<u>Travel Demand and Charging Capacity for Electric Vehicles in Rural States: A Vermont</u> <u>Case Study</u>

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1 ABSTRACT

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3 As the number of electric vehicles (EVs) increase we must consider not only how this fuel switch may affect electrical power infrastructure but also mobility. Specifically, the suitability and charging 4 5 requirements of these vehicles may differ in rural areas, where the electrical grid may be less robust and 6 miles driven higher. Although other studies have examined issues of regional power requirements of EVs, 7 none have done so in conjunction with the spatial considerations of travel demand. We use three datasets 8 to forecast the future spatial distribution of EVs, as well as these vehicles' ability to meet current daily 9 travel demand: the National Household Travel Survey (NHTS), geocoded Vermont vehicle fleet data, and 10 an E911 geocoded dataset of every building statewide. We consider spatial patterns in daily travel and 11 home-based tours to identify optimal EV charging locations, as well as any area-types that are unsuited for widespread electric vehicle adoption. We found that hybrid vehicles were more likely to be near other 12 13 hybrids than conventional vehicles were. This suggestion of clustering of current hybrid vehicles, in both 14 urban and rural areas, suggests that the distribution of future EVs may also cluster in rural areas. Our analysis suggests that between 69 and 84% of the state's vehicles could be replaced by a 40-mile range 15 16 EV, depending on the availability of workplace charging. Problematic areas for EV adoption may be suburban areas, where both residential density is high (and potential clustering of hybrids), as well as 17 18 miles driven. Our results suggest EVs are viable for rural mobility demand but require special 19 consideration for power supply and vehicle charging infrastructure.

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1 INTRODUCTION

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3 As electric (EV), hybrid electric (HEV), and plug-in hybrid electric (PHEV) vehicle technologies

4 advance, these vehicles are increasingly seen as a means of reducing GHG emissions and dependence on

5 foreign energy. Previous research has shown that depending on the mix of electricity used for charging,

6 there may be substantial environmental benefits associated with EV use. A 2007 study by EPRI [1]

examined PHEVs with all-electric ranges of 10, 20 and 40 miles and found gasoline displacement ranging
from 42% to 78% relative to conventional vehicles and from 12% to 66% relative to HEVs. Other studies

9 that quantified gasoline displacement found reduction values within these ranges [2-5].

Most research on the feasibility of EVs has either been focused on the overall power requirements, the electric system's ability to meet that demand or the vehicle technology required to provide a given driving range. Except for a few studies, data are regionally based and there is an assumption that EVs may be an urban, not rural, transportation energy solution [9, 10]. These studies generally do not consider the spatial distribution of travel demand in assessing EV and PHEV market penetration. PHEVs offer the ability to travel on gasoline when trip distances exceed the electric range, an important factor for rural areas.

17 Overall, there is a need to consider where we want EVs to be deployed and travel and how this spatial distribution impacts not just overall efficiency of energy and emissions, but also mobility. The 18 19 distribution of away-from-home charging stations, the robustness of electrical infrastructure, and pricing 20 schemes will impact where EVs are adopted and where they travel. For rural areas, the policies and infrastructure needed to make efficient use of EVs, or PHEVS in electric mode, may be different from 21 22 urban areas. Choosing an EV over an HEV and PHEV will be a decision for individual households that is 23 based not only on their total travel demand, but also on the availability of non-home charging stations 24 over their activity space. There has been a general acceptance that rural trips are longer and will require 25 more range. However, transportation demand modelers have focused less on non-urban travel and there is not solid established data on how, and to what extent, rural travel is different from urban travel. These 26 27 differences may have implications for designing sustainable transportation systems including the fleet 28 conversion to EVs.

29 Whether in urban or rural areas, very little consideration has been given to the overlap of travel 30 demand and EV power demand in a spatial context. In this paper, we use three spatial datasets to 31 consider this problem. The first is the National Household Transportation Survey (NHTS) and the 32 associated add-on survey collected in the rural state of Vermont in 2009. The second dataset consists of 33 home address and vehicle type of every vehicle registered in the state from the Vermont Department of 34 Motor Vehicles (DMV). The third dataset, referred to as the Vermont E911 data, is a Geographic 35 Information System (GIS) point layer of all residences and commercial buildings in the state of Vermont. 36 This paper is aims to assess the potential patterns of spatial clustering of EVs, whether the travel demand 37 served by existing household vehicles can be met with EVs, and possible locations for EV charging. 38 Particular emphasis is placed on considering how a rural versus urban landscape results in different travel 39 patterns and charging opportunities.

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41 FRAMEWORK FOR PROBLEM DEFINITION

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There are broad policy questions related to desirable EV market penetration. The issues and answers are presumably different in rural areas due to the spatial nature of the transportation system. Based on

45 evidence of environmental and sociopolitical benefits from EVs, there is a public interest in optimizing

the use of EVs but it is unclear whether this equates with maximizing the use of EVs in all contexts.

