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.

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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.

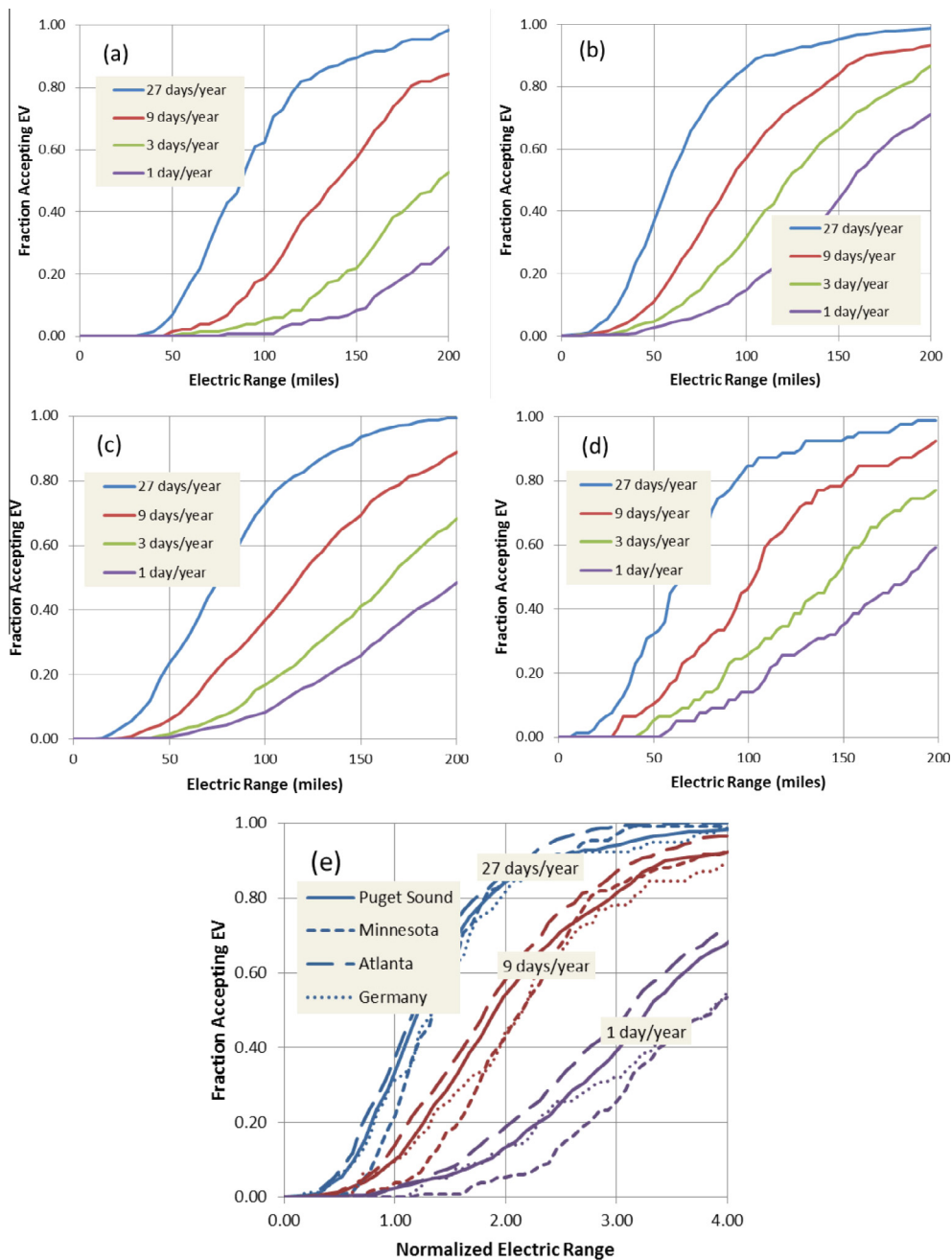|	k_i		μ_i		λ_i		$<\lambda_i w_i>$	d_{50}	Z_k/d_{50}	α_k/d_{50}	Habitual Fraction
	Z_k	α_k	Z_μ	α_μ	$1.1 - Z_\lambda$	α_λ					
Puget Sound	29.4	3.0	22.0	2.9	0.80	4.0	0.49	42	0.70	0.057	0.21
Minnesota	48.5	4.2	38.5	3.5	0.66	4.95	0.41	67	0.72	0.086	0.39
Atlanta	36.7	3.4	32.9	2.4	$<\lambda_i> = 0.89$		0.54	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

Fig. 1. (a–e) Fraction of users accepting an EV (based on inconvenience only) as a function range for four values of the inconvenience threshold in four regions: (a) Minneapolis-St. Paul, (b) Puget Sound, (c) Atlanta, (d) Germany, and (e) all four regions shown with electric range normalized to d_{50} for each region. (The 3-day/year curves are omitted from Fig. 1e for visual clarity.)

