LIGHT DUTY VEHICLE CHOICE MODELS EXAMINING ALTERNATIVE FUEL TECHNOLOGY PREFERENCES AMONG COMMERCIAL FLEET OWNERS

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ABSTRACT

Agent-based transportation models are critical tool for evaluating energy use, emissions and mobility impacts of transportation. In this context, vehicle ownership models are critical for linking agent activities to their impacts on the transportation system. However, no agent-based freight transportation models to date has been developed that predicts the fuel technology that is preferred by establishments when purchasing a Light Duty Vehicle (LDV) for business purposes. This research addresses this gap by using recently collected survey data to estimate a discrete choice model that can be applied in the agent-based context.

INTRODUCTION

Background and Motivation

Agent-based models are a powerful tool for evaluating interactions between transportation supply and demand by analyzing decisions of and interactions among individual agents. Agents in urban freight models are typically business establishments or vehicle operators. Decisions to model for freight agents include supply chain partnership, vehicle or fleet ownership, and production decisions among others.

Literature Review

The transportation field has a rich history of agent-based modeling for passenger travel (e.g., Bowman, 1998; Sokolov et al., 2012). However, agent-based models for freight transportation have emerged more recently—examples include Stinson et al. (2018), de Jong and Ben-Akiva (2007), Cambridge Systematics, Inc. (2011) and Alho et al. (2017)—and still have many development challenges to overcome.

One major gap in freight modeling is the scarcity of fleet ownership models for establishments. This gap is due in part to the recent emergence of freight modeling, but is exacerbated by a lack of sufficient data for model development. Vehicle ownership models can focus on one or more of the following decisions: current fleet ownership, next transaction, or some combination of vehicle transaction and other major event (such as a location change).

This gap cannot be ignored since fleets are an essential part of freight transportation supply. Modeling establishment vehicle ownership has important implications for the development of sound, realistic freight transportation models since they impact tour start and end points, maximum transportable volume on a tour, parking options, and route options. Each of these elements can significantly impact freight mobility and energy use.

Moreover, models used in practice have serious limitations for evaluating the energy implications of freight transportation. This is especially true in today's world with rapidly changing technologies on the marketplace. The cost, reliability and driving range of alternative technologies have improved in recent years, increasing the competitiveness of these technologies compared to conventional technologies. Existing models are insightful but have not addressed fuel technology preferences (Abate & De Jong, 2014; Holguín-Veras & Patil, 2008; Hunt & Stefan, 2007; Nuzzolo & Comi, 2014; Rashidi & Roorda, 2018; Wang & Hu, 2012).

Objective

The objective of this study is to address this gap in the literature by developing a behavioral-based choice model that predicts the light-duty vehicle (LDV) fuel technology that is preferred by individual commercial establishments that own LDVs. The resulting model can be implemented in an agent-based simulation context for the purpose of predicting alternative fuel choices made by establishments over some time span when their next vehicle purchase is made. Discrete choice models of fuel type choice for the next LDV purchase were estimated. Additionally, factor analysis was performed to explore underlying reasons for fuel type preferences.

METHODOLOGY

The analysis utilizes two methodologies. First, discrete choice models – specifically, nested logit models – were the basis of the choice evaluation. Second, factor analysis was applied to shed additional insights into underlying factors that can explain establishment preferences for various alternative fuels. In interest of brevity, the reader is referred to the following two sources for technical information on the formulation of the nested logit model and the factor analysis.

Ben-Akiva and Lerman (1985) describe the nested logit formulation. Briefly, the nested logit (NL) model is a type of discrete choice model. Its key features is its ability to capture reasonable substitution patterns for related alternatives. In other words, the NL mathematical formulation effectively addresses the intuition that alternatives within the same nest share some unobserved characteristics.

Technical details of factor analysis can be reviewed on the educational website developed by Penn State (STAT 505: Applied Multivariate Statistical Analysis). Factor analysis enables the identification of a small number of latent (or unobservable or hidden) factors that underlie a set of observed variables. It is considered to be an exploratory method that is suitable for examining fundamental causes of judgments or decisions. In this work, factor analysis is used to examine underlying attitudes and preferences for various LDV body types.

