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Evaluating the Efficacy of Zero-Emission Vehicle Deployment Strategies: The Maryland Case

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Abstract: This study aimed to develop a model to estimate the impacts of zero-emission vehicle (ZEV) adoption on CO_2 emissions and to evaluate efficacy of ZEV deployment strategies in achieving greenhouse gas (GHG) emission reduction goals. We proposed a modeling scheme to represent ZEVs in four-step trip-based travel demand models. We then tested six ZEV scenarios that were a cross-combination of three ZEV ownership levels and two ZEV operating cost levels. The proposed modeling scheme and scenarios were implemented on the Maryland Statewide Transportation Model (MSTM) to analyze the impacts of different ZEV ownership and cost combinations on travel patterns and on CO_2 emissions. The main findings were the following: (1) A high-ZEV ownership scenario (43.14% of households with ZEVs) could achieve about a 16% reduction in statewide carbon dioxide equivalent (CO_2Eq) emissions from 2015 base year levels; and (2) CO_2Eq emissions at a future year baseline (2030) (the Constrained Long-Range Plan) level dropped by approximately 11% in low-ZEV ownership scenarios, 17% in medium-ZEV ownership scenarios, and 32% in high-ZEV ownership scenarios. The high-ZEV ownership results also indicated a more balanced distribution of emissions per unit area or per vehicle mile traveled among different counties.

Keywords: zero-emission vehicles; travel demand model; scenario analysis; GHG emission; mode choice

1. Introduction

As a result of greenhouse gas emissions (GHGs) (mainly CO_2) emitted through human activities, global warming and anthropogenic climate change has drawn worldwide concern [1]. The transportation sector emitted about 20% of global CO_2 emissions in 2012, and an even higher percentage in developed countries such as the United States, members of the E.U., Japan, and others [2]. The transport sector produces the second largest share of CO_2 emissions among all sectors in the E.U., in which passenger cars are responsible for about 70% of total CO_2 emissions [3]. Transportation represented 26% of total U.S. GHG emissions in 2014, and within the transportation sector, light-duty vehicles were by far the largest category, with 61% of GHG emissions [4]. Lopes Toledo and Lèbre La Rovere [5] have estimated that individual motorized transport accounts for 60% of total emissions from the urban transportation sector. Vierth et al. [6] have shown that road transportation contributes by far the most to emission costs in Sweden.

Electric vehicles (EVs) show promise for improving the environmental sustainability of the transport system since, as opposed to conventional vehicles, they have no tailpipe exhaust gas emissions [7]. Zero-emission vehicles (ZEVs) have been found to potentially reduce greenhouse gas emissions by up to 60% under ideal conditions [8]. However, different cities may have conditions that are characterized by diversity in landforms, congestion patterns, driving styles, etc., and policies that support the adoption of ZEVs would need to take these differences into account to effectively contribute to CO_2 emissions reduction efforts [9]. A comprehensive analysis is needed to understand the extent of the benefits that the deployment of ZEVs could generate and how these benefits are spatially distributed for a given region or state. A number of practical tools have been developed for estimating CO_2 emissions from transportation, including MOBILE6, COMMUTER, the Motor Vehicle Emissions Simulator (MOVES), and the Intelligent Transportation Systems Deployment Analysis System (IDAS) [10]. Some researchers have also built GHG emission models on the basis of car ownership, vehicle kilometers traveled (VKTs), and CO_2 emissions factors [1,11–14]. While these models are capable of estimating CO_2 emissions, they are not suitable for analyzing the effects of e.g. ZEV cost on mode choice, destination choice, travel path choice, and resulting travel patterns.

Travel behavior and the resulting GHG emissions are affected by factors such as fuel economy and the ZEV adoption rate, which consists of a high level of uncertainty. Schipper [15] has stated that fuel economy technology is not the only factor that can yield significant reductions in CO_2 emissions and that it will be difficult for technology alone to lower CO_2 emissions from the transport sector because of the increasing number of vehicles and vehicle kilometers traveled. Gerard et al. [16] found that people interested in hybrids are much "greener" than are diesel enthusiasts, and hybrid drivers log fewer annual miles and have a higher percentage of in-city driving. Akar and Guldmann [17] found that an SUV, a pickup truck, a van, or a hybrid are likely used and result in producing more vehicle miles traveled (VMTs). Yu et al. [18] examined the rebound effects when replacing current vehicles with a plug-in hybrid and electric vehicles in Japan and found that improvements in vehicle efficiency caused a rebound effect in the transport sector, such as increased vehicle kilometers traveled and frequency of car use, as well as in the consumption of domestic goods. Mishina and Muromachi [19] have concluded that the potential reductions in CO_2 emissions offered by the higher tested fuel economy of hybrid electric vehicles (HEVs) have been offset markedly by the deterioration in test fuel economy and the direct rebound effects in real traffic over a certain period. Langbroek et al. [7] found that EV users make significantly more trips and choose driving for a significantly larger percentage of their total travel distance than conventional vehicle users. This research suggests a rebound effect, that is, EVs will still consume a considerable amount of energy and contribute to other external effects such as congestion. Thus, the benefits of EVs in reducing GHG emissions should be explored carefully, considering such rebound effects.

The Greenhouse Gas Emissions Reduction Act (GGRA), enacted by the State of Maryland in 2009 required the state to achieve a 25% reduction in statewide GHG emissions from 2006 levels by 2020, and the GGRA of 2016 set a new benchmark goal of a 40% reduction in emissions from 2006 levels by 2030 [20]. To what extent could ZEV deployment strategies achieve this ambitious GHG emission reduction goal? This paper aims to answer this question by quantifying the amount of CO_2 emissions from road passenger transport by varying ZEV ownership and cost levels and analyzing whether ZEV deployment strategies could achieve the GHG emissions reduction goal in the state of Maryland by 2030. A modeling platform, the Mobile Emissions Model (MEM), developed by integrating the Maryland Statewide Transportation Model (MSTM) and the Environmental Protection Agency's MOVES model, was used for this analysis. The MSTM is a multilayer model that works at regional, statewide, and urban levels, and uses a traditional four-step travel forecasting process with the addition of a time-of-day model. MOVES estimates emissions from mobile sources by using data such as climate, fuel economy, and other variables. The MEM estimates transportation emissions by applying emissions rates from the MOVES model to MSTM-generated traffic flows [21]. We utilized this modeling platform to conduct various ZEV adoption scenarios to gain insight into, e.g., travel behavior changes, VMTs, and carbon dioxide equivalents (CO_2Eqs).