Previous investigators have used several different distributions to describe day-to-day variation in individual travel distance. These include the Weibull distribution (Kitamura et al., 1997; Traut et al., 2011), the normal distribution (Neubauer et al., 2012) and the Gamma distribution (Greene, 1985). More recently, Lin et al. (2012) used the Puget Sound data to compare the log-normal, Weibull and Gamma distributions and found the last to be the most effective of the three in capturing individual driving patterns. While it is no surprise that an additional parameter can improve the quality of fit in all cases, we suggest Eq. (1) does a better job capturing travel behavior for more fundamental reasons. First, it appears to be effective in identifying repeated travel routines without need for travel diary or GPS location analysis that specifies travel purpose. Second, the Weibull and Gamma distributions cannot simultaneously have finite value near zero and a peak away from zero. In consequence, they will underestimate the frequency of short trips whenever a distinct habitual peak appears. Inspection of
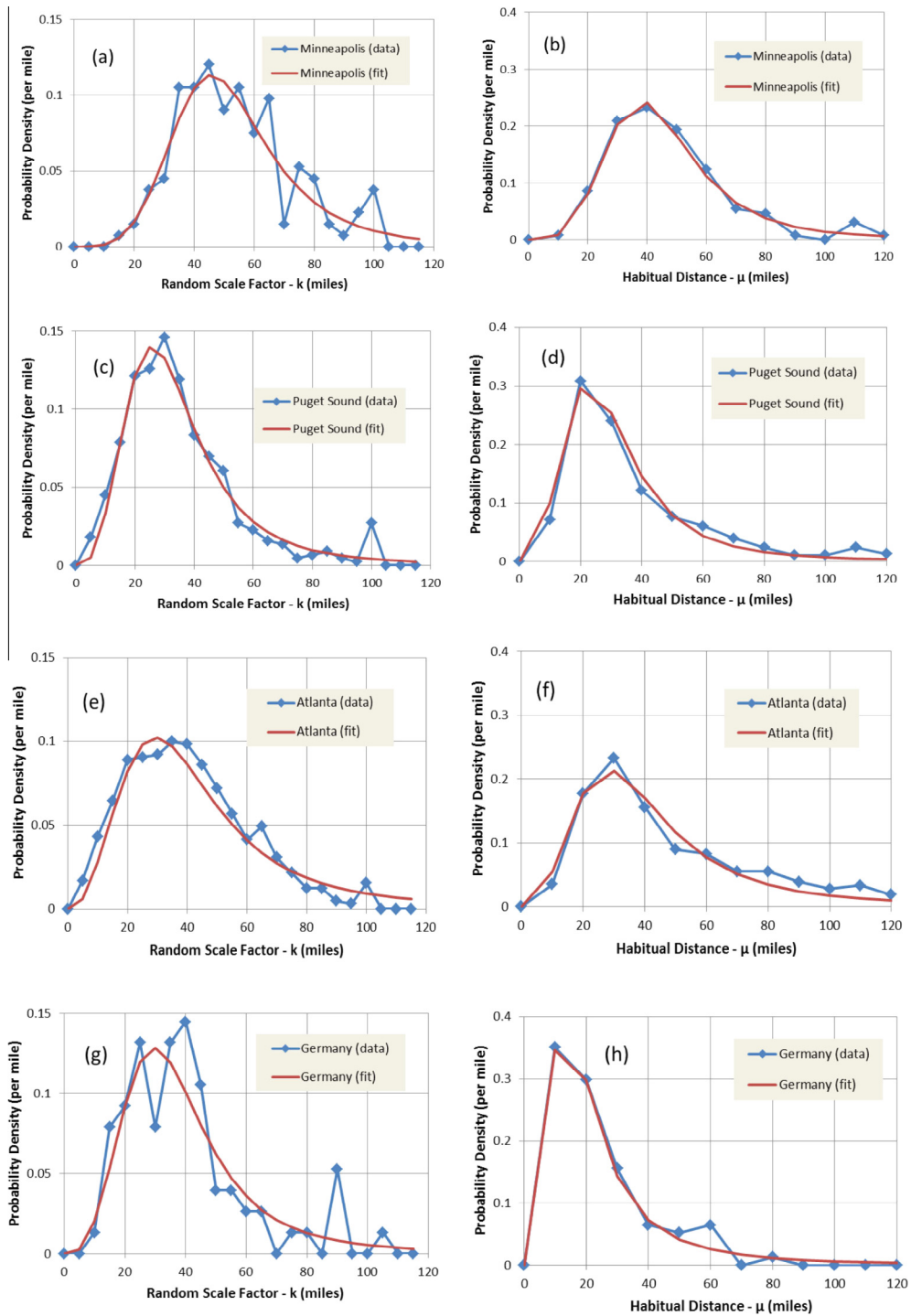
Fig. 2. The probability distributions of the random scale factor, k_i, and habitual distance, μ_i, for the four vehicle usage data sets: (a) and (b); Minnesota, (c) and (d); Puget Sound, (e) and (f) Atlanta, and (g) and (h); Germany. The fit function, Eq. (2), is integrated over the same bin intervals as the data.

the sample distributions for Minnesota (Tamor et al., 2013), Puget Sound (Fig. A4) and Atlanta (Fig. A7) confirms the importance of the additional degrees of freedom in Eq. (1). While some of these examples do resemble the Gamma or Weibull distributions, many clearly do not.

Following the procedure described in analysis of the Minnesota usage data, Eq. (1) was fit to each individual daily travel distance distribution using a non-sorting genetic algorithm (Deb et al., 2000). The normalized log-likelihood, $\ln(\Lambda)/N$, where
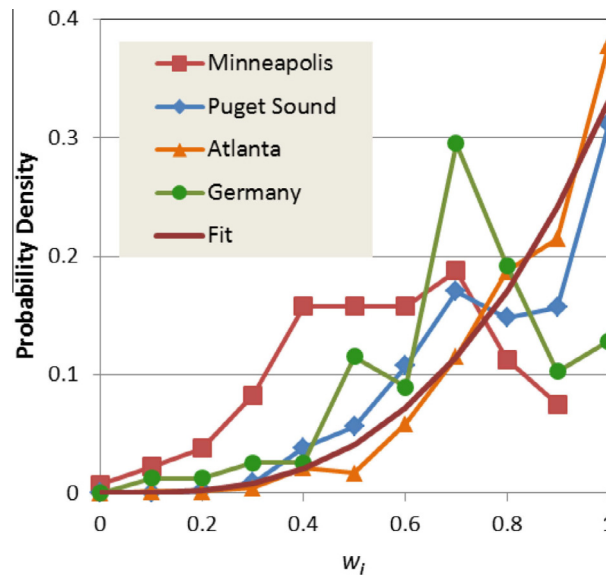
Fig. 3. Distribution of w_i, the probability that a given day of travel is 'random' (i.e. a member of the exponential distance–frequency distribution) for the four vehicle usage studies. The greater frequency of lower values of w_i in the Minnesota data is attributed to a bias toward commuting trips where only one 'primary' vehicle in each household has been instrumented. The solid curve is a simple function approximating the distributions for Atlanta and Puget Sound.
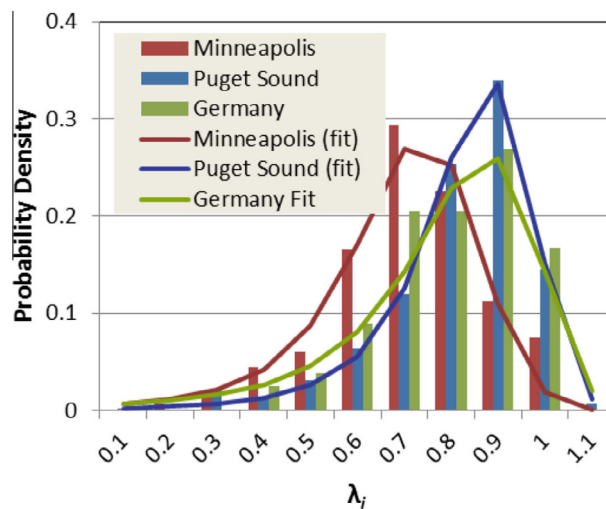

Fig. 4. Distribution of λ_i, the probability that a given vehicle is driven on a given calendar day, for three of the four usage studies. Values computed for the Atlanta data were unreliable due to an analysis error. The solid curves are a modification of Eq. (2) fit to the distributions.

