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The effect of uncertainty on US transport-related GHG emissions and fuel consumption out to 2050

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ABSTRACT

The future of US transport energy requirements and emissions is uncertain. Transport policy research has explored a number of scenarios to better understand the future characteristics of US light-duty vehicles. Deterministic scenario analysis is, however, unable to identify the impact of uncertainty on the future US vehicle fleet emissions and energy use. Variables determining the future fleet emissions and fuel use are inherently uncertain and thus the shortfall in understanding the impact of uncertainty on the future of US transport needs to be addressed. This paper uses a stochastic technology and fleet assessment model to quantify the uncertainties in US vehicle fleet emissions and fuel use for a realistic yet ambitious pathway which results in about a 50% reduction in fleet GHG emissions in 2050. The results show the probability distribution of fleet emissions, fuel use, and energy consumption over time out to 2050. The expected value for the fleet fuel consumption is about 450 and 350 billion litres of gasoline equivalent with standard deviations of 40 and 80 in 2030 and 2050, respectively. The expected value for the fleet GHG emissions is about 1360 and 850 Mt CO_2 equivalent with standard deviation of 130 and 230 in 2030 and 2050 respectively. The parameters that are major contributors to variations in emissions and fuel consumption are also identified and ranked through the uncertainty analysis. It is further shown that these major contributors change over time, and include parameters such as: vehicle scrappage rate, annual growth of vehicle kilometres travelled in the near term, total vehicle sales, fuel economy of the dominant naturally-aspirated spark ignition vehicles, and percentage of gasoline displaced by cellulosic ethanol. The findings in this paper demonstrate the importance of taking uncertainties into consideration when choosing amongst alternative fuel and emissions reduction pathways, in the light of their possible consequences.

1. Introduction

In the US light-duty vehicles consume a significant share of the national oil supply as well as about 10% of the world oil consumption (Davis, 2007). Light-duty vehicles are responsible for more than one third of the total US greenhouse gas emissions (EIA, 2007a). The total fuel consumption from cars and light trucks—SUVs, vans, and pickup trucks—was about 528 billion litre and GHG emissions of about 1260 million metric tons of CO_2 in 2005 (Davis, 2007; Transportation, 2008). The impact of transportation on climate change and future of energy supply is an increasingly important challenge faced by the US.

A number of deterministic scenarios have been developed in transport research literature to depict the future of light-duty vehicles. This paper uses the Stochastic Transport Emissions Policy model (STEP) (Bastani et al., 2011) to analyze a

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realistic fuel use and GHG emissions reduction pathway under uncertainty and determine the impact of uncertainty on the US fleet fuel use and GHG emissions out to year 2050. The significance of the results in the context of emissions mitigation and transport policy planning are further discussed.

2. Literature

Transport research has sought to explore the potential of engine and vehicle technologies, fuel developments, market and travel demand changes in reducing the US fleet fuel use and GHG emissions, and to examine the impact of various policies to enforce a substantial change in the future of on road transport in the next couple of decades. A number of approaches have been taken in the transport literature to better understand the different dimensions of what determines the future US road transport fuel use and emissions. Such dimensions include, for example, what determines travel demand and what measures can be taken to reduce demand, travel mode choice and intermodal shifts, individual's travel time and budget, as well as how congestion and other constraints, such as work schedule, affect one's travel mode choice. Certain aspects of transport demand and mode choice have been well researched, including what determines choices and shifting between private and public transport modes (Bass et al., 2011; Buehler, 2011a), making public transport financially and practically viable (Thompson and Peter Schofield, 2007; Buehler et al., 2011b), methodologies for measuring satisfaction of customers who use both public and private modes of transportation (Diana, 2012), travel time and budget, time value, and the extent to which factors such as congestion and work schedule drive an individual's commuting mode choice (Habib, 2012; Mokhtarian and Cynthia Chen, 2004; Habib et al., 2009; Abrantes and Wardman, 2011). Further, various strategies have been proposed for reducing the use of private vehicles and changing people's attitudes towards cars (Wright and Egan, 2000; Cullinane, 1992; Marshall and David Banister, 2000), in addition to better understanding the psychological and behavioural determinants in choosing private cars over other modes of transport (Stradling et al., 2000; Hiscock et al., 2002). Understanding the logic of how individuals choose certain travel modes and what factors affect these choices is crucial in exploring policies to discourage private vehicle ownership, and in projecting how light-duty vehicle travel demand will evolve in the next few decades, as research seeks to shape the future of cleaner transportation.