The reader should note that in the estimation of the nested logit models within this paper, normalization of the nesting parameter was for the upper nest. Therefore, significant nesting parameters are expected to be greater than one.

Lastly, average annual vehicle cost was approximated for each vehicle as follows. The initial capital cost and operating fuel costs were used. The cost calculation used was: Annual Cost = Purchase price/10 + Average per-mile fuel cost*Avg. Annual Vehicle Miles Traveled (VMT) per LDV. A 10-year vehicle life is assumed. Average annual VMT is establishment-specific and was obtained from the CEC survey data. Purchase prices are based on data from the Alternative Fuels Data Center supplemented with information from a web search which indicate that a conventional vehicle price is about 85 percent that of an HEV and a Full EV about 60 percent more expensive than a conventional vehicle. Assumed purchases prices by vehicle type are: $24,000 (conventional), $28,200 (HEV), $32,500 (PHEV) and $38,400 (Full EV) based on a web search of typical light duty vehicles. Per-mile fuel costs are assumed to be 11 cents per mile (conventional), 7.5 cents per mile (HEV), 5.4 cents per mile (PHEV) and 3.3 cents per mile (Full EV) using vehicle performance information from the Alternative Fuels Data Center.

Future iterations of this study may include a provision to obtain more accurate cost data or to enhance the estimation process. Resale value and maintenance costs, which were assumed to be the same for different vehicles in this study, can be treated in greater detail.

DATA

The dataset used for analysis is the 2017 California Vehicle Survey (California Energy Commission, 2018). The sample universe was commercial light-duty fleet owners in California. The sample size is 1,712 establishments. Numerous body types are included: car, SUV, Van, and Pick-up truck. The following fuel types are included: gas, diesel, flex/E85, gas-hybrid (HEV), hybrid plug-in (PHEV), full electric (EV), other (Hydrogen, CNG). The key limitations of this dataset are that (a) only information on LDV ownership is available, (b) only coarse geographic detail on establishment location is provided, and (c) firm affiliations are unknown. Despite these limitations, the dataset contains sufficient information to develop an establishment-level model of LDV ownership with fuel type.

In Figures 1 and 2, the number of vehicles owned is on the x-axis and number of establishments on the y-axis. Figure 1 shows the distribution of total LDV ownership among sampled establishments. The distribution is heavily right-skewed with a large portion of establishments owning less than five LDVs. Figure 2 shows that a similar distribution occurs for each fuel type (HEV denotes Hybrid Gas Electric; PHEV denotes Hybrid Plug-in Electric; EV denotes Full Electric; and Other denotes other fuel type, including hydrogen and natural gas).