Λ is the maximum likelihood value and N is the number days the vehicle was driven, was the metric of quality of each fit. The appropriateness of Eq. (1) was confirmed for the Puget Sound and Atlanta data sets by the well-behaved distributions of $\ln(\Lambda)/N$, and by visual assessment of the three best, three worst and many randomly selected intermediate-quality fits in each data set. Eq. (1) is found to be a good representation of the actual distribution of daily driving distance for well over 95% of vehicles in all four studies. [The quality-of-fit parameters were not available for the euroFOT data set, but the observed quality of the fits was similar to that of the other three data sets.] The distribution of the quality-of-fit parameter (where available), sample daily drive distance distributions, and the matrix plots indicative of correlations between the fit parameters are included in Appendix A. The value of μ_i/σ_i was limited to a minimum of 4 to prevent the appearance of a very broad peak that does improve the fit but is not plausibly associated with a repeated travel routine. This limit also assures that the finite probability of a negative trip length that is allowed by Eq. (1) is miniscule (i.e. the habitual peak is always at least $2\sigma_i$ away from the origin). A secondary consequence of this limit is that the fitting routine would occasionally assign the
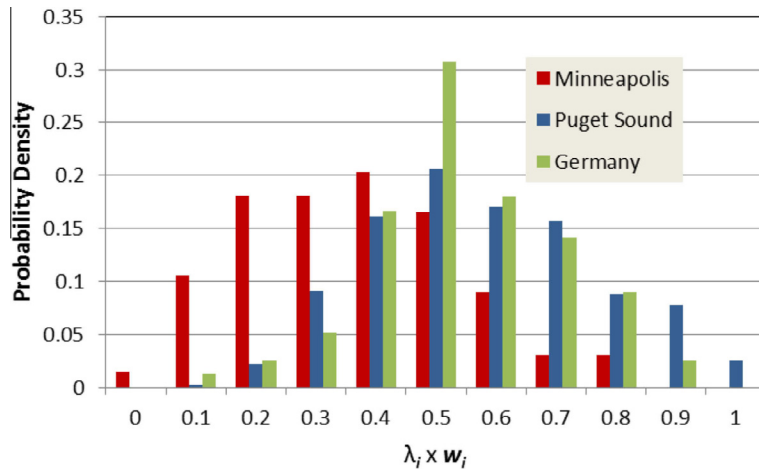
Fig. 5. Distribution of the product $\lambda_i \times w_i$ for three usage studies. The bias toward lower values in the Minnesota data is attributed to the high fraction of commuting in the single 'primary' vehicle instrumented in each household.

habitual peak to a single outlying drive event resulting in a large value of μ_i with $w_i = 1$. Because no weight is assigned to this long 'habitual' trip, the error does not affect any further analysis.

Again similar to Tamor et al. (2013) we computed the fraction of each sample population that might 'accept' an EV as a substitute for a conventional vehicles based on a threshold of inconvenience. This threshold is defined in terms of the number of days per year that a given EV range was insufficient for that day's driving. Users (actually vehicles) below the threshold of inconvenience, are presumed to have 'accepted' an EV and will use it on all days for which its range is sufficient and find alternative transportation on those days for which it was not sufficient, while those above the threshold simply refuse to use an EV at all. The threshold was varied from 1 to 27 days per year to reflect a wide range of individual tolerance and availability of alternatives. Fig. 1a–d show the fraction of the vehicle population that may be replaced with EVs as a function of electric range for several values of the inconvenience threshold in each of the four regions studied. The general shapes of these acceptance curves are remarkably similar. This similarity was tested by scaling the electric range in each case to a distance, d_{50}, defined as the 50% point in the cumulative driving distance of the entire population as a function of single-day driving distance (i.e. 50% of all driving by the entire population was accomplished on driving days covering d_{50} or fewer miles). As shown in Fig. 1e, the acceptance curves tend to superpose with this scaling. This finding strongly suggests a deeper commonality of individual variations in vehicle usage, and therefore that the acceptability (as defined here) of an electric vehicle of given range in a given region might be estimated from a single ensemble metric, d_{50}, for that region.

3. Meta-distributions

With the usage of each individual vehicle characterized by the set of parameters in Eq. (1), it follows that the entire population might be described by the distributions of those parameters: the 'meta-distributions.' However, to do so requires an understanding of any correlations between those parameters. Such correlations would be apparent in the matrix plots of the parameters (included in the Appendix). As described earlier, the only significant correlations are due to artifacts of the fitting procedure itself. This complete lack of correlation is a huge simplification in that the distribution of individual vehicle usages can be represented by the independent distributions of the fit parameters.

Fig. 2a–h show the distribution of k_i and μ_i for the four data sets analyzed. Fig. 3 shows the distribution of w_i for the four data sets. Fig. 4 shows the frequency distribution of λ_i for three of the four sets. Unfortunately, the λ_i values for the Atlanta data were lost due to a scripting error. For this analysis we substitute $\langle \lambda_i \rangle = 0.89$, computed from a later survey of travel in the same region (Atlanta Regional Commission, 2011). The parameter distributions are similar in all cases except that of w_i.

We find that distributions of k_i and μ_i are well characterized by the log–logistic distribution:

$$f(x) = \left(\frac{\alpha x^{\alpha-1}}{Z^{\alpha}}\right)\left(1 + \left(\frac{x}{Z}\right)^{\alpha}\right)^{-2}, \qquad (2)$$

where Z locates the peak and α characterizes the 'sharpness' of the frequency distribution. The distribution of λ_i is similarly characterized by Eq. (2) by replacing x (a distance) with $1.1 - \lambda_i$. (The offset value of 1.1 was chosen by visual inspection and is not a fit parameter.) The values of the resulting fit parameters are listed in Table 1.

