the highest Spearman rank correlation to stated willingness to consider a PHEV) in each of seven qualitatively distinct and complementary categories. Specifically, these 7 questions were (i) where participants saw themselves on the political spectrum, (ii) the importance of the potential for PHEVs to reduce greenhouse gas emissions, (iii) the importance of the need for the U.S. to reduce energy consumption related to transportation, (iv) the importance of the potential for PHEVs to create financial savings in fuel costs, (v) their level of concern regarding the potential inconvenience of recharging, (vi) the importance of projecting a strong environmental image by owning a PHEV, and (vii) the current vehicle size class of their primary vehicle (recognizing that PHEVs are currently only available in compact models). Using a 5-fold cross-validation method, we found that this statistical model had a misclassification rate of only 16.4% on the training sets and 20.2% on the testing sets.

The results of this analysis will enable us to improve our ABM of potential PHEV consumers and will also provide valuable information for vehicle manufacturers, marketers, and policy makers seeking to promote PHEV adoption. The manuscript regarding the survey analysis is currently in review; when accepted for publication, we will post the actual survey and all survey responses on the web for public access.

7. Conclusions

In summary, the work conducted under the purview of this award has advanced the field in several ways. We developed several useful complex systems computational methods, including an agent-based model (ABM) of potential PHEV market penetration, an artificial neural network based approach for efficient up-scaling of the non-linear systems behaviors of agent-based models to much larger systems, and a new method of automatically identifying clusters in high-dimension non-linear data sets based on self-organizing maps. Some of these methods have much broader applicability than this PHEV study, and have already proven useful in other engineering domains. We have also looked at specific questions regarding potential market penetration of PHEVs, both by studying the sensitivities our agent-based model to various market and policy forces and by studying and making recommendations regarding the legal regime that will affect PHEVs. To fill identified gaps in the data, we designed, conducted, and analyzed an extensive survey on consumer attitudes towards PHEVs using the Amazon Mechanical Turk crowd-sourcing platform. Our findings have been widely disseminated through top-tier journal publications, conference publications, poster presentations, seminars, and invited talks. We are currently using the results of the PHEV survey to improve both the decision-making rules and distributions and correlations between agent attributes in our ABM. Inspired by this research, one of us (MJE) directly contributed to increasing PHEV market penetration by purchasing a 2013 Chevy Volt. ☺

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