This paper is organized as follows: Section 2 gives the details of the methods we developed to incorporate ZEVs into the MSTM and MEM and describes a set of ZEV scenarios designed to estimate the impacts on CO_2 emissions. Section 3 provides a detailed analysis of scenario results at various geographic scales. Section 4 discusses the practical and policy implications of the results and tries to answer the research question. The last section summarizes the main contributions, limitations, and future research directions.

2. Method

2.1. Modeling Platform

To analyze the impacts of ZEVs on emissions in Maryland, we used the MSTM to estimate travel patterns. The MSTM results were used as an input into the MEM in conjunction with the United States Environmental Protection Agency's Motor Vehicle Emissions Simulator (MOVES) model to determine the emissions estimates. The MSTM is a multilayer model working at a regional, statewide, and urban level and is driven by economic and land use data. The MSTM uses a traditional four-step travel forecasting process with the addition of a time-of-day model, which divides trips into four time periods: a.m. peak, mid-day, p.m. peak, and night-time. Figure 1 contains a flow diagram of the MSTM and illustrates how the four steps are applied to each type of travel [22].

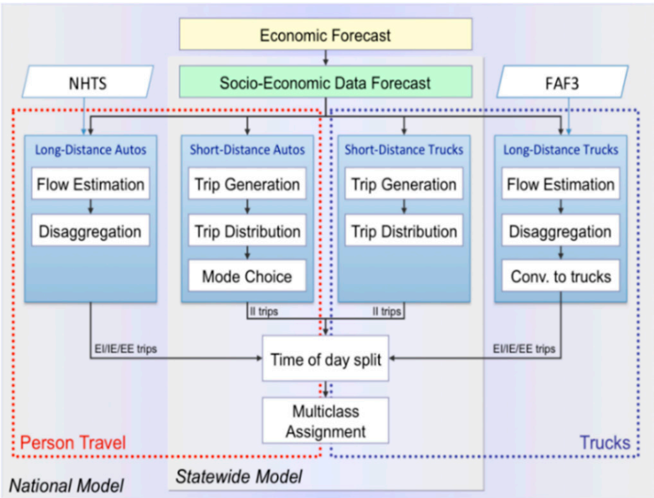


Figure 1. Overview of the Maryland Statewide Transportation Model (MTSM) components.

MEM [21,23] integrates the MOVES with the MSTM and calculates total emissions by applying emissions rates calculated by the MOVES model to MSTM-produced trip tables and loaded networks (VMTs and speeds for each network link). This model outputs both running and nonrunning emissions, and these emissions include oxides of nitrogen (NOx), volatile organic compounds (VOCs), and CO_2Eqs (Figure 2). The link level estimates then can be summarized at multiple scales, including statewide, county, corridor, and individual lanes [24].

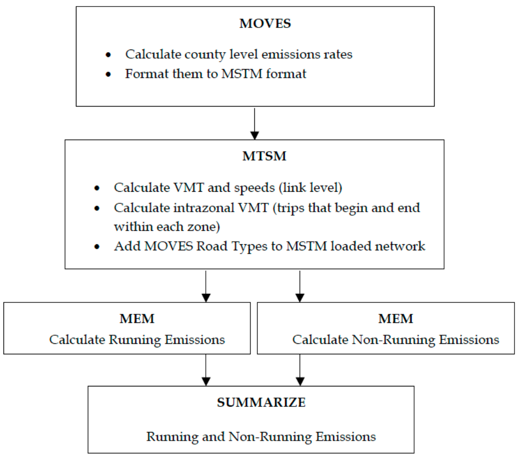


Figure 2. The combined modeling platform.

2.2. Demand Forecasting Model

ZEVs, as a new mode, were introduced into the MSTM by making necessary changes in the short-distance auto component of the MSTM (Figure 3). We divided the households into two groups: Households without ZEVs and with ZEVs, and modeled the following four steps (i.e., trip generation, trip distribution, mode choice, and time-of-day split) of the travel demand forecasting model separately for the two groups. The origin–destination [25] trip tables obtained as a result after the last step (time-of-day split) for households with ZEVs and without ZEVs were combined for the highway and transit assignment steps. This revised MSTM model output the assigned ZEV and non-ZEV volume, VMTs, and vehicle hours traveled (VHTs) for every link of the network, which were then used as inputs into the MEM for calculating CO_2Eq emissions estimates.