There may be some households for which the private and public cost of providing vehicle and power

47 Infere may be some nouseholds for which the private and public cost of providing vehicle and power 48 infrastructure given travel and trip patterns is greater than the total costs of alternative modes of travel.

48 The public sector does not currently subsidize fueling stations for the gasoline and diesel-based system

50 but promoting EV penetration in rural areas may require public provisioning of away-from-home

50 but promoting LV penetration in tutal areas may require public provisioning of away-from-nome 51 electrical charging where the market will not. In addition, there is likely to be public demand for charging 1 stations that may not be cost effective or increase net societal benefits. Public policy makers in rural

areas will have to consider whether to provide these additional stations. It will be necessary to consider
whether the public's travel demand can be met throughout a region in an electrically fueled system and if
longer distance trips will be possible in all locales.

5 Figure 1 illustrates how the range and charging of EVs is an inherently spatial system that differs 6 for rural versus urban areas. In this figure, the elements that are typically part of transportation demand 7 planning modeling are shown in boxes. Where you live affects the accessibility of destinations and how

8 far you travel to reach them. These trip lengths together with the topography of your region impact the

9 total power or charging needed on a daily basis that in turn affects the impact on the local electricity

10 infrastructure that delivers power at home. Rural areas tend to have less robust electrical infrastructure,

11 thus affecting the power capacity and smart systems needed to charge EVs, and the number of EVs that

12 can be charged at one time in a given locale. If trips are long and one-way distance exceeds half the

vehicles' range, away-from-home charging will be needed. The same power capacity and infrastructure questions then apply to the electrical infrastructure at the destinations where charging options may be

15 provided. Destinations in urban areas, large or small, presumably offer more robust charging.

16 Destinations in rural areas, however, may suffer from the same limited robustness as rural home locations.

17 If destinations are small and attract limited demand (e.g., a small shopping center) the capital and

18 operating costs of the charging infrastructure may be prohibitive. Moreover, destinations with short

19 dwell times (e.g., a bank) do not provide adequate time for vehicle re-charge.

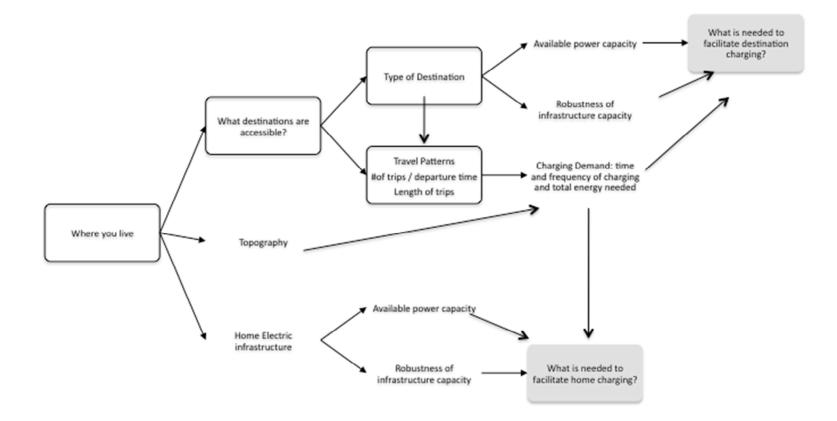


FIGURE 1: Potential Spatial Impacts of Home Location in Travel and Electric Vehicle Charging Needs.

We hypothesize that in rural states, the limited land uses, smaller scale activities, and lower land 1 2 use density increases travel distances and reduces the opportunities for cost effective away-from-home 3 EV charging because activity centers are smaller and lower volume. Ideally, charging stations should be 4 placed where people are parked for more than 1 hour to allow sufficient charging. Conversely, charging 5 stations should not be located where vehicles are parked for too long (an intercity rail station where 6 vehicles may park for multiple days for example) or the electric infrastructure capacity will be used only 7 part of the time and therefore is less efficient. Charging stations should be located at destinations where 8 trip lengths are long which may include workplaces with long commutes, tourist destinations or 9 entertainment centers. In order to make efficient use of infrastructure parking lots should be large in size 10 with high 24-hour utilization including turnover of vehicles to justify capital costs. Moreover, parking lot 11 charging stations need to be located where the electric grid is robust, not commonly the case in rural 12 areas, but perhaps more likely in the case of industrial rural areas.