As shown in Fig. 3, the distributions of w_i are similar in that very low values (vehicles for which most days of travel are habitual) are rare, and there is a general trend toward an increasing frequency of cases with fewer 'habitual' driving days. However, while the Puget Sound and Atlanta distributions appear very similar, the Minnesota distribution is biased toward
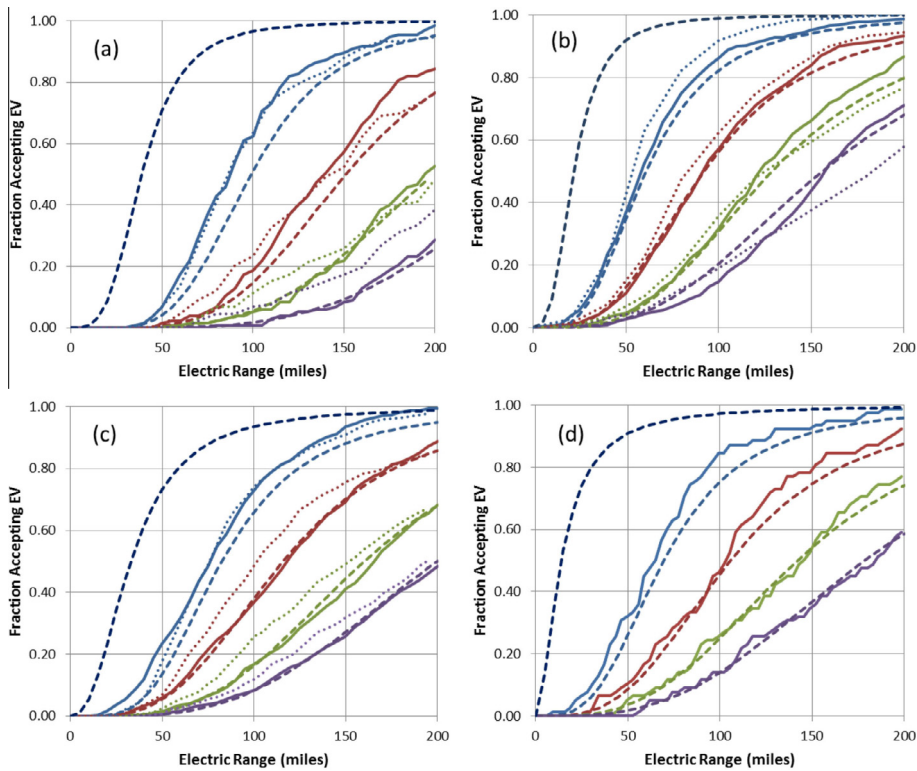
Fig. 6. Replica of Figs. 1a through 1d including the acceptance computed from the product of Eqs. (3) and (6) using distribution parameters in Table 1 (dashed lines) and the result of brute force trip counting (dotted lines). The values of the inconvenience threshold are the same (from bottom to top, 1, 3, 9 and 27 days per year). The uppermost curve is Eq. (3), the acceptance limit due to habitual travel alone.

lower values of w_i, consistent with the much higher fraction of 'habitual' travel shown in Table 1. We suspect that this is due to an important difference between the studies: the Puget Sound and Atlanta studies included a demographically appropriate fraction of multi-vehicles households in which all vehicles were instrumented, while the Minnesota study instrumented only one vehicle in each participating household – presumably the vehicle driven most, and therefore of greater interest in a road pricing study. The inclusion of only the primary (or only) vehicle in each household also explains why the Minnesota and FOT data sets do not exhibit many cases of w_i near 1.0. In short, a 'second' car is often not used for a regular trip. Although we do not use it in the simplified representation below, we can approximate the distribution of values of w_i for the Puget Sound and Atlanta studies with a simple exponential, $f(w_i) = (\alpha + 1)(w_i)^{\alpha}$ with $\alpha = 3.8$ (the solid curve in Fig. 3). As explained in the next section, the distribution of the product $\lambda_i \times w_i$ is more important to our analysis, and is shown for the same three vehicle populations in Fig. 5. Again, the relative shift in the Minnesota distribution is attributed to the higher fraction of 'habitual' travel days.

4. Analytic acceptance

The stated purpose of this work is to create a general, analytic estimate of EV 'acceptance' that is simple to compute. To do so, we represent the fraction of the population that might accept an EV of a given range, R, as the product of two probabilities: (1) the probability that any given vehicle will have a 'habitual' daily range, μ_i, less than R, and (2) the probability that the inconvenience of longer trips from the 'random' distribution for that vehicle will not exceed a chosen threshold. The first is given by:

$$P(\mu_i < R) = \frac{1}{1 + \left(\frac{R}{Z_{\mu}}\right)^{-\alpha_{\mu}}}. \tag{3}$$

Implicit in Eq. (3) is the assumption that every vehicle makes enough 'habitual' trips (more than 27 per year) that the exact value of w_i is irrelevant. The fraction of vehicles not exceeding an inconvenience threshold is determined in two steps. First, from the random term in Eq. (1), for a single vehicle labeled i, the probability that a single-day travel distance, x, will exceed the electric range, R, is given by

$$P_i(x > R) = e^{-R/k_i} \tag{4}$$

Second, we define a critical value of k_i, k_c where substitution of a vehicle with k_i greater than k_c by an electric vehicle with range R will cause unacceptable inconvenience. This is given by

$$k_c(N, R) = -\frac{R}{\ln(N/(365^* <\lambda w>))} \tag{5}$$

where N is the threshold of inconvenience and $<\lambda_i w_i>$ is the population-average probability of making a random trip on a given day (shown in Table 1). We have made this simplification to eliminate the need for mathematically elaborate convolution integrals over the distribution of $\lambda_i \times w_i$ (Fig. 5). The impact of this simplification was tested by computing the appropriately weighted average of the results for five values of $\lambda_i \times w_i$ centered on $<\lambda_i w_i>$. The result was indistinguishable from those shown below. The probability that k_i for a given vehicle selected at random will not exceed k_c is then given by

$$P(k_i < k_c(N, R)) = \frac{1}{1 + \left(\frac{k_c(N,R)}{Z_k}\right)^{-\alpha_k}} \tag{6}$$

Fig. 6a–d compare EV acceptance estimated by the generalized model (the product of Eqs. (3) and (6) using the parameters from Table 1) to that computed using the more elaborate statistical characterization of each individual vehicle (Fig. 1a–d).