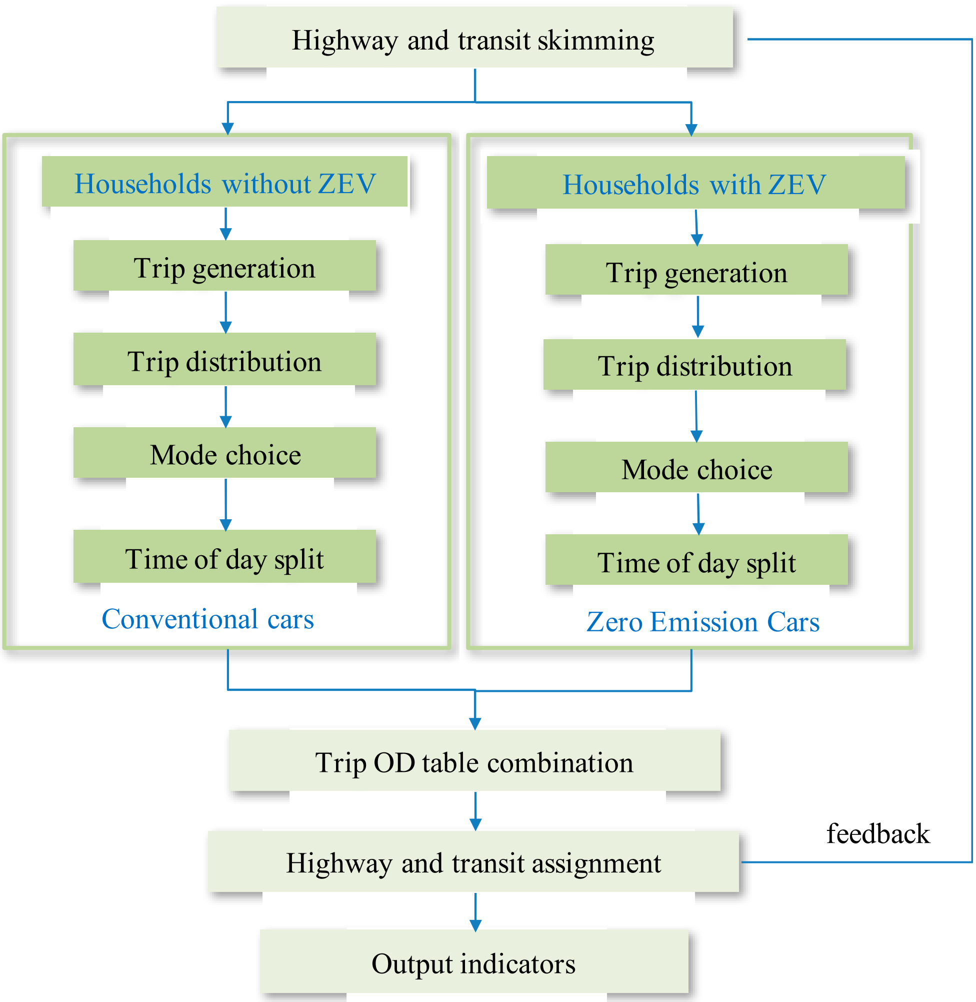


Figure 3. The revised model for short-distance autos of the MSTM.

Determining which households will own a ZEV in the future was a challenge we needed to address. The literature suggests that the early EV owners were wealthier, more educated, and had a stronger environmental attitude [26,27]. The Maryland Department of Transportation (MDOT) [28] has projected that as many as 100,000 EVs will be registered in the state of Maryland in 2020, and 1,472,084 EVs will be registered in 2040. We based our models and scenario design on these projections. We hypothesized that as household income increases, the possibility of possessing a ZEV increases as well. Thus, we designed three ZEV ownership scenarios based on income levels: Low ownership assumption, medium ownership assumption, and high ownership assumption in 2030. We first divided all households into two groups: Households without ZEVs and households with

ZEVs. We assumed that the households without ZEVs were the households that do not choose ZEVs as a mode of travel for various reasons, e.g., cost and limited driving range, and that households with ZEVs were the ones that can choose ZEVs as a mode of travel. Figure 4 illustrates the percentage of households with ZEVs by five income groups for three scenarios. For all the scenarios, we assumed that every statewide modeling zone (SMZ) in Maryland had the same percentage of households with ZEVs for every income group. The percentage of households with ZEVs was 14.49% in low-ZEV ownership scenarios, 23.18% in medium-ZEV ownership scenarios, and 43.14% in high-ZEV ownership scenarios. These percentages were computed using the following formula:

$$P_{low}^{zev} = \left(\sum_i P_{low}^i * Pop_i \right) / \sum_i Pop_i, \tag{1}$$

$$P_{medium}^{zev} = \left(\sum_i P_{medium}^i * Pop_i \right) / \sum_i Pop_i, \tag{2}$$

$$P_{high}^{zev} = \left(\sum_i P_{high}^i * Pop_i \right) / \sum_i Pop_i, \tag{3}$$

where P_{low}^{zev} is the percentage of households with ZEVs in low-ZEV ownership scenarios; P_{medium}^{zev} is the percentage of households with ZEVs in medium-ZEV ownership scenarios;P_{high}^{zev} is the percentage of households with ZEVs in high-ZEV ownership scenarios; *i* is the income group, i.e., the low income group, medium-low income group, medium income group, medium-high income group, and high income group;P_{low}^i is the percentage of income group *i* households with ZEVs in low-ZEV ownership scenarios;P_{medium}^i is the percentage of income group *i* households with ZEVs in medium-ZEV ownership scenarios; P_{high}^i is the percentage of income group *i* households with ZEVs in high-ZEV ownership scenarios; and Pop_i is the population of income group *i* households.

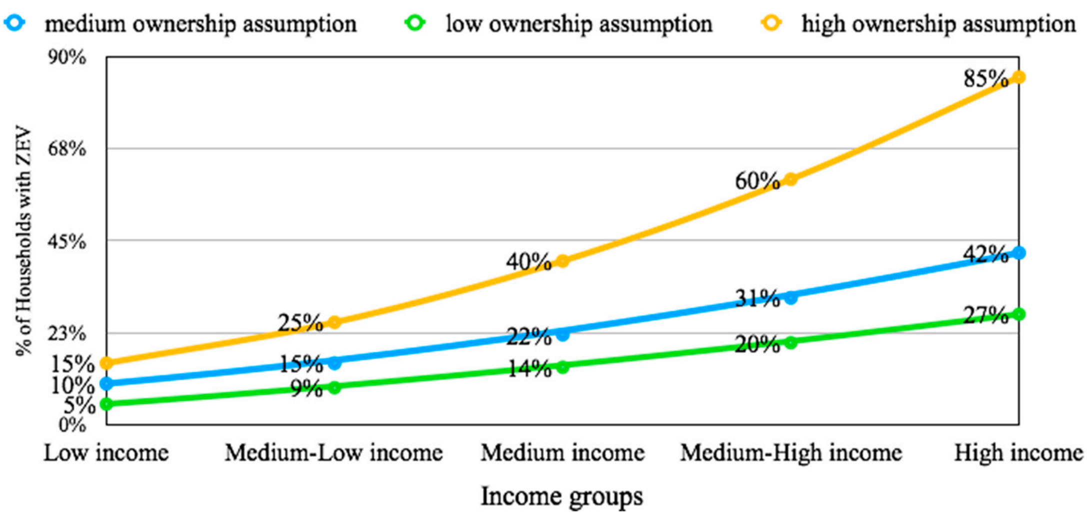


Figure 4. The percentage of households with ZEVs by income groups for three ZEV ownership scenarios in 2030.