Moreover, technological improvements in engine and vehicle systems, fuel developments, as well as alternative vehicle market deployment, are ongoing areas of research, in promoting more efficient vehicles and helping reduce the fleet fuel use and GHG emissions. A number of analyses have assessed the technological potential for improving vehicle fuel economy in conventional engine and powertrains as well as shifting to alternative vehicles such as battery electric vehicles, plug-in hybrids, and fuel-cell vehicles (Cheah et al., 2008; Kromer and Heywood, 2007; Heywood et al., 2003; Kasseris and Heywood, 2007; Kromer and Heywood, 2008). The tradeoffs between fuel economy improvements and weight and performance increases have further been an important area of research in recent years (Cheah et al., 2009; Knittle, 2012). The deployment of alternative vehicles and the rate at which they penetrate remains a highly contentious area, due to initial market barriers such as high cost, and technology reliability and development delays, as well as consumer acceptance (Graham-Rowe et al., 2012; Karplus et al., 2010).

Research has further sought to explore the determinants of vehicle kilometres travelled, transport demand, and policies that could influence these parameters, such as road pricing and VKT taxation schemes and congestion. However, the projection of future travel demand remains highly uncertain (Moore et al., 2010; Graham-Rowe et al., 2011; Tal and Galit Cohen-Blankshtain, 2011; Su, 2010; Stanley et al., 2011; Macharis et al., 2010; Wadud, 2011). These aspects all play an important role in analyzing the integrated impact of technological, economical, and behavioural changes on the future of light-duty vehicle fleet fuel use and GHG emissions. Scenario analysis is often used to bring these aspects together quantitatively and estimate their aggregated impact on reducing fuel use and emissions into the future.

A number of recent studies have used scenario analysis to explore the future of road transport in the US. Some of the prominent studies include: On the Road in 2035 by Bandivadekar et al., LEVERS by Yang et al., fleet scenarios by Greene and Plotkin, NEMS by Morrow et al., and the CGE-MARKAL Hybrid by Schafer and Jacoby (Bandivadekar et al., 2008; Mccollum and Yang, 2009; Yang et al., 2009; Greene et al., 2011; Morrow, 2010; Schäfer and Jacoby, 2006) These studies are pursued in different contexts: the studies by Marrow, and Schafer et al. are pursued in a macro-economic context, whereas On the Road in 2035 study, LEVERS, and Plotkin et al. are based on bottom-up technology and fuel development details. The US Department of Energy and US Department of Transport also analyze different scenarios when assessing the impact of future CAFE standards on the light-duty vehicle fleet to support the rulemaking process (DOT, 2010).

Discrete deterministic scenarios, however, are unable to identify the range of possible outcomes that may result from choosing a particular emissions reduction pathway, as well as the associated likelihood of each outcome. This is a critical shortfall given the inherent real-world uncertainties in vehicle technology and fuel developments over time. Assessing the impact of these uncertainties is further made difficult given the interactions amongst variables and that each variable affects the outputs in a different direction. It is here that this paper seeks to contribute to the development of the future transport research literature. This work builds on the vehicle fleet modelling literature in transport research and stochastic modelling techniques in the climate change literature (Hope, 2006). This paper thus uses the Stochastic Transport Emissions Policy model (STEP) (Bastani et al., 2011) to quantify the uncertainties in the integrated impact of technological and fuel developments, and demand and market changes, on reducing the light-duty vehicle fleet fuel use and emissions, to help decision makers in the transport sector analyze the future of light-duty vehicle fleet in the light of real-world uncertainties.

In some fields, such as climate change, the distinction between deterministic scenario analysis and stochastic modelling has been clearly established: major analyses used in IPCC assessments are based on probabilistic studies, which use integrated assessment models such as DICE, PAGE, ICAM, SLICE, and FUND (Parry et al., 2001, 2007; Nordhaus, 1994; Hope et al., 1993; Dowlatabadi, 1993; Morgan, 1995; Kelly et al., 1998; MIT, 1994; Tol, 1995; Lempert, 1994; Mendelsohn et al., 1994; Hope, 2006). However, in the transport sector the distinction remains blurry, and scenario analysis is sometimes considered as an alternative for dealing with uncertainties. Scenario analysis, however, identifies what the "average" outcome would be given a set of deterministic inputs. Simply changing the average scenario thus does not provide one with a range of possible outputs because each scenario has a different set of underlying assumptions and is thus equivalent to taking different pathways in the real-world, let us say to reduce emissions. Further, deterministic scenarios cannot quantify the likelihood associated with the possible range of outcomes. In contrast, the aim of this paper is to provide a methodology that quantifies the uncertainties in the outputs: it provides decision makers with a more complete picture showing the range of possible outcomes and the probability associated with each outcome, given a chosen fuel use and emissions reduction pathway.