We can further test the accuracy of the generalized model by brute force counting of days of inconvenience (driving distance greater than an assumed electric range) with results shown as the dotted curves in Fig. 6a–c. [This is the method used by both Pearre et al. (2011) and Khan and Kockelman (2012).] The coincidence of the acceptance curves shows that for the purpose of estimating EV acceptance, the very simple analytic method is just as effective as the most painstaking method based on a record of each drive for each vehicle over many months operation. Fig. 2 suggests why this should be the case: the 'habitual' travel distance, whether for commuting or some other purpose, is very rarely more than 60 miles, well within the capability of EVs on the market today. The rarity of long 'habitual' trips is reflected in the habitual limit to acceptance in Fig. 6. In other words, occasional longer trips have much greater impact on EV acceptability than regular commuting travel.

A further simplification is possible. Table 1 shows that $<\lambda_i w_i>$, Z_k/d_{50} and α_k /d_{50} are nearly the same for all four data sets. This implies that the only calibration parameter needed to represent the inhomogeneity of vehicle usage or estimate EV acceptance in a given region is d_{50}, which is readily obtained from ordinary survey reports of one-day travel distances from a large population. For example, the NHTS could be used to determine d_{50}, and thereby EV acceptance for the US as a whole or for subsets based on region, vehicle type, family income and numerous other descriptors.

5. Conclusions and directions for further research

We have shown that a simple analytic equation (Eq. (6)) using only a single distance parameter – d_{50}, the 50th percentile of the regional ensemble cumulative daily distance distribution – can predict with surprising accuracy the inconvenience of replacing conventional vehicles with electric vehicles of a given range. For this purpose, the first, 'random' term in Eq. (1) dominates, and from Eq. (6) we show that even with at-home charging only, the inconvenience of EVs with an all-weather range of roughly 60 miles, for examples the Ford Focus Electric, BMW i3 and Nissan Leaf, is not driven by regular travel such as for commuting, but rather by the occasional long trips nearly all vehicles make. This implies that the popular focus on urban commuting and at-work or public charging infrastructure may be misplaced; long commutes are rare and commuting accounts for a surprisingly small fraction of all automobile travel. While comforting, at-work and public charging may not be essential to a high degree of electrification of personal travel. Conversely, very long range EV, such as the Tesla, have no need for charging away from home on a daily basis and so would rely on daytime charging only on much longer journeys. Plug-in hybrids (PHEV) are a very different case where Eq. (3) can be used to estimate the incremental increase in electrified travel by charging the much smaller PHEV battery at a presumed habitual destination. Here the benefit may be significant, but the rate of charging need not be very high. Together, these observations suggest a very different strategy for the design and location of EV and PHEV chargers.

While only the three US studies are demographically representative, the less representative data from Germany is also well described by the same set of distributions. This invites the hypothesis that usage patterns in all rich-world regions with high rates of vehicle ownership can be described the same way. Our ongoing research seeks to test the validity of this hypothesis. Our findings suggest two directions for further research. First, up to this point we have assumed a common tolerance for the inconvenience of limited EV range regardless of individual circumstances. Studies that analyze the availability of and willingness to use alternative transportation modes in specific regions would replace an intuitive estimate in the middle of the range we have studied (i.e. three to nine days per year) with real data. By far the most convenient form of alternative transportation is another automobile in the same household. In the US, nearly 85% of all

automobiles have one more 'housemates.' We have completed a similar analysis of EV acceptance in two-vehicle households the results of which are in preparation for publication. Second, our generalized characterization of personal vehicle usage is easily applied to other studies related to emissions, fuel economy or even consumer choice with simple adjustments for regional characteristics. It also can be reversed in a Monte Carlo simulation that first generates a realistic population of 'vehicles' (each characterized by randomly selected values of w_i, λ_i, k_i and μ_i) and then uses $f_i(x)$ (Eq. (1)) to generate a realistic distribution of daily trip distances for each vehicle. This would generate a much more realistic representation of day-to-day vehicle usage than did previous attempts to create synthetic usage patterns (c.f. Kitamura et al., 1997 and Mohammadian et al., 2010). By direct application of the meta-distributions when mathematically tractable or by the Monte Carlo method when necessary, it should be possible to compute virtually any parameter that is sensitive to day-to-day variations of individual behaviors within a larger population. These might include the prospective benefits of at-work or public charging infrastructure, the distribution of the costs and benefits electrification and other fuel economy technologies, or the distribution of fuel economy reports across a population.
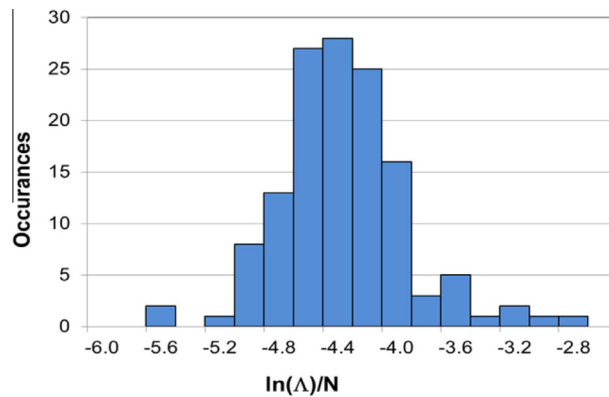
Appendix A