Equations (1)–(3) describe how the number of households with ZEVs in an SMZ was calculated, i.e., the original number of households in an SMZ was multiplied by the assumed percentage of the households with ZEVs. The trip generation step in the MSTM is modeled as a cross-classification model (by income and number of workers for work trips, and by income and household size for other trips) for the production and attraction of 19 types of trips. As in past studies [29,30], we assumed that the trip generation behavior of ZEV users would not be significantly different from the users of conventional internal combustion engine vehicles (ICEVs). Thus, we assumed that the parameters of this model were the same for the households without ZEVs and the households with ZEVs. However, we hypothesized that differences in some factors between ZEVs and ICEVs, such as vehicle operating costs, parking costs, and tolls, would likely influence the choice of trip destination and mode choice. For example, ZEVs reduce the cost of travel since the cost of electricity is less than the equivalent cost of gasoline. We investigated this hypothesis by applying cost differences in the corresponding choice models in the MSTM. The trip distribution model is a nested-logit destination choice model that distributes passenger trips by five travel purposes: home-based work (HBW), home-based other (HBO), non-home-based work (NHBW), non-home-based other (NHBO), and home-based shop (HBS). A gravity model is used for distributing the home-based school (HBSc) trips. The nested-logit mode choice model splits passenger trip matrices into 11 travel modes (3 automobile modes and 8 transit modes) [31]. The mode split for the households without ZEVs and the households with ZEVs are different because of the different generalized travel costs. Equation (4) presents the generalized cost function in the MSTM:

$$GC_{inc,ij} = t_{ij}^{0} + \frac{Toll_{ij}}{VOT_{inc}} + \alpha.d_{ij}, \tag{4}$$

where, $GC_{inc,ij}$ is the generalized cost of traveling on link ij by auto and it varies by income group inc (in minutes); t_{ij}^{0} is the free-flow travel time for traversing link ij; $Toll_{ij}$ is the value of the toll for using link ij if any toll is applied (in cents); VOT_{inc} is the value of time of the traveler's income group category; α is a factor that represents impedance for long-distance trips; and d_{ij} is the distance between origin and destination (in miles).

Figure 5 illustrates the nested-logit model structure of the mode choice model in the MSTM as applied to the households with ZEVs. We assumed that these households abandoned conventional cars and that ZEVs replaced their conventional cars.

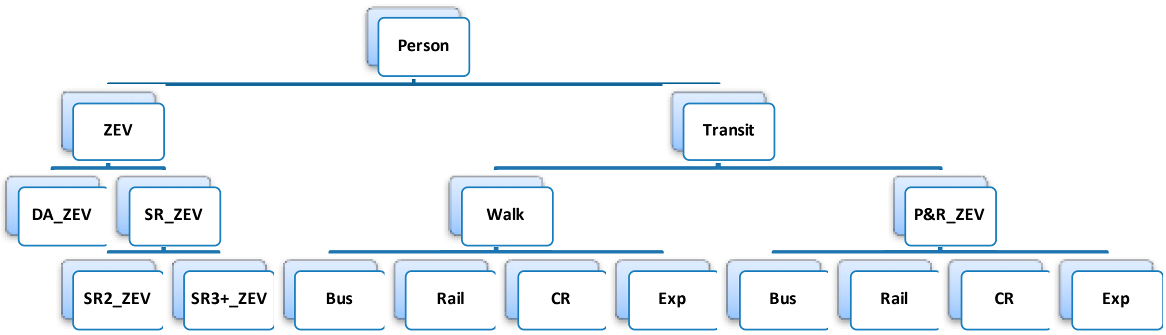


Figure 5. The nested logit model structure for households with ZEVs.

2.3. ZEV Scenarios

The average cost of the electricity used to fuel Pure Electric Vehicle (PEV) could be as high as \$0.24–\$0.34 per kilowatt-hour (kWh), equivalent to \$2.70–\$4.70 per gallon of gasoline, and paying off-peak rates of \$0.10 per kWh is equivalent to paying around \$1 per gallon of gasoline [32]. Since there is high uncertainty in future fuel cost estimates (year 2030 in this study), we tested two cost level scenarios, where we assumed that vehicle operating costs and parking costs were reduced to 20% or 80% of conventional cars in 2030. We assumed that ZEVs would not pay tolls. In combination with three aforementioned ZEV ownership scenarios (see Figure 4), six ZEV scenarios were constructed to illustrate the impacts of ZEVs on GHG emissions (Table 1). All scenarios were developed for a typical day in the year 2030, with sociodemographic data and network data developed from the Constrained Long-Range Plan (CLRP). Besides the six ZEV scenarios, a 2015 base year model and a 2030 CLRP baseline model without ZEV were used as benchmarks for results analysis.

Table 1. ZEV scenarios with different costs.

Number of Scenarios	Scenarios *	ZEV Ownership Level	ZEV Cost (Percentage of ICEV' Cost)
(1)	LZO20C	low	20%
(2)	LZO80C	low	80%
(3)	MZO20C	medium	20%
(4)	MZO80C	medium	80%
(5)	HZO20C	high	20%
(6)	HZO80C	high	80%

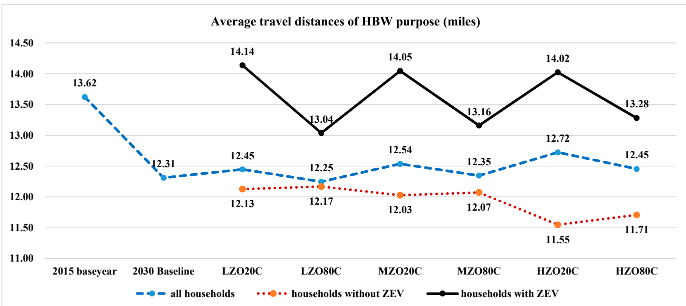
* Scenario names represent ZEV ownership level (e.g., LZO stands for low-ZEV ownership, MZO for medium-ZEV ownership, and HZO for high-ZEV ownership; and 20 and 80 represents the cost level in the scenarios (e.g., 20C stands for 20% of internal combustion engine vehicles (ICEVs)).

3. Results

We summarize the scenario results, focusing on behavioral changes and CO_2Eq emissions at various scales to understand the geospatial impacts of the scenarios.

