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Rapid estimation of electric vehicle acceptance using a general description of driving patterns

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ABSTRACT

A reliable estimate of the potential for electrification of personal automobiles in a given region is dependent on detailed understanding of vehicle usage in that region. While broad measures of driving behavior, such as annual miles traveled or the ensemble distribution of daily travel distances are widely available, they cannot be predictors of the range needs or fuel-saving potential that influence an individual purchase decision. Studies that record details of individual vehicle usage over a sufficient time period are available for only a few regions in the US. In this paper we compare statistical characterization of four such studies (three in the US, one in Germany) and find remarkable similarities between them, and that they can be described quite accurately by properly chosen set of distributions. This commonality gives high confidence that ensemble data can be used to predict the spectrum of usage and acceptance of alternative vehicles in general. This generalized representation of vehicle usage may also be a powerful tool in estimating real-world fuel consumption and emissions.

1. Introduction

Large-scale introduction of electric vehicles (EVs) is widely viewed as an important contributor to reducing the energy consumption and atmospheric emissions of automobile transportation. The degree to which EVs will displace chemical fuel and deliver zero-emissions driving will be determined by their acceptance in the market, and once accepted, the details of how they are used in the field. Unlike the case of plug-in hybrid electric vehicles (PHEV) where the first portion of any trip may be electrified and any remainder completed using chemical fuel, finite range is a critical limitation for EV because trips (defined as the distance traveled between adequate charging opportunities) longer than the battery range cannot be undertaken at all. Thus, reliable estimates of the electrification potential of EV in a given region must begin with understanding of individual transportation needs (how each existing vehicle is used) combined with individual willingness to accept any shortcomings of an EV as a substitute for that existing non-plug-in vehicle. While individual response to the inconvenience of limited range depends on the specific context, such as availability and willingness to use alternatives as well as purely emotional needs, the frequency of that inconvenience – or more precisely, the distribution of the that inconvenience across the population – can be inferred from vehicle usage data. Acceptance of EV in a given population can then be estimated based on an assumed typical tolerance for inconvenience. However, while there is interest in electrification all over the world, individual vehicle usage data suitable for such analysis is available from instrumented vehicles participating in just a few multi-day usage studies – usually designed for other purposes. Pearre et al. (2011), Khan and Kockelman (2012) and Tamor et al.

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(2013) recently analyzed private vehicle usage data from Atlanta, Puget Sound and Minneapolis-St. Paul respectively to characterize the inconvenience of finite EV range, and obtained similar results. In all cases this inconvenience, as measured by the number of days per year on which the instrumented vehicle was driven a distance greater than a presumed EV range, was substantial for any realistic value of that range. With highly detailed usage data that include GPS positioning, it is possible to conduct much more elaborate studies that optimize both vehicle capabilities and the location of battery charging (for example, Dong et al., 2014). The goal of this work is to develop tools for estimation of the acceptance and electrification impact of EV in regions where such data is not available.

Usage data is more generally available at higher levels of aggregation. At an intermediate level of detail, ensemble data that reflect the distribution of daily driving distances for a population – but not that of any individual – is available for many regions. For the US, the most widely cited of these is the National Household Travel Survey (NHTS, 2009). At the extreme of simplicity and general availability, the average annual miles traveled per vehicle (annual VMT) can be found in economic and demographic databases for nations and cities all over the world, but there is no obvious means to transform total annual travel into a distribution of daily trip distances. Given the paucity of detailed usage data and the regional variations in usage that might impact the design and utility of electrified vehicles, even a crude method to approximate the distribution of individual usages from ensemble data would be extremely valuable. We develop such a general method via several steps. First, we describe the results of a statistical analysis of usage data from Puget Sound, Minnesota and Germany using the methodology we have described previously (Tamor et al., 2013). Next, we show that the strong similarity between those results is attributable to similar distributions of the parameters that describe individual vehicle usage. Finally, we show how the readily-described distribution of just one of those parameters can be used to estimate EV acceptance (at an assumed tolerance for inconvenience) as a function of range with surprising fidelity. We also suggest other applications of this simplified representation of vehicle usage.

2. Statistical description of travel

For this study we consider only the simplest case of overnight charging for EV and so characterize the frequency distribution of full-day driving distance. The frequency distribution of daily driving distance of individual vehicles was extracted from three additional studies: the Puget Sound Regional Council Traffic Choices Study (PSRC, 2008); 446 vehicles in the greater Seattle area, the Commute Atlanta Value Pricing Program (Guensler and Williams, 2002 and Ogle et al., 2005); 651 vehicles in greater Atlanta, and the Europe Field Operations Test (euroFOT, 2012); 100 midsized Ford vehicles in several German cities. Like the Minnesota study, the Puget Sound and Atlanta studies are based on demographically representative participant selection. The euroFOT was a non-representative study conducted to study safety-related systems in suitably equipped Ford vehicles, but is included here as demonstration of our methodology for non-US vehicle usage.

We characterize the driving pattern of each vehicle using the methodology previously applied to vehicle data from the 133 vehicles participating in the Minnesota Mileage-Based User Fee Demonstration Project (Minnesota, 2006; Tamor et al., 2013). In that work we showed that the distance-frequency distribution of daily travel distance for an individual vehicle, labelled i, is well represented by a simple distribution,

$$f_i(x) = \lambda_i \times \left[\frac{w_i}{k_i} e^{-x/k_i} + (1 - w_i) \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-(x-\mu_i)^2/2\sigma_i^2} \right] \tag{1}$$

where x is the one-day travel distance. The first term represents a broad, 'random' distribution with characteristic distance k_i that includes both frequent short-distance travel days and occasional very long ones. The second term represents a repeated 'habitual' daily distance, μ_i (with variability σ_i) that we associate with commuting to work or another regular destination. The parameter w_i is the probability that a given day of driving is a member of the 'random' distribution. [With no information other than daily travel distances, this identification of habitual travel is in good agreement the fraction of 'commuting' travel in the NHTS (2009) where the purpose of each trip is known (see Table 1).] The fifth parameter, λ_i, is the probability that a given vehicle is driven on a given day.

Table 1
Fit parameters for Figs. 2 and 4. The habitual fraction is the fraction of actual travel distance (as opposed to number of travel days) associated with the habitual term of Eq. (1), and can be compared to the fraction of commuting survey studies such as the NHTS. The value of $<\lambda_i w_i>$ for Atlanta is actually $<\lambda_i><w_i>$ due to the scripting error described in the text. The two parameters that dominate the estimated acceptance, Z_k and α_k appear to vary in proportion to d_{50}, a widely available metric of daily driving behavior.

	k_i		μ_i		λ_i		$<\lambda_i w_i>$	d_{50}	Z_k/d_{50}	α_k/d_{50}	Habitual Fraction
	Z_k	α_k	Z_μ	α_μ	$1.1 - Z_\lambda$	α_λ					
Puget Sound	29.4	3.0	22.0	2.9	0.80	4.0	0.49	42	0.70	0.057	0.21
Minnesota	48.5	4.2	38.5	3.5	0.66	4.95	0.41	67	0.72	0.086	0.39
Atlanta	36.7	3.4	32.9	2.4	$<\lambda_i>$ = 0.89		0.54	55	0.67	0.062	0.20
Germany	33.5	3.1	14.3	1.8	0.77	3.25	0.45	48	0.69	0.065	0.23
NHTS (2009)								64			0.29