See Figs. A1–A9

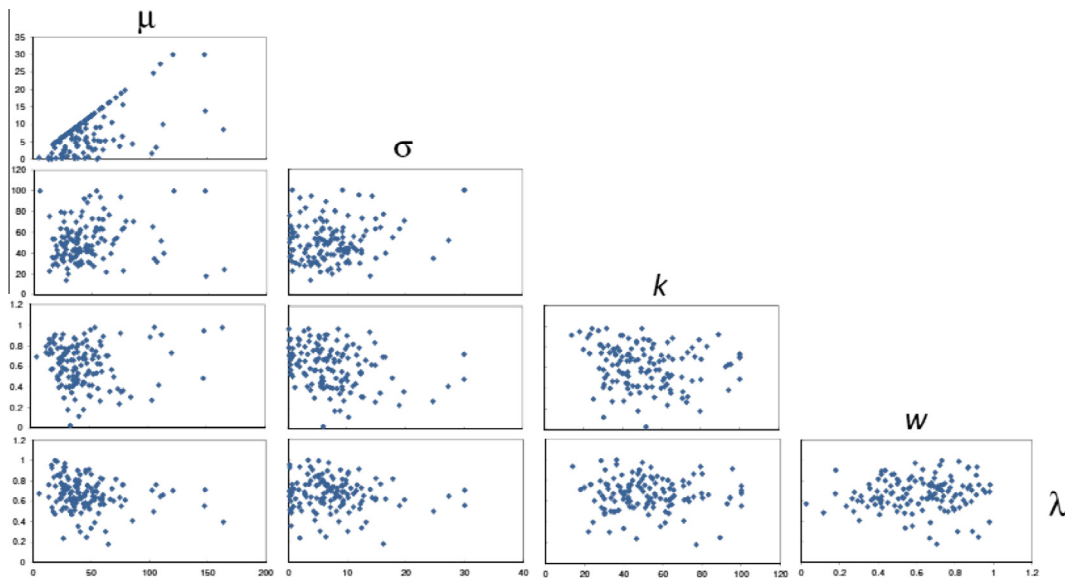Fig. A1. The distribution of the quality-of-fit metric, $\ln(\Lambda)/N$ for the Minnesota data set.

Fig. A2. The matrix plot illustrating the correlation between the fit parameters for the Minnesota. The correlation of μ with σ is an artifact of the fitting procedure.
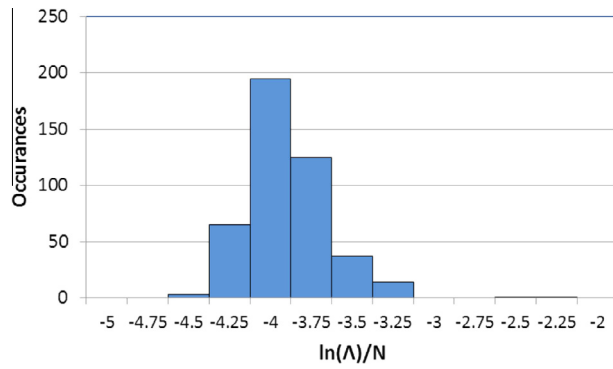
Fig. A3. The distribution of the quality-of-fit metric, $\ln(\Lambda)/N$ for the Puget Sound data set.
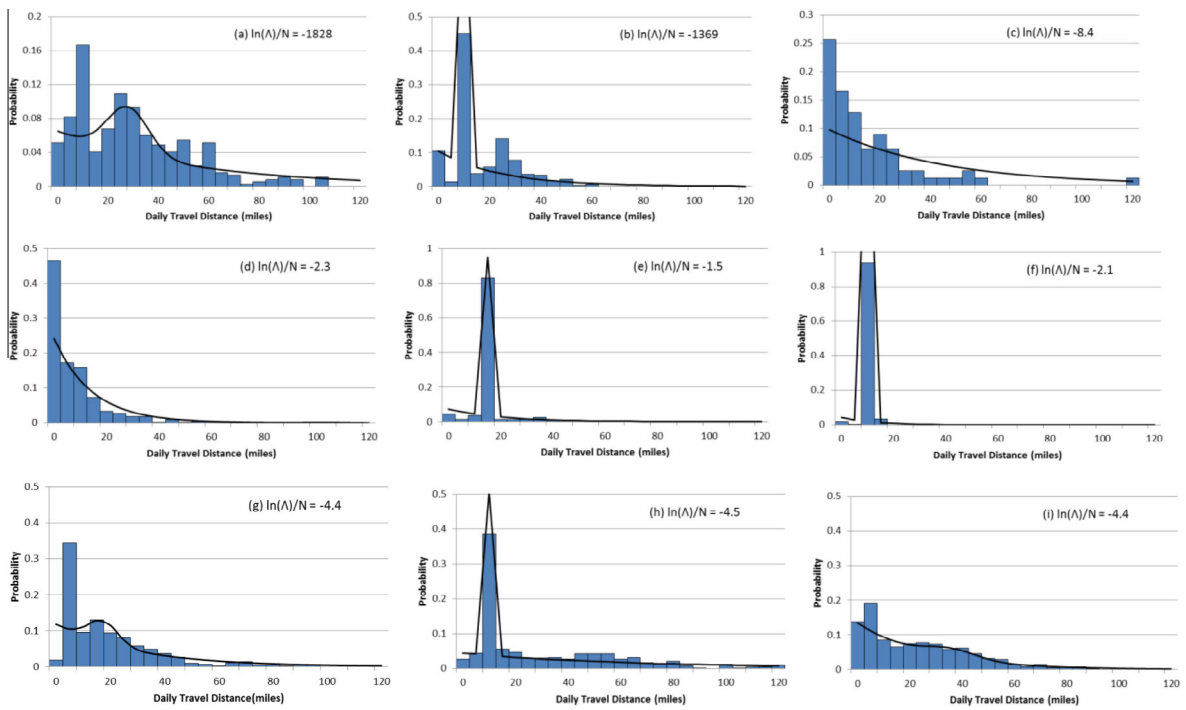