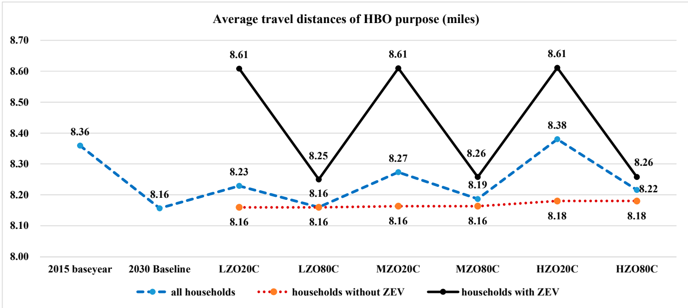
3.1. Changes in Travel Distance and Mode Choice

We analyzed the travel distance changes for all households, households without ZEVs, and households with ZEVs by six travel purposes: HBW, HBO, NHBW, NHBO, HBS, and HBSc (Figure 6). We observed that the average travel distance in the 2030 baseline was shorter than that of the 2015 base year, likely because of increased congestion from growing total travel demand for all travel purposes. In the scenarios with ZEVs, all households' average travel distance showed a minor increase compared to the 2030 baseline for all travel purposes. Moderate differences in average travel distances were found between different ZEV cost scenarios (20% and 80% of operational costs and parking costs), especially for the households with ZEVs. For the households with ZEVs under the same scenario, their average travel distance for four purposes (HBW, HBO, NHBW, and NHBO) was longer than that of the households without ZEVs. However, for the HBS and HBSc purposes, the average travel distance of households without ZEVs was longer than that of the households with ZEVs. The change in average travel distance remained small relative to the scenarios with the same cost percentage, such as for scenarios LZO20C, MZO20C, and HZO20C. In other words, ZEV ownership had a small impact on travel destination choice results for the scenarios with the same ZEV costs.



(**a**)

Figure 6. *Cont.*



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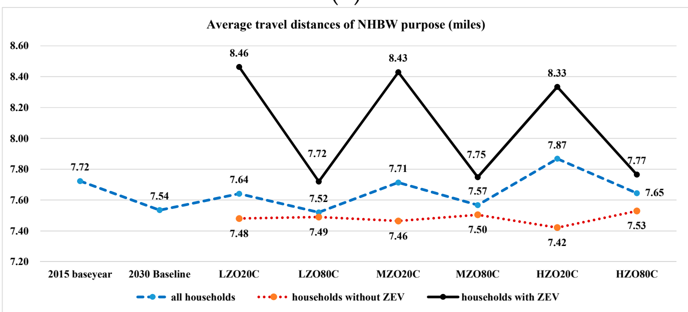

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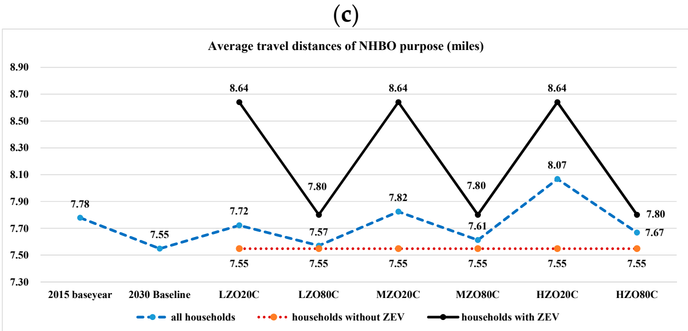

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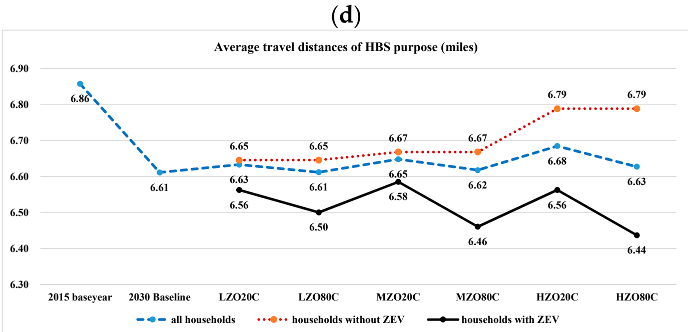

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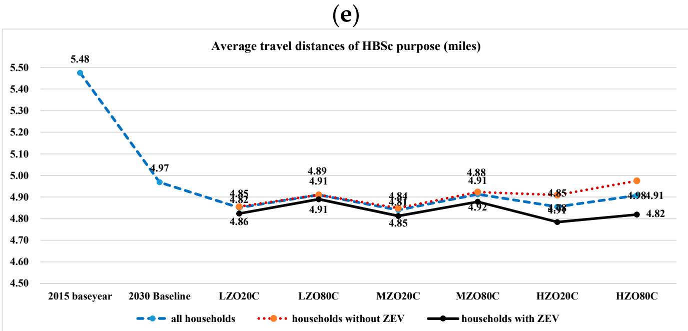


(**f**)

Figure 6. The average travel distance changes by travel purpose: (**a**) Home-based work (HBW); (**b**) Home-based other (HBO); (**c**) Non-home-based work (NHBW); (**d**) Non-home-based other (NHBO); (**e**) Home-based shop (HBS); (**f**) Home-based school (HBSc).

We observed that the transit share did not show a significant change (5% to 6%) for all 2030 scenarios, while ICEVs or ZEVs remained as the main travel mode, with about a 94% share. Table 2 summarizes the ICEV and ZEV mode choice results. For all ZEV scenarios, the mode choice results of the households without ZEVs (i.e., households with ICEVs) showed a minor difference from the 2030 baseline. Thus, for the scenarios with a 20% cost of ICEVs (LZO20C, MZO20C, and HZO20C), the drive alone(DA) mode for households with ZEVs, compared to households without ZEVs, increased by about 5%, shifting from shared ride with two persons (SR2) and shared ride with three or more persons (SR3+). For the scenarios with 80% cost of ICEVs (LZO20C, MZO20C, and HZO20C), the change in mode shift was only 2%. This showed that with lower operating costs, ZEVs would be preferred over carpooling, increasing the DA share. This behavior is consistent with the rebound effect in the literature.

Table 2. ZEV or ICEV mode choice results.

Scenarios	Households	DA	SR2	SR3+	Total ZEV or ICEV Share
2015 base year	all households	53.53%	38.89%	2.69%	95.10%
2030 baseline	all households	53.87%	37.53%	2.61%	94.01%
LZO20C	households without ZEV	53.74%	37.66%	2.61%	94.01%
	households with ZEV	58.65%	34.13%	2.00%	94.79%
LZO80C	households without ZEV	53.92%	37.76%	2.61%	94.29%
	households with ZEV	55.35%	36.85%	2.35%	94.56%
MZO20C	households without ZEV	53.67%	37.74%	2.62%	94.02%
	households with ZEV	58.53%	34.20%	2.02%	94.76%
MZO80C	households without ZEV	53.70%	37.75%	2.62%	94.08%
	households with ZEV	55.39%	36.29%	2.36%	94.04%
HZO20C	households without ZEV	53.30%	38.18%	2.65%	94.13%
	households with ZEV	58.47%	34.10%	2.03%	94.59%
HZO80C	households without ZEV	53.39%	38.21%	2.65%	94.25%
	households with ZEV	55.41%	36.17%	2.37%	93.95%