13 Socially desirable and/or economically viable charging stations will have a number of common 14 characteristics. For example, stations are more likely to be established in places that have existing 15 electricity infrastructure, such as lighted parking lots. Most agree that charging stations will need to control vehicle charging to some extent through "smart charging" technology, and will need to 16 17 communicate with the electric distribution utility through emerging smart grid systems to ensure that 18 vehicle charging does not overburden the electricity infrastructure. Pricing schemes are needed to ensure 19 appropriate time of day charging. Finally, fee-based stations will need to have a minimum fee of some 20 sort to reduce the chance that EV owners will occupy stations for extended periods merely to "top off" 21 their vehicle batteries.

This study considered the spatial patterns of potential EV market penetration in the rural state of Vermont by considering travel demand data from the NHTS as well as geocoded vehicle fleet data from the Vermont DMV. Rather than considering overall power demand at the network or regional level, we are interested in examining limitations to wide-spread market penetration of EVs in rural areas by assessing the following four research questions:

Question 1: Does the expected pattern of vehicle adoption show uniform dispersion or a more clustered pattern? It is conceivable that social networks and socioeconomics will result in PHEV or EV adoption that is clustered at the street/block or neighborhood level. If this is the case, high density demand for electric vehicle charging in areas with aging or weak electricity distribution infrastructure could create the need for significant localized infrastructure investments.

Question 2: What percentage of Vermont vehicles, given existing daily travel demand, could be replaced by a 40-mile range EV with different levels of workplace charging? Based on dwell time within vehicle-based tours by stop purpose in the NHTS, we propose that vehicle charging will be mainly at home or work. By re-tabulating the NHTS data, we consider daily vehicle tour length away from home and whether a tour includes work.

40 Question 3: Are there rural areas where vehicles in need of non-home non-work charging converge? 41 For rural travel, when one-way trip distances exceed half the EV range and home or work charging is 42 not possible, other charging options will be required if the travel demand is to be met by an EV. If 43 these types of tours have stops or clusters of stops in similar areas, this could be a target for charging 44 station provision that would support the adoption of EVs in rural areas.

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Question 4: Are there spatial patterns or clusters of travel demand that suggest areas where EV adoption should not be encouraged?

DATA AND STUDY AREA 1

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3 Vermont is a largely rural state encompassing approximately 9,250 miles sq. with a population of

4 626,000. As of the 2010 census, 66% of the state's population is estimated to live in rural areas. For the

5 analysis in this paper, we used the 2000 census categories of urban area, urban cluster, and not urban

6 (rural) which are contained in the NHTS. There are a total of 19 urban clusters in Vermont (four with 7 populations between 10,000 and 20,000) and one urbanized area (Burlington with population 38,000).

8 According to the U.S. Census, areas with a density of at least 1,000 people per square mile and a

9 population between 2,500 and 50,000 people are defined as urban clusters. Areas with a density of at least

10 1,000 people per square mile and a population of at least 50,000 are defined as urbanized areas.

11 Vermont's urbanized areas and clusters, shown as red stars on Figure 2, are dispersed throughout the state 12 with most counties containing at least one urban cluster. Vermont's town centers are small; the state is

13 predominantly rural and mountainous as are the proximate areas in neighboring states.

14 We used vehicle registration data from the Vermont DMV to calculate the total number of

15 hybrids currently registered in the state. This data set contains all personal vehicles registered in the state,

16 totaling 558,464 vehicles, 324,182 of which are geocoded by home address, and includes vehicle fuel

17 type (e.g., gasoline, hybrid, diesel). We used the spatial distribution of current hybrid vehicles, 5,237 18 (5.237 geocoded), as a surrogate for the spatial pattern of future EV and PHEV adoptions. For each of the

19

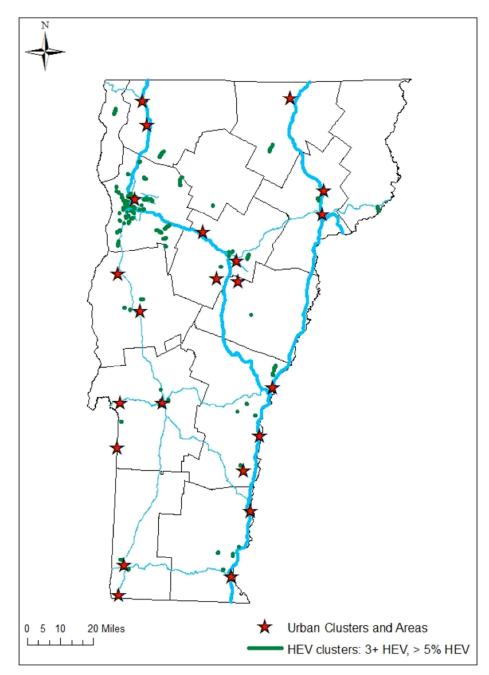
76,529 road links in the state-wide GIS dataset of roads (Source: Vermont Agency of Transportation), we 20 calculated the number of total vehicles, the number of hybrids, the percent of vehicles that were hybrids,

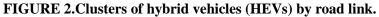
21 and the number of hybrids per mile by associating each vehicle location with the closest road link. The

22 average road link length was 0.26 miles (SD = 0.27). The number of road links with registered vehicles

23 was 38,345. The number of road links with registered HEVs was 4,261.