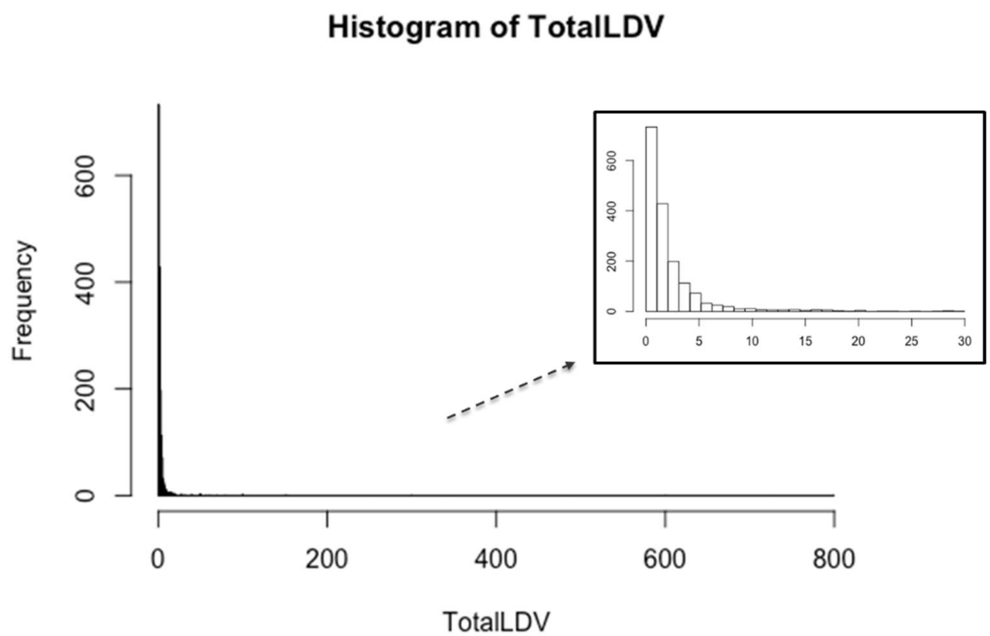

Figure 1. Frequency distribution: LDV ownership

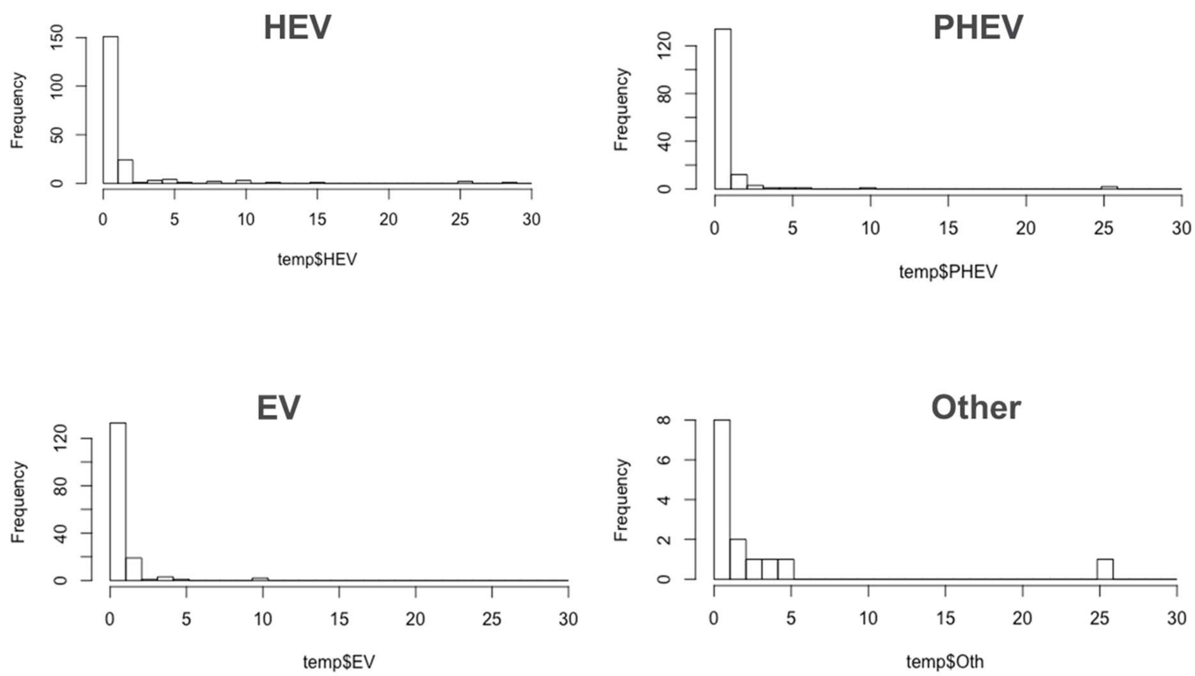

Figure 2. Frequency distribution: LDV ownership by fuel type

Industries were grouped in order to obtain sample sizes to support parameter estimation. The categories used (and the sample size n for each) are:

- NAICS 1-42 (n=357): Agriculture, Mining, Utilities, Construction, Manufacturing, Wholesale Trade
- NAICS 44-49 (n=249): Retail trade & Transportation and Warehousing
- NAICS 51-55 (n=624): Information, Finance, Insurance, Real Estate, Professional, Management
- NAICS 56, 72, 81 (n=284): Waste management, Accommodation and food services, Other services
- Other NAICS (n=198) Educational services (NAICS 61), Health care and social assistance (NAICS 62), Arts, entertainment, and recreation (NAICS 71)

Some of these categories, such as NAICS 1-42, contain a fair amount of heterogeneity among establishments. While the groupings led to strong statistical significance in the resulting models, future efforts should identify ways to use more refined industry groupings.

The following geographic regions were used in the model: Los Angeles metro area, San Francisco metro area, San Diego metro area, Sacramento metro area, Central Valley, and Rest of state.