Fig. A4. Examples of daily trip distance distributions for vehicles in Puget Sound with the three worst (a–c), the three best (d–f) and three typical (g–i) fits to Eq. (1).
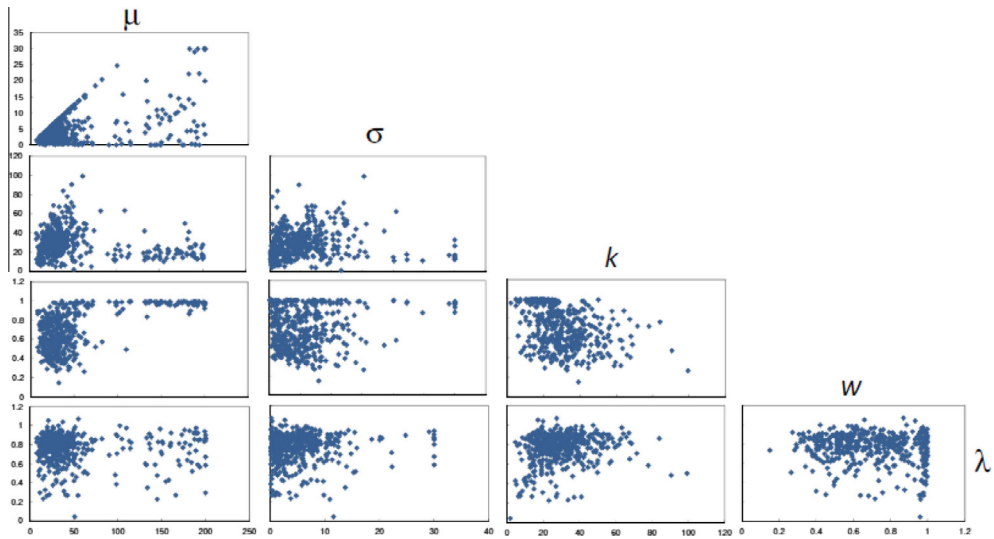
Fig. A5. The matrix plot illustrating the correlation between the fit parameters for the Puget Sound data set. The correlation of μ with σ, and cases of large μ associated with $w = 1$ are both artifacts of the fitting procedure.
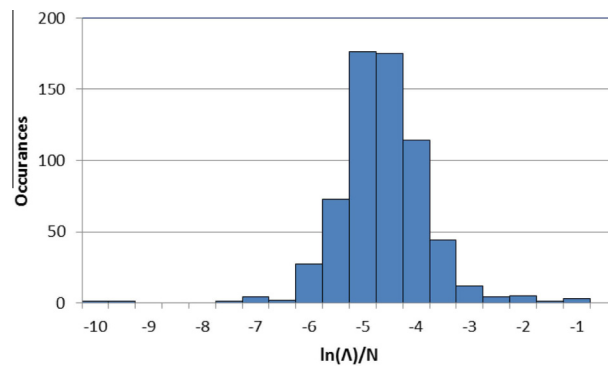

Fig. A6. Distribution of the quality-of-fit parameter for the Atlanta vehicle usage data set.
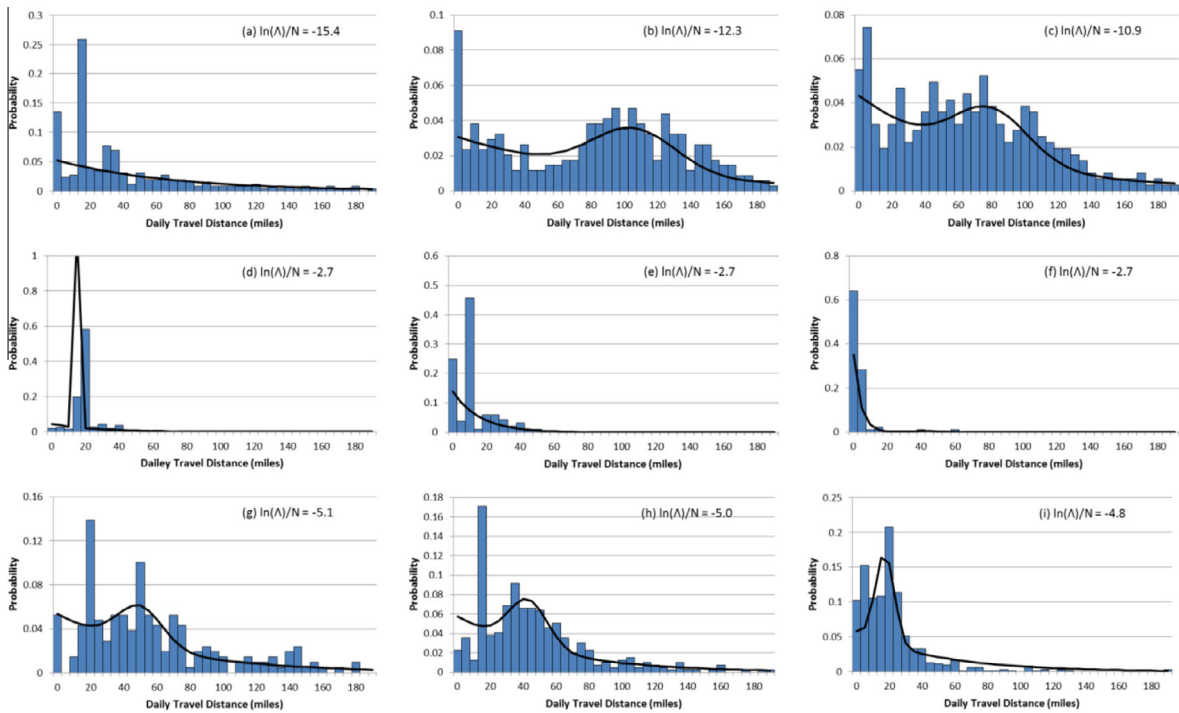
Fig. A7. Examples of daily trip distance distributions for vehicles in Atlanta with the three worst (a–c), the three best (d–f) and three typical (g–i) fits to Eq. (1).
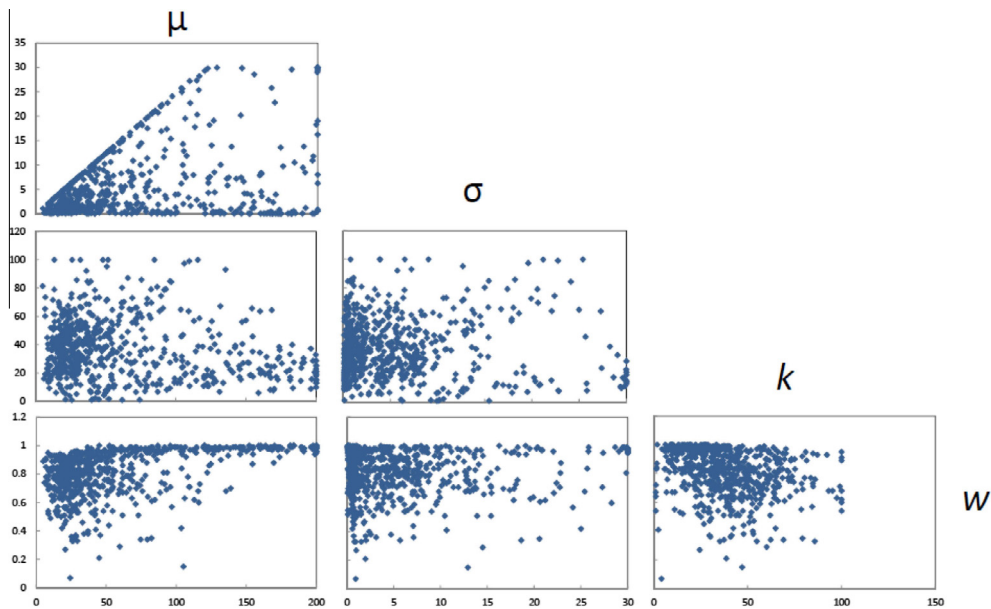