24





Here vehicle clusters are defined as those road links with 3+ hybrid vehicles and > 5% hybrids total. Red stars signify census-designated Urban Clusters and Urban Areas. Blue lines represent arterial roads and bold blue lines represent interstate highways.

1 An NHTS add-on was purchased for the State of Vermont. Travel information on a total of 3,550 people

2 is included in the Vermont NHTS, including 1,650 households and 3,521 vehicles. For this study, we re-

3 aggregated the Vermont NHTS person-trip file by vehicle and then used this vehicle-based trip file to 4 develop home-based tours for each vehicle. A home-based tour includes any series of trips that occur

5 between departing from and returning to home. Home-based tours thus have a minimum of two legs (e.g.

6 home to work, work to home) but potentially many more (home to work, work to shopping, shopping to

7 home). Calculating home tour lengths allowed us to estimate the miles that Vermonters would drive

8 between potential home charging of EVs. In our analysis, we use the longest tour length in a day

- 9 (henceforth 'tour length') calculated for each vehicle. We also totaled each vehicle's miles traveled on
- 10 the given travel day across all tours (daily VMT).

11 A total of 1,359 households and 1,926 vehicles were included in our analysis. Of the longest tour 12 made by each vehicle in a day, the mean tour length was 32.3 miles (SD = 38.7). The mean number of 13 tours completed by a vehicle in the survey day was 1.4 tours (SD = 0.7). The mean total daily VMT by a 14 vehicle was 37.3 miles (SD = 41.6). The distribution of tour length by census area type (urban, urban 15 cluster and rural) is shown in Figure 3. Homes were geocoded by the NHTS to exact address for 84% of our sample. For destinations, 63% were geocoded to exact address and 25% were geocoded to the nearest 16 intersection.



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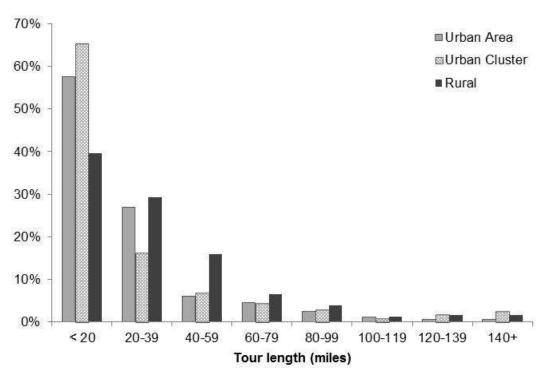


FIGURE 3. Distribution of home-based vehicle tour length (miles) by census area type. Area types include: a. urbanized area (n=330), b. urban cluster (n=254), c. rural (n=1,342).

1 ANALYSIS AND RESULTS 2

3 Question 1: Clustering Patterns of Vehicle Adoption

4 To assess the spatial clustering of existing HEVs we considered the percent HEVs per road link, the

5 percent per unit length, and the percent HEVs in neighborhoods surrounding existing hybrid vehicles.

6 Figure 4 illustrates the percent hybrids as a function of total number of vehicles per road link. Naturally,

7 the number of vehicles varies not only by land use but also because road links vary in length. The distinct

8 curves on the graph are a function of the discrete count of HEVs on the various road links (e.g., 1

- 9 HEV/road link, 2 HEVs/road link, etc.) on the graph.
- 10

We used two methods to identify HEV clusters. In the first, we defined a HEV cluster as any road link in the state with three or greater hybrids and greater than 5% total hybrids. In the second method, we defined a cluster as any road link with at least 10 hybrids/mile and greater than 5% hybrids total. Using method

14 1, we identified 106 clusters throughout the state (Figure 1). In urbanized areas, urban clusters and rural 15 areas, there were 41, 32, and 33 clusters respectively. These clusters are concentrated primarily in the

15 areas, mere were 41, 52, and 55 clusters respectively. These clusters are concentrated primarily in the 16 greater Burlington area, the state's largest city and only urbanized area. The remaining HEV clusters are

spread fairly evenly among the remaining two census area types: urban cluster, and rural. Using method

spread ranny eventy among the remaining two census area types: urban cluster, and rural. Using method
 we identified considerably more HEV clusters; 900 road links (Figure 5). By method 2, there were

19 300, 313, and 297 clusters in urbanized areas, urban clusters and rural areas respectively. These clusters

20 are similarly distributed throughout the state, with a high concentration in the Burlington area, and the rest

spread among smaller urban clusters and rural areas. Approximately a third of HEV clusters are in rural

areas suggesting EV adoption could be clustered in rural residential areas creating challenges for electric

- 23 infrastructure.
- 24

25 Finally, we investigated whether these clustering patterns were due to variability in vehicle density, or if

the patterns resulted from certain locations having an increased preference for hybrid vehicles. To do so

27 we counted the number of hybrid vehicles within a 1 mile radius of each vehicle in the state. Areas that

encompassed fewer than 50 total vehicles within the 1 mile radius were excluded from this analysis.