Respondents were asked to report the fuel type of the next LDV purchase that was planned by the establishment. A total of 1,036 respondents reported that they would purchase a conventionally fueled (diesel or gasoline) LDV; 320 would buy a hybrid gas LDV; 149 would buy a hybrid plug-in; and 188 would buy a full electric vehicle. These answers formed the basis of the choice model.

Respondents were asked to indicate their top five concerns related to alternative fuel vehicles from pre-specified list (details in California Energy Commission, 2018). Responses to this question set were used in the factor analysis.

RESULTS

Alternative Fuel Choice Model

Nested logit models were used to model the fuel choice decision. Table 1 shows the model results for four different nests, with nest membership and nesting parameter estimates noted at the bottom. A few statistically insignificant parameter estimates are included in the table so the reader can compare the results among models and because the parameter signs were in the expected directions. The results can be interpreted as follows.

Industries in more freight-intensive sectors, such as agriculture and manufacturing, prefer conventional fuels. This is perhaps due to concerns about hauling deliveries over medium to long distances (a limitation of alternative fuel vehicles). Establishments in major metropolitan areas, including Los Angeles (LA) and even more so San Diego and San Francisco, are less likely to purchase a conventional vehicles than establishments in more rural areas. This is likely due to higher rates of short-distance driving in urban regions. Respondents in rural areas appeared to be impartial to conventional vs. non-conventional, all else equal, but this finding needs further investigation as it could be attributed to the industry mix in rural areas (where freight-intensive industries are more heavily represented). Interestingly, cost was only a deterrent to Full EV purchasing—this aspect should be revisited in future iterations of the model by testing a single generic cost specification. Moreover, larger establishments were not as interested in alternative vehicles as smaller establishments. This might reflect higher cargo hauling needs of larger establishments, although more investigation is needed to determine this.

Model D yielded the best model in terms of overall fit using the rho-bar-squared criterion (which measures the improvement in log-likelihood relative to a model with no parameters). In this model, a nest with Conventional fuel, Hybrid gas, and Full electric was highly significant. Hybrid plug-in is in its own nest. Model C also produced meaningful parameters for a Conventional and Full electric nest. The interpretation of this result is as follows. The significant nest in each model did not contain the Hybrid plug-in alternative. This may indicate a preference for relying primarily on a single technology—e.g., the driver needs to either stop for gas or plug in the vehicle, but doesn't do both. In other words, this finding suggests that fleet managers or drivers would rather put forth effort for only one refueling type (at least for today; this would change as alternative technologies become more prevalent). A similar finding was observed for Model B, which had a parameter for a Hybrid gas and Full electric (B) that was well above 1.0. However, the standard error of the Model B nest parameter is very high. Overall, Model D is recommended for application since its nesting structure has an intuitive explanation, the goodness-of-fit measure is relatively high, and parameter values are reasonable.

Factor Analysis

Table 2 shows the selected results of the factor analysis. It is common practice to select only loadings over a certain absolute magnitude (0.4 was used here). Three relevant dimensions emerge. The first factor represents concern over operational factors, including operating cost, driving range, charging infrastructure, and other considerations. The third factor also represents a very clear concern – in this case, body characteristics. Fully electric vehicles and their variations have almost no models outside of the sedan, which poses serious limitations to any business that hauls cargo or transports passengers. The second factor, in contrast, can be summarizes as an attitude of relative fearlessness of the unknown aspects of alternative fuels and the lack of any particular concerns related to operational or body characteristics.

CONCLUSION

This study presents the parameter estimates of discrete choice models that were estimated to evaluate LDV fuel type choice for establishments. The models remedy a gap in the literature, as there currently are no known models of this decision. This decision is important to model since it has impacts on modeling transportation supply and subsequently mobility and energy use associated with freight transportation. As discussed in the Results section, the model results are intuitive. The estimated models can be applied in practice to predict the fuel type chosen by an establishment in its next LDV purchase decision. Additional factor analysis helps explain hesitations toward adopting alternative fuels, namely body type and operational concerns. While the main purpose of this research is to develop models that can be used for forecasting, the models can also be used to inform policy and outreach by identifying which sectors are predisposed to using alternative fuels.