3.2. Spatial Analysis: Regional Level

Table 3 compares the performance of different scenarios in the state of Maryland spatially. VMT increased by approximately 21.71% to 31.52% in 2030 from the 2015 base year level. Within 2030 scenarios, VMT increased by approximately 0.47% to 8.06% from the 2030 baseline level. The MZO20C scenario produced the largest change in VMT, with 31.52% and 8.06% from the 2015 base year and 2030 baseline level, respectively. While VMT increased with higher ownership levels, CO_2Eq emissions declined. The change in CO_2Eq emissions was between −16.35% and +23.94% from the 2015 base year level and between −32.50% and −10.92% from the 2030 baseline level. From the 2015 base year level, the results of the high-ZEV ownership scenarios, HZO20C and HZO80C, showed that the two scenarios (HZO20C and HZO80C) could achieve a 16.35% and 15.80% reduction in statewide CO_2Eq emissions, respectively, while other scenarios did not lead to a reduction from the 2015 base year level. CO_2Eq emissions dropped by approximately 11% in low-ZEV ownership scenarios, 17% in medium-ZEV ownership scenarios, and 32% in high-ZEV ownership scenarios from the 2030 baseline levels. An interesting result was that CO_2Eq emissions did not change significantly (<1%) for two scenarios with the same ZEV ownership level, HZO20C and HZO80C, either from the 2015 base year level or the 2030 baseline level. This result indicates that the cost percentage assumption for the operational costs and parking costs has no significant effect on statewide CO_2Eq emissions. These results are also consistent with the rebound effect, i.e., as more ZEVs travel, they travel longer distances and contribute to congestion and increase emissions indirectly.

Table 3. Comparisons of scenario performances. VMT: Vehicle Miles Traveled; CO_2Eq: Carbon Dioxide Equivalent.

Measures	2015 Base Year	2030 Baseline	LZO20C	LZO80C	MZO20C	MZO80C	HZO20C	HZO80C
VMTs (millions)	168.16	204.66	210.21	205.63	213.55	206.85	221.16	208.92
VMT % changes from 2015 base year	-	21.71	25.00	22.28	26.99	23.01	31.52	24.24
VMT % changes from 2030 baseline	-	-	2.71	0.47	4.34	1.07	8.06	2.08
CO_2Eqs (tons/day)	85,889	106,450	94,766	94,826	88,059	88,384	71,850	72,397
CO_2Eq % changes from 2015 base year	-	23.94%	10.33	10.41	2.53	2.90	−16.35	−15.80
CO_2Eq % changes from 2030 baseline	-	-	-10.98	−10.92	−17.28	−16.97	−32.50	−32.07

3.3. Spatial Analysis: Local Level

Considering that cost had no significant effect on statewide CO_2Eq emissions, we focused on comparisons of scenarios with 20% of ICEV costs between the 2015 base year and 2030 baseline. At the county level, the results are reported in Tables 4 and 5. Table 4 presents the percent changes of CO_2Eq emissions in each county from the 2015 base year level and 2030 baseline level. Although considerable CO_2Eq emission reductions were observed at the statewide level, the amount of change differed from county to county. Compared to the 2015 base year level, the counties that showed the greatest change (increase or decrease) in CO_2Eqs are highlighted in red and light red, e.g., Somerset, Montgomery, Dorchester, and Prince George's. When the same county results were compared to the 2030 baseline level, they showed a small decrease in CO_2Eq emissions compared to other counties under the same scenario, such as Allegany, Frederick, Garrett, and Washington. Compared to other counties, these counties (corresponding to cells with green and light green backgrounds) had massive CO_2Eq emissions reductions. The yellow backgrounds represent the medium level.

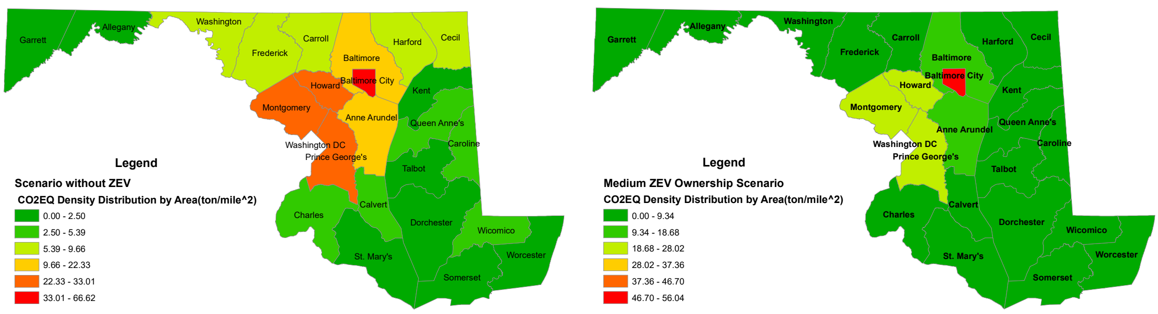
Table 4. CO_2Eq emissions changes of counties.