29 These vehicle counts were compared for hybrids and non-hybrids. For non-hybrids, surrounding vehicles

30 within the 1 mile radius were comprised of 1.6% hybrids. The proportion of hybrids surrounding hybrid

31 vehicles was 1.8%. While this difference is not large, a Kolmogorov-Smirnov test revealed that the two

32 distributions differ significantly (p<0.0001). This result provides additional evidence that hybrid adoption

has been clustered in rural Vermont and that potentially electric vehicle adoption will also be clustered.

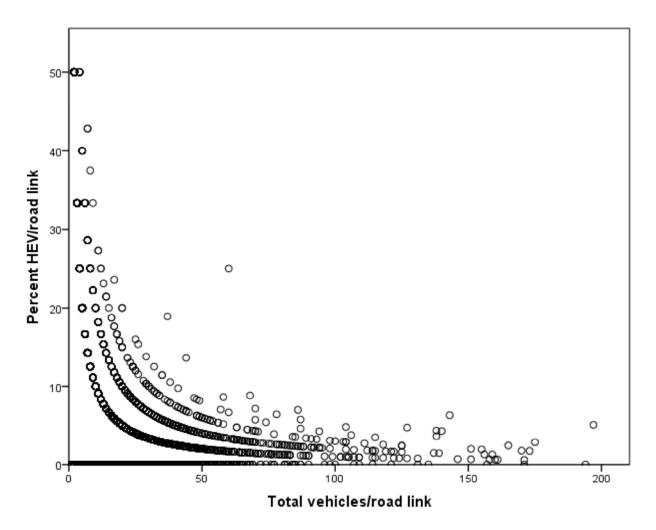


FIGURE 4. Percent hybrid electric vehicles /road link vs. total vehicles/road link in Vermont.

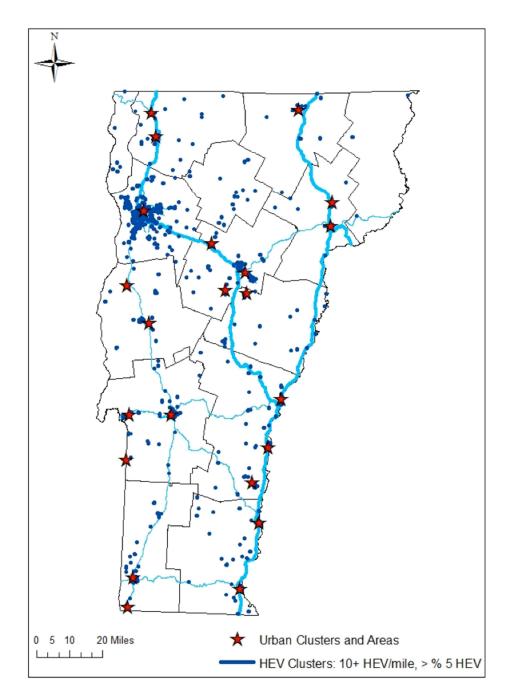


FIGURE 5. Clusters of hybrid vehicles (HEVs) by road link.

Here clusters are defined as those road links with 10+ hybrid vehicles/ road link mile and > 5% hybrids total. Red stars signify census-designated Urban Clusters and Urban Areas.

1 Question 2: 40-mile range EV Substitution

2 To estimate EV substitution rates for existing Vermont travel, we queried the re-tabulation of NHTS

3 vehicle tour data using the decision tree in Figure 6. Of the 1,926 vehicles in the sample, 63% of the

4 vehicles have total daily VMT under 40-miles. Of the 37% of vehicles that have daily travel longer than

5 40-miles, 6% of the total number of vehicles have tours less than 40 miles and are home for greater than

6 one hour between tours to re-charge at home. For vehicles with tours longer than 40 miles that include a

- 7 work stop, availability of work charging affects the number of vehicles whose daily travel demand could
- 8 have been served by an EV. Overall we estimate that between 69-84% of the Vermont fleet could be
- 9 substituted while still meeting existing travel demand (69% if 0% of workplaces have charging and 84%
- 10 if 100% of workplaces have charging).