Fig. A8. Matrix plot illustrating correlations between the fit parameters for vehicles in the Atlanta data set. Values of λ were not reliable due to a scripting error and are not shown here. The apparent correlations are artifacts of the fitting procedure.
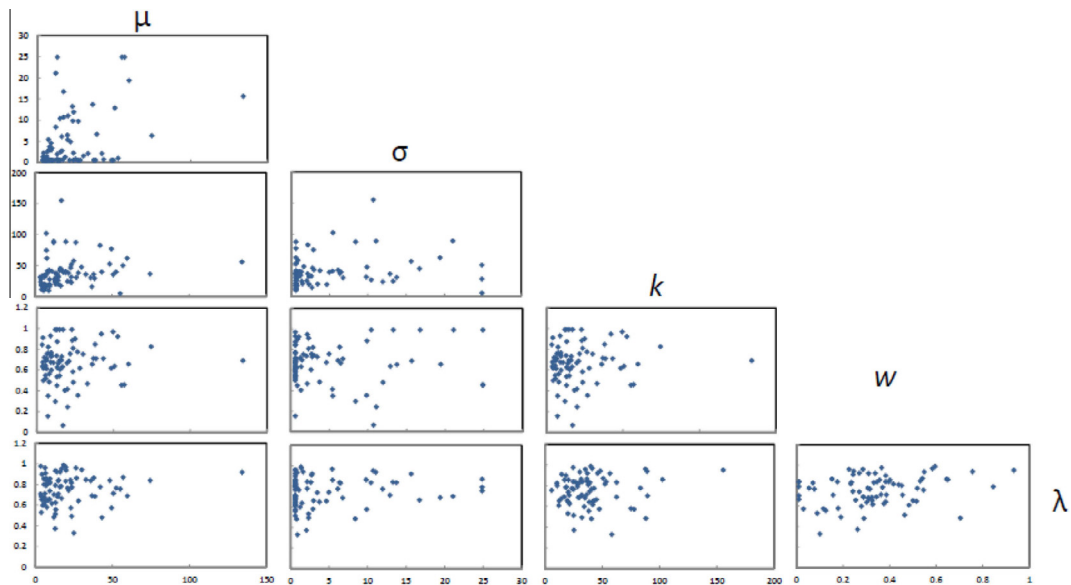
Fig. A9. Matrix plot illustrating correlation of the fit parameters for vehicles in the euroFOT study.

References

Atlanta Regional Commission, 2011, Regional Travel Survey Final Report, http://www.atlantaregional.com/transportation/travel-demand-model/household-travel-survey.

Deb, K., Pratap, A., Agarwal, S., Mayarivan, T., 2000. A fast elitist multi-objective genetic algorithm, NSGA-11. IEEE Trans. Evol. Comput. 6, 182–197.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: an activity-based approach using multiday travel data. Transp. Res. Part C 38, 44–55.

euroFOT, 2012, European Field Operational Test, http://www.eurofot-ip.eu/en/welcome_to_eurofot.htm. Only data from Ford vehicles was used for the analysis described here.

Greene, D.L., 1985. Estimating daily vehicle usage distributions and the implications of limited range vehicles. Transp. Res. Part B 19 (4), 347–358.

Guensler, R., Williams, B. Ogle, J., 2002. The role of instrumented vehicle data in transportation decision making. In: Fourth International Conference on Decision Making in Urban and Civil Engineering, London, England.

Khan, M., Kockelman, K.M., 2012. Predicting the market potential of plug-in vehicles using multiday GPS data. Energy Policy 46, 225–233.

Kitamura, R., Chen, C., Pendyala, R.M., 1997. Generation of synthetic daily activity-travel patterns. Transp. Res. Rec. 1607, 154–162.

Lin, Z., Dong, J., Liu, C., Greene, D.L., 2012. Estimation of energy use by plug-in hybrid electric vehicles: validating the gamma distribution for representing the random daily driving distance. Transp. Res. Rec. 2287, 37–43.

Minnesota, 2006. Minnesota Department of Transportation Report 2006–39A, Mileage-Based User Fee Demonstration Project: Pay-As-You-Drive Experimental Findings, URL: www.lrrb.org/PDF/200639A.pdf.

Mohammadian, A., Javanmardi, M., Zhang, Y., 2010. Synthetic household travel survey data estimation. Transp. Res. Part C 18, 869–878.

Neubauer, J., Brooker, A., Wood, E., 2012. Sensitivity of battery electric economics to drive patterns, vehicle range, and charge strategies. J. Power Sources 209, 269–277.

NHTS, 2009. Summary of Travel Trends: 2009 National Household Travel Survey, http://nhts.ornl.gov/2009/pub/stt.pdf.

Ogle, J., Guensler, R. Elango, V., 2005. Commute Atlanta value pricing program: recruitment methods and travel diary response rates, Transportation Research Record, National Academy of Sciences, Washington, DC, No. 1931, pp. 28–37.

Pearre, N.S., Kempton, W., Guensler, R.L., Elango, V.V., 2011. Electric vehicles: how much range is required for a day's driving? Transp. Res. Part C 19, 1171–1184.

PSRC, 2008. Puget sound regional council traffic choices study – summary report, <http://psrc.org/assets/37/summaryreport.pdf>. Data available from NREL Secure Transportation Data Project, <http://www.nrel.gov/vehiclesandfuels/secure_transportation_data.html>.

Tamor, M.A., Gearhart, C., Soto, C., 2013. A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. Transp. Res. Part C 26, 125–134.

Traut, E., Hendrickson, C.T., Klampfl, E, Liu, Y., Michalek, J.J., 2011. Optimal design and allocation of electrified vehicles and dedicated charging infrastructure for minimum greenhouse gas emissions, 90th Annual Meeting of the Transportation Research Board.