Counties	% Changes (from 2015 Base Year)				% Changes (from 2030 Baseline)		
	2030 Baseline	LZO20C	MZO20C	HZO20C	LZO20C	MZO20C	HZO20C
Allegany	−10.02%	−16.00%	−19.55%	−27.51%	−6.64%	−10.58%	−19.43%
Anne Arundel	16.87%	3.10%	−4.65%	−24.20%	−11.78%	−18.41%	−35.14%
Baltimore	10.63%	−1.58%	−8.55%	−25.43%	−11.04%	−17.34%	−32.60%
Calvert	18.74%	4.76%	−3.35%	−22.73%	−11.77%	−18.60%	−34.92%
Caroline	38.55%	23.28%	14.34%	−6.38%	−11.02%	−17.48%	−32.43%
Carroll	8.16%	−3.98%	−10.83%	−28.44%	−11.22%	−17.55%	−33.84%
Cecil	38.47%	25.54%	18.09%	0.03%	−9.34%	−14.72%	−27.76%
Charles	3.29%	−8.52%	−15.53%	−31.54%	−11.43%	−18.22%	−33.73%
Dorchester	43.20%	27.03%	17.39%	−4.27%	−11.29%	−18.02%	−33.15%
Frederick	34.36%	22.44%	15.35%	−1.53%	−8.88%	−14.15%	−26.72%
Garrett	−20.90%	−26.95%	−30.46%	−38.32%	−7.65%	−12.08%	−22.02%
Harford	16.35%	5.01%	−1.46%	−17.08%	−9.74%	−15.31%	−28.73%
Howard	25.84%	11.69%	3.41%	−16.76%	−11.24%	−17.83%	−33.85%
Kent	26.73%	10.67%	2.10%	−18.78%	−12.67%	−19.43%	−35.91%
Montgomery	38.83%	22.35%	12.97%	−10.02%	−11.87%	−18.62%	−35.19%
Prince George's	49.50%	31.24%	20.98%	−4.09%	−12.21%	−19.08%	−35.84%
Queen Anne's	32.52%	19.36%	12.84%	−4.82%	−9.93%	−14.85%	−28.18%
Saint Mary's	−38.62%	−46.33%	−50.82%	−61.70%	−12.56%	−19.87%	−37.59%
Somerset	73.14%	52.96%	41.04%	14.11%	−11.65%	−18.54%	−34.09%
Talbot	21.96%	8.83%	1.66%	−16.45%	−10.77%	−16.65%	−31.50%
Washington	17.05%	8.85%	4.09%	−7.02%	−7.01%	−11.08%	−20.57%
Wicomico	30.39%	14.80%	5.18%	−15.23%	−11.95%	−19.33%	−34.99%
Worcester	22.96%	8.88%	0.11%	−18.47%	−11.45%	−18.58%	−33.70%
Baltimore City	19.41%	7.64%	0.44%	−15.85%	−9.85%	−15.88%	−29.53%

Table 5 shows CO_2Eq emissions per unit area and per VMT in each county. The results are divided into different classes with different color backgrounds. For one of two parts of the measures (emissions by area and VMT), the comparisons are among all four scenarios. The results showed that high CO_2Eq emissions by area were mainly distributed in Baltimore City, Prince George's, Montgomery, Howard, Baltimore, and Anne Arundel counties. Figure 7 depicts the distribution of CO_2Eq emissions by area for the 2030 baseline and MZO20C scenario. Although some counties had high CO_2Eq emissions by area, these counties had relatively low CO_2Eq emissions by VMT, such as Baltimore City, Prince George's, Montgomery, and Anne Arundel. On the contrary, some counties with low CO_2Eq emissions by area had high CO_2Eq emissions by VMT, such as Saint Mary's, Somerset, Calvert, and Caroline. We found that the difference in CO_2Eq emissions by VMT among all counties became insignificant with increasing ZEV ownership. For example, HZO20C had more harmonious CO_2Eq emissions by VMT.

Table 5. CO_2Eq emissions by area and VMT changes of counties.

Counties	CO_2Eq Emissions by Area (Tons/Day/Square Miles)				CO_2Eq Emissions by VMT (g/VMT)			
	2030 Baseline	**LZO20C**	**MZO20C**	**HZO20C**	**2030 Baseline**	**LZO20C**	**MZO20C**	**HZO20C**
Allegany	2.39	2.23	2.14	1.93	0.49	0.45	0.43	0.38
Anne Arundel	15.43	13.61	12.59	10.01	0.44	0.38	0.35	0.26
Baltimore	22.33	19.87	18.46	15.05	0.53	0.46	0.42	0.33
Calvert	3.92	3.46	3.19	2.55	0.64	0.55	0.50	0.38
Caroline	3.41	3.04	2.82	2.31	0.62	0.54	0.49	0.39
Carroll	7.35	6.52	6.06	4.86	0.55	0.47	0.43	0.33
Cecil	8.52	7.73	7.27	6.16	0.47	0.42	0.39	0.32
Charles	3.01	2.66	2.46	1.99	0.54	0.46	0.42	0.33
Dorchester	0.99	0.88	0.81	0.66	0.59	0.51	0.46	0.36
Frederick	9.07	8.27	7.79	6.65	0.53	0.47	0.44	0.36
Garrett	1.04	0.96	0.91	0.81	0.46	0.42	0.39	0.34
Harford	9.66	8.71	8.18	6.88	0.48	0.43	0.40	0.32
Howard	28.25	25.07	23.21	18.68	0.47	0.41	0.37	0.29
Kent	1.44	1.26	1.16	0.92	0.56	0.48	0.43	0.33
Montgomery	28.92	25.49	23.53	18.74	0.55	0.47	0.43	0.33
Prince George's	33.01	28.98	26.71	21.18	0.54	0.46	0.42	0.32
Queen Anne's	3.90	3.51	3.32	2.80	0.62	0.55	0.50	0.41
Saint Mary's	1.56	1.37	1.25	0.98	0.60	0.51	0.46	0.35
Somerset	1.53	1.35	1.25	1.01	0.65	0.56	0.50	0.39
Talbot	2.50	2.23	2.08	1.71	0.57	0.49	0.45	0.36
Washington	6.64	6.18	5.91	5.28	0.47	0.44	0.41	0.36
Wicomico	5.39	4.75	4.35	3.51	0.53	0.46	0.42	0.32
Worcester	2.17	1.92	1.77	1.44	0.59	0.50	0.46	0.35
Baltimore City	66.62	60.06	56.04	46.95	0.50	0.44	0.41	0.33

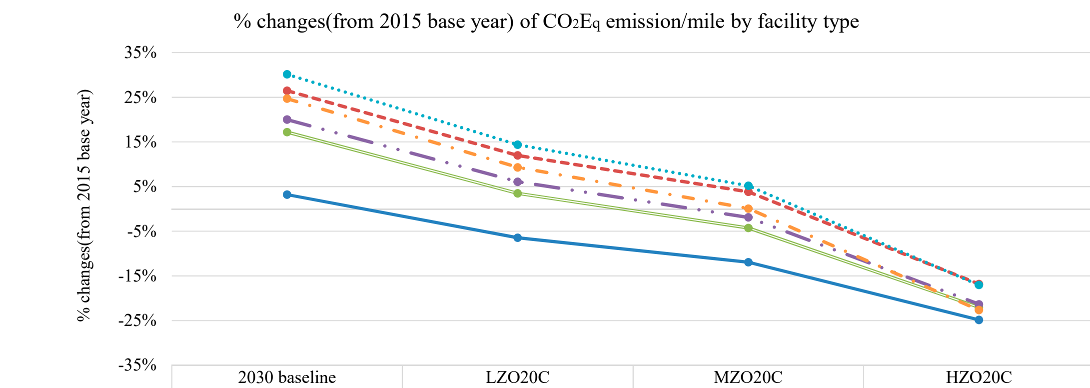


(**a**) (**b**)

Figure 7. Distribution of CO_2Eq emissions by area: (**a**) 2030 baseline; (**b**) MZO20C.