11 Note that these estimates assume the NHTS survey day data represents travel throughout the year.

12 It is reasonable to assume on other days shorter and longer tours are made by many vehicles compared to

13 the survey day. If many tours are longer than those reflected in the NHTS data, our estimates for EV

14 deployment potential will be somewhat high. However, households that generally drive fewer than 40

15 miles but sometimes drive longer distances (as is the case with most American households), could opt for

16 PHEVs, which can use gasoline to extend their range.

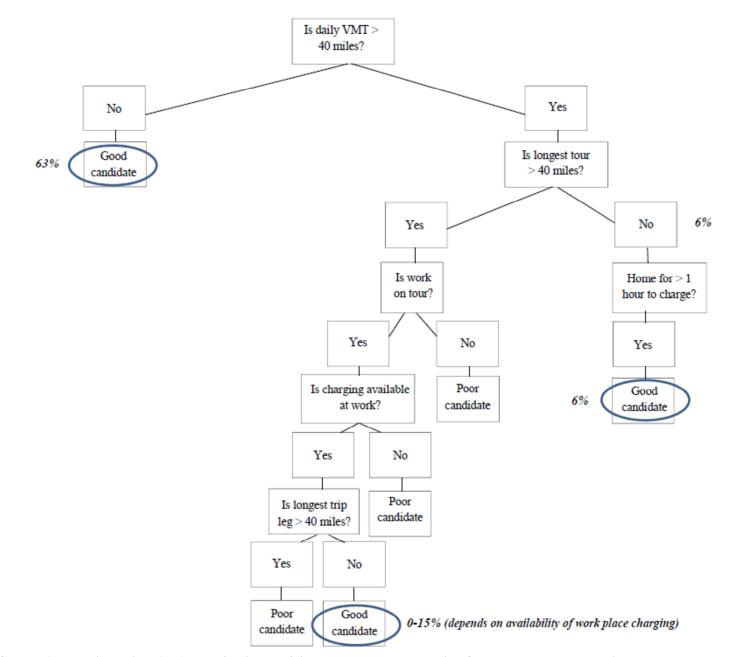


FIGURE 6. Electric vehicle (EV) substitution decision tree under a scenario of home and work charging. Ovals indicate those vehicles that are viable candidates for substitution, accompanied by estimated proportion of the Vermont fleet that could be substituted by 40 mile range EVs while still meeting daily travel demand.

1 Question 3: Spatial Patterns of Non-home Non-work Charging

- 2 Given that the Vermont data do not show distinct rural versus urban patterns in PHEV clusters or vehicle
- 3 tour length, this section models vehicle miles traveled (VMT), which is a strong predictor of the
- 4 additional electric energy required for vehicle charging, to identify spatial patterns of home location with
- 5 higher demand that might be discouraged from EV adoption. We identified 150 vehicles (or 7.8%) in the
- 6 Vermont NHTS that made home-based tours greater than 40 miles that did not include a stop at work. Of
- 7 these 474 tour stops or destinations (not including trips returning home), 104 were stops of at least one
- 8 hour (our minimum designated required charging time). Figure 7 illustrates that these destinations are not
- 9 clustered and are not consistently in urban or suburban locations. Most are in rural locations that suffer
- 10 from the barriers for charging station provision discussed previously. Among these trip legs, the most
- 11 common purposes were those for recreation (39%), shopping (22%), and meals out (15%). These results
- 12 suggest provision of rural charging at non-home and non-work locations will be challenging.
- 13

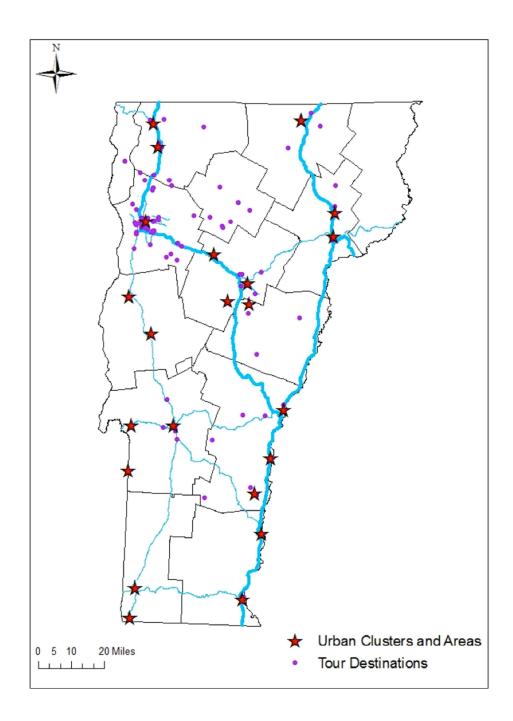


FIGURE 7. Tour destinations of home-based vehicle tours > 40 miles, with no work leg and dwell time > 60 minutes (n=104 destinations). Destinations outside of Vermont are not included. Red stars signify census-designated Urban Clusters and Urban Areas.