Future work will examine the joint body type-fuel technology decision. Improving the financial inputs by including maintenance costs and resale value would enhance the model as well.

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Table 1. Nested logit model results

MODEL	A		B		C		D	
MODEL STATISTICS								
Number of parameters:	18		18		18		17	
Sample size:	1693		1693		1693		1693	
Excluded observations:	19		19		19		19	
Init log likelihood:	-2346.996		-2346.996		-2346.996		-2549.683	
Final log likelihood:	-1714.609		-1714.15		-1708.583		-1714.4	
Likelihood ratio test:	1264.775		1265.692		1276.827		1670.566	
Rho-square-bar:	0.262		0.262		0.264		0.321	
Iterations:	81		99		100		48	
PARAMETER ESTIMATES								
Name	**Value**	***Rob. t***	**Value**	***Rob. t***	**Value**	***Rob. t***	**Value**	***Rob. t***
Alternative-specific constants (base: Conventional)								
Full Electric	0.67	*0.71*	-0.184	*-0.24*	0.129	*0.26*	0.537	*0.65*
Hybrid Gas	-1.23	*-4.7*	-0.727	*-1.95*	-1.31	*-5.99*	-1.02	*-2.57*
Hybrid Plugin	-1.82	*-5.39*	-1.79	*-3.76*	-1.75	*-5.99*	-1.85	*-5.78*
Industry indicators (Base: All NAICS not listed)								
Conventional: NAICS 44-49	0.744	*3.67*	0.757	*3.73*	0.582	*3.7*	0.626	*2.33*
Full Electric: NAICS 51-55	0.21	*1.11*	0.16	*0.83*	0.0442	*0.38*	0.219	*1.33*
Conventional: NAICS 56, 72, & 81	0.577	*2.97*	0.581	*2.98*	0.417	*2.86*	0.489	*2.19*
Conventional: NAICS 1-42	1.24	*6.2*	1.25	*6*	0.882	*4.27*	1.06	*3.06*
Region indicators (base: non-conventional fuel)								
Conventional: LA	-0.711	*-4.16*	-0.711	*-4.16*	-0.475	*-2.97*	-0.592	*-2.36*
Conventional: San Diego	-0.952	*-4.41*	-0.956	*-4.05*	-0.673	*-3.5*	-0.817	*-2.92*
Conventional: San Francisco	-0.888	*-4.86*	-0.891	*-4.86*	-0.666	*-4.08*	-0.744	*-2.59*
Cost								
Full Electric ($)	-0.000417	*-1.91*	-0.000131	*-0.59*	-0.000173	*-1.42*	-0.00035	*-1.65*
Establishment Size (Number of Employees)								
Full Electric	-0.488	*-4.17*	-0.255	*-1.91*	-0.237	*-3.08*	-0.406	*-2.57*
Hybrid Gas	-0.0816	*-1.22*	-0.169	*-2.06*	-0.053	*-0.8*	-0.0699	*-1.19*
Hybrid Plugin	-0.217	*-1.81*	-0.216	*-1.75*	-0.21	*-1.74*	-0.212	*-1.77*
Nesting structure	Nest 1:	*Conv, Hgas*	Nest 1:	*Conv, Hplug*	Nest 1:	*Conv, FullEV*	Nest 1:	*Conv, Hgas, FullEV*
	Nest 2:	*Hplug,FullEV*	Nest 2:	*Hgas, FullEV*	Nest 2:	*Hgas, Hplug*		
Nest parameters	**Value**	***Std.Err.***	**Value**	***Std.Err.***	**Value**	***Std.Err.***	**Value**	***Std.Err.***
Nest 1	1	*9E+06*	1	*4.72*	2.03	*0.44*	1.2	*0.35*
Nest 2	1	*0* *	4.16	*8.25* *	1	*0* *		

Table 2. Factor analysis results

Area of concern	Factor1	Factor2	Factor3
No concerns	-0.545	0.568	-0.415
Seating capacity			0.403
Hauling capacity			0.501
Body type			0.457
Cost	0.588		
Range (electric)	0.402		
Battery life (electric)	0.512		
Lack of infrastructure	0.477		
Charge time (electric)	0.51		
EV not well known		-0.58	
PHEV not well known		-0.637	

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