3.4. Spatial Analysis: Roadway Level

A further comparison was summarized by roadway facility type. Figure 8 shows the percent changes (from the 2015 base year) of CO_2EQ emissions/mile by facility type under the four scenarios. We found that the percent changes in CO_2Eq emissions/mile differed by facility type, but those changes showed a similar pattern. The facility types were ordered based on the change in CO_2Eq emissions/mile, with an increasing order as follows: Minor arterials, freeways, collectors, major arterials, expressways, and interstates. In addition, gaps in percent changes gradually decreased with an increase in ZEV ownership. For example, the HZO20C scenario had a small interval change of 8% (between −17% and −25%), which was less than other scenarios (2015 baseline (27%), LZO20 (20%), and MZO20C (17%)).



	2030 baseline	LZO20C	MZO20C	HZO20C
Interstate	3%	-6%	-12%	-25%
Freeway	26%	12%	4%	-17%
Expressway	17%	3%	-4%	-22%
Major Arterial	20%	6%	-2%	-21%
Minor Arterial	30%	14%	5%	-17%
Collector	25%	9%	0%	-23%

Figure 8. Percent changes (from 2015 base year) of CO_2EQ emissions/mile by facility type.

4. Discussion and Conclusions

In this study, we showed that ZEVs could play a significant role in reducing CO_2 emissions from road passenger transport at different levels.

The scenario results presented in this paper demonstrated that all ZEV ownership levels led to an increase in DA trips by ZEV users and moderately longer travel distances because of our reduced operating cost and parking cost assumptions. From the 2015 base year level, total VMT increased by approximately 21.71% to 31.52%, and only in two high-ZEV ownership scenarios did statewide CO_2Eq emissions drop by 16.35% and 15.80%, respectively. From the 2030 baseline level, total VMT increased by approximately 0.47% to 8.06%, and the changes in CO_2Eq emissions was between −32.50% and −10.92%. Compared to the percentage of households with ZEVs, 14.49% (low-ZEV ownership), 23.18% (medium-ZEV ownership), and 43.14% (high-ZEV ownership), the change in CO_2Eq emissions was less than the corresponding increase in percentage of ZEV ownership. The main reason was that we did not consider the impact of truck trips and long-distance trips on CO_2Eq emissions, and truck and long-distance trips also make up a large part of all MSTM trips. Thus, in order to achieve a pre-established goal of emissions reductions, more aggressive measures and policies should be implemented, such as encouraging ICEV users to choose ZEVs and using more clean freight vehicles.

In contrast with other research [1,11,13,25,33], we calculated the CO_2Eq emissions per unit area and per VMT in each county and per mile by facility type. The estimated results showed that the high-ZEV ownership scenarios could reduce the CO_2Eq emissions per VMT (shown in Table 5) among all counties and the gaps in CO_2Eq emissions per mile among six road types (shown in Figure 8). In recent years, public transportation's role in reducing GHG emissions has gained renewed attention [34], so convenient and competitive public transport options should be provided to attract more car users to transit, especially in dense metropolitan areas. In counties with high emissions per VMT values, which are rural and where typically more low-income households reside, subsidies can be provided to incentivize ZEV purchasing. The results by road type can guide policies to improve environmental quality and address environmental justice questions. For example, road types with high emissions per mile, such as minor arterials, freeways, and collectors, can be given priority when deploying ZEV charging infrastructure to support their use, and residents along them can be given incentives.

Increasing the use of ZEVs led to lower statewide and regional GHG emissions, and it shortened the gaps in emissions per unit area or per VMT among different counties. The operational costs and parking costs under a ZEV ownership scenario had no significant effect on statewide CO_2Eq emissions, likely due to the rebound effect from congestion. To reduce CO_2 emissions, priority should be given to encouraging more households to switch to ZEVs. Although our results showed that the operational costs and parking costs had no significant effect on emissions, the lower cost would attract more households to own ZEVs.

This research established a ZEV deployment policy testing model based on Maryland. Our analysis had some limitations. First, all results were concluded under suggested ZEV ownership assumptions: a ZEV ownership estimation model should be established in further work. Second, we used the same nested-logit mode choice model with different operational costs and parking costs for analyzing the behavioral changes of households with ZEVs. Little is known about potential behavioral changes that occur after adopting electric vehicles or behavioral differences between EV users and non-EV users [7]. Charging facility availability, driving range limitation, and other factors have impacts on ZEV adoption. As data becomes available, ZEVs, as a new mode, should be added to the mode choice model, and the model parameters should be recalibrated and revalidated. Third, there are certainly more variables that may have a significant impact on GHG distribution, such as the deployment of zero-emission trucks and autonomous vehicles. Further research is also needed to determine other variables and their effects on GHG emissions.

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Abbreviations

ZEV	Zero-emission Vehicles
GHG	Greenhouse Gas
MSTM	Maryland Statewide Transportation Model
EV	Electric Vehicles
HEV	Hybrid Electric Vehicles
MEM	Mobile Emissions Model
MOVES	Motor Vehicle Emissions Simulator
NOx	Oxides of Nitrogen
VOC	Volatile Organic Compounds
CO_2Eq	Carbon Dioxide Equivalents
VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
SMZ	Statewide Modeling Zone
ICEV	Internal Combustion Engine Vehicles
HBW	Home-Based Work
HBO	Home-Based Other
NHBW	Non-Home-Based Work
NHBO	Non-Home-Based Other
HBS	Home-Based Shop
HBSc	Home-Based School
CLRP	Constrained Long-Range Plan
LZO20C	Low-ZEV ownership with a 20% cost level of ICEVs
LZO80C	Low-ZEV ownership with an 80% cost level of ICEVs
MZO20C	Medium-ZEV ownership with a 20% cost level of ICEVs
MZO80C	Medium-ZEV ownership with an 80% cost level of ICEVs
HZO20C	High-ZEV ownership with a 20% cost level of ICEVs
HZO80C	High-ZEV ownership with an 80% cost level of ICEVs

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