1 Question 4: Spatial Patterns of Travel Demand

2 Given that the Vermont data do not show distinct rural versus urban patterns in PHEV clusters or vehicle 3 tour length, this section models vehicle miles traveled (VMT), which is a strong predictor of the 4 additional electric energy required for vehicle charging, to identify spatial patterns of home location with 5 higher demand that might be discouraged from EV adoption. We aggregated our dataset by vehicle so 6 those households with more than one vehicle are represented multiple times. We analyzed daily VMT in a 7 variety of ways, initially looking at home-home tour length and vehicle-based VMT. 8 9 We used general linear mixed models (in SAS v9.2) to evaluate those environmental factors and attributes 10 of the built environment that may affect tour length and total travel for each vehicle. We constructed two 11 separate models: one for total travel and one for longest tour driven in each vehicle. In both models, miles 12 traveled served as the dependent variable. Independent variables included: urban/rural 2000 census 13 designation, residential and commercial density of the home address at multiple scales, distance to closest 14 urban center, access to retail locations and season. 15 16 Because travel patterns may be in large part determined by the built environment around someone's 17 residence [8, 9, 10], we generated a number of spatial variables to relate where NHTS respondents live to 18 the number of miles their vehicles drove on their assigned travel day. These spatial variables were 19 created in the ArcGIS and include: 20 21 1. Distance to closest urban area or urban cluster (Figure 1) 22 2. Commercial density at scales ranging from 0.5 km radii to 30 km radii from each individual 23 household using the Vermont E911 database. 24 3. Residential density from Vermont E911 database (as an alternative, we also used a 25 categorical measure of residential density, based on 2000 U.S. Census definitions) 4. Retail access using a gravity function and the E911 data: 26 Retail Access = $\sum 1/d^{1.7}$ 27 28 where d is the distance to each retail locations within 50 km of each surveyed household [11]. 29 Travel patterns can be heavily influenced by household structure [12 and 13 for example], so we 30 also included the NHTS variable household 'life cycle' in our models. There are 12 life cycles included in 31 the NHTS and these are categorized by the number of adults in the household, the number and age of 32 children present, and the number of retirees [14]. 33 A total of 1,359 households and 1,926 vehicles were included in our analysis and all life cycle 34 groups were represented. Both tour length and daily miles traveled exhibited highly positive-skewed 35 distributions. Transformations did not improve model power. 36 Because of the large number of models tested and relatively low explanatory power of most of 37 them, we only report on the top model for each dependent variable (total miles traveled and miles traveled 38 on the vehicle's longest tour). Our models (Table 1) were able to explain only a small portion of the 39 variability seen in daily vehicle miles traveled (~3%). Models for total miles traveled and miles traveled 40 on longest tour had similar results, and included census designation, life cycle and commercial density as 41 significant factors. The following five observed patterns are particularly notable: 42 43 1. Distance to city center: Distance to urban cluster was not a significant model effect, nor was the 44 interaction effect between this distance and urban cluster population. 45 2. Commercial density: Commercial density at 5 and 10 km had similar model effects and were both 46 marginally significant factors in the model of tour length, although our gravity function of retail 47 access was not. Although miles driven generally decreased with commercial density, the 48 relationship is weak due to high variability, especially at lower levels of commercial density. 49 3. Residential density: The urban/rural census designation (a categorical variable with 3 levels) was 50 a better predictor of travel than residential density, a continuous variable included in models at a 51 variety of scales.

- 4. Retail access: A similar pattern is seen between total miles traveled vs. retail access although this was not a significant factor in either model.
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5. Life cycle: Life cycle was a significant model factor. Retirees for example tended to have shorter tour lengths (~25-28 miles) while those households with two adults and children tended to have higher daily VMT.

5 6

| TABLE 1. Model variables and results (n=1,926) | | | | | |
|--|-----------------------------|-----------------------|------|--------|-------|
| Dependent variable | Independent variable | Parameter estimate | F | р | R^2 |
| Model 1: Total miles traveled | Census designation | | 4.16 | 0.02 | |
| | Life cycle | | 2.46 | 0.01 | |
| | Commercial density at 10 km | -0.4 | 2.17 | 0.14 | |
| Model results | - | | 4.22 | < 0.01 | 0.03 |
| Model 2: Tour length (miles) | Census designation | | 7.19 | < 0.01 | |
| | Life cycle | | 2.75 | < 0.01 | |
| | Commercial density at 10 km | -0.4 | 7.70 | 0.06 | |
| Model results | - | | 4.17 | < 0.01 | 0.03 |

7

8 Daily VMT and home-home tour length had similar means and distributions and behaved similarly in our

9 models regardless of the home location and home context of the vehicle. Variability was high for both of 10 these travel variables, reducing model explanatory power. Life cycle was an important explanatory

variable, affirming that travel patterns are in part a function of life style and demographics, in addition to

12 environmental factors. While commercial density was significant at multiple scales in our models, the

parameter estimates and r-square values were minimal, due most likely to the large amount of variation in

the data. Miles traveled (daily total and on the longest tour) generally decreased with increased density of

15 commercial and residential buildings, the relationship was inconsistent, though, due in large part to high

16 variability at levels of low density. While mileage tends to be higher in these areas, low mileage vehicles

17 occur everywhere.

Our analysis of vehicle tours revealed that urban residents generally took shorter tours, and when they did take longer tours, destinations included more suburban and rural areas. Clustering of EVs and PHEVs is expected in urban areas where residential density is higher. Electric infrastructure will probably

21 be more robust in these areas but it may also be more variable. In contrast, while we may not see dense

22 clustering of EVs in rural areas, miles driven is higher in these areas, meaning electricity demand will

also be greater. Clustered vehicle adoption within suburban areas, where clusters of both hybrids and

24 longer vehicle tours are likely, may trigger more significant needs for investments in electricity

25 infrastructure. In more populous suburban areas, neighborhoods can have both relatively high residential

26 density and long travel distances to work and amenities. High rates of vehicle adoption in these areas

27 could expose weaknesses in the electricity infrastructure.

28

29 **DISCUSSION**

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31 The objective of this case study was to assess whether the spatial patterns in travel demand or vehicle

32 adoption in rural areas suggested a particular direction for desirable market penetration of EVs. Our

results suggest that HEV and PHEVs will have substantial utility in rural areas due to the need for some

34 longer distance trips, the frequent hilliness of some rural areas and the presumed longer distances between

35 charging stations. Further in colder northern climates, the electric range of these vehicles may be

36 reduced. The travel demand data considered here indicate a large proportion of daily travel of the vehicles

37 in Vermont could be served with a 40-mile range EV even with only home and work charging. Note that

40 miles range is relatively low for pure EVs and charging infrastructure is less critical for PHEVs.

We found little evidence to support our hypotheses that rural demand may vary by household
 location in space. It appears that travel in rural areas may simply be unpredictable as a function of

location. Our models of tour length and total daily VMT were very weak. We tried disaggregate focal 1 2 spatial variables such as residential and commercial density as well as measures of accessibility to 3 commercial destinations all of which had weak predictive power. The results presented here do not show 4 a significant relationship between tour length and spatial location, area type, or accessibility to 5 destinations. The lack of significant relationships reported may be due to the relatively small data set. 6 compounded by the substantial variability in individual vehicle travel patterns. Future work could include 7 development of improved measures to capture the spatial patterns of rural travel. Ultimately, the 8 variability in rural travel patterns and the diversity of landscapes suggests a need for larger travel datasets 9 in the rural areas where we have routinely collected little if any travel data due to lack of congestion 10 concerns. While previous research has shown patterns in urban and suburban settings, with residential 11 density generally inversely related to VMT, considerably less is known of vehicle travel in rural areas. 12 Our research suggests that this relationship may not be linear. Variability was generally highest in the 13 most rural areas, suggesting that lack of proximate accessibility to destinations may reduce rather increase 14 VMT after a certain distance, or for some individuals.

15 Our spatial analysis of current vehicle registrations as well as current vehicle-based demand in 16 Vermont suggests we should expect street and block level clustering of EVs in both urban and rural areas. 17 Therefore, rural clusters of EVs should be expected and local power infrastructure ability to support this 18 fleet change should be investigated. None of the evidence suggests promising non-home and non-work 19 charging locations in rural areas. Therefore, a limited amount of rural daily travel will not be served by 20 EVs which may in turn have an impact on mobility or EV penetration rates. We recommend relatively inexpensive multi-day longitudinal vehicle-based data collections using GPS to provide a more accurate 21 22 assessment of the extent to which current rural travel demands will be met with EVs and the extent to 23 which non-home charging stations may have to be provided. Of course the penetration and utility of EVs 24 in all areas, but especially rural areas will change as charging infrastructure is implemented.

25 Despite limitations, this study represents an important contribution in terms of data and methods. The use of spatially located vehicle and travel data allowed new questions to be addressed regarding 26 27 where demand needs to be served that are only possible when datasets can be related in space. Our 28 findings suggest expected EV clustering in rural areas. Current daily travel for Vermont vehicles 29 suggests 69-84% of current vehicles could be replaced by a 40-mile range EV. We find that vehicle 30 charging will occur mainly at home or work. There are very limited relationships between spatial 31 location and vehicle-based travel demand. We find some evidence of lesser demand in urban areas and 32 higher demand in suburban areas but recommend more robust rural travel data collection to more fully 33 consider these questions. 34

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