Although scenario analysis can be useful, it does not tell decision makers what the range of possible outcomes and their associated likelihood would be if a certain pathway is taken. This has significant practical importance as policy makers are motivated to choose the pathway that best addresses their objectives. They thus would need to understand the risk profile of the outcomes and the chances of hitting a certain target, under a consistent set of assumptions and given the input uncertainties.

This paper therefore uses the Stochastic Transport Emissions Policy model (STEP) (Bastani et al., 2011) to quantify and analyze the integrated impact of uncertainty on the light-duty vehicle fleet fuel use and emissions, as well as the major contributing variables and their relative importance in determining the outcomes out to year 2050. There are few studies to date that project fleet fuel use and GHG emissions out to year 2050. To the best of our knowledge, no other study has yet examined the impact of uncertainties on such projections using a systematic methodology.

3. STEP model

This paper uses STEP (Stochastic Transport Emissions Policy model) to analyze the impact of uncertainty on the future of US light-duty vehicles (Bastani et al., 2011). An overview of STEP is shown in Fig. 1. This model takes a number of stochastic inputs which describe the performance of various vehicle technologies, fuel availability and life-cycle emissions, as well as demand and market deployment of the new vehicle technologies and alternative fuels. STEP then outputs the total light-duty vehicle fleet GHG emissions (Mt CO_2 equivalent/year) and fuel use (billion litres gasoline equivalent/year) as a probability density function overtime out to the year 2050, showing the range of possible outcomes that can be expected from a chosen policy pathway, and the probability of each outcome occurring. The model uses a Monte Carlo simulation to perform stochastic calculations.

The basic calculation logic that is used to compute fuel use and emissions here follows the MIT fleet model (Bandivadekar et al., 2008). The fleet turnover is tracked based on the calendar year, vehicle model year, the market penetration rate of advanced technologies, and scrappage rate of vehicles on the road. Full life-cycle emissions of fuels are taken into account by tracking the fuel consumption of each powertrain as well as the WTT (well-to-wheel) and TTW (tank-to-wheel) of conventional and alternative fuels. Vehicle weight reduction is further taken into account through powertrain fuel use improvements over time. Refer to the authors' 2011 methodology paper (Bastani et al., 2011) for the full model details and equations. The fleet fuel use calculated here includes liquid based fuels, excluding electricity primary fuel use. The full life-cycle energy consumption of electrify is included in the life-cycle energy consumption results, discussed later in the paper.

The input values and distributions are determined by the decision theory, which is designed to distinguish between a set of alternatives, where each alternative faces uncertain states of the world that can be represented by probability distributions (Lindley, 1985). Subjective probability is used to estimate the underlying uncertainty in the inputs based on expert assessments. These probabilities are subjective because they depend on the experts' judgement, which is likely to vary based on the information they each have available (Lindley, 1985). These subjective assessments will be subject to representativeness, availability and anchoring effects leading to predictable biases (Tversky, 1974). For instance, anchoring leads to a bias in the uncertainty range by the experts, which are often stated as narrower than can be justified by the experts' knowledge (Tversky, 1974; Alpert and Raiffa, 1969; Holstein, 1971; Winkler, 1967). To reduce such biases, a range of different sources were consulted to determine the probability distribution in the inputs represented in this paper, and probability elicitation techniques were followed using direct probability assessment techniques to obtain probability estimates while minimizing bias and overconfidence (Henrion et al., 1991; Morgan and Henrion, 1990). First, experts are briefed on why the study is conducted, then a clear understanding is reached on what the quantities mean and their units of measure. The experts are then asked to estimate the upper and lower bounds for each parameter, to minimize anchoring and overconfidence biases. The interviewer then proposes more extreme values and asks the experts whether there is a reason for such values to occur. Then, if there is a sensible explanation, the expert is asked to extend the bounds. The rest of the distribution is then completed in consultation with the expert (Morgan and Henrion, 1990). Refer to the authors' methodology paper (Bastani et al., 2011) for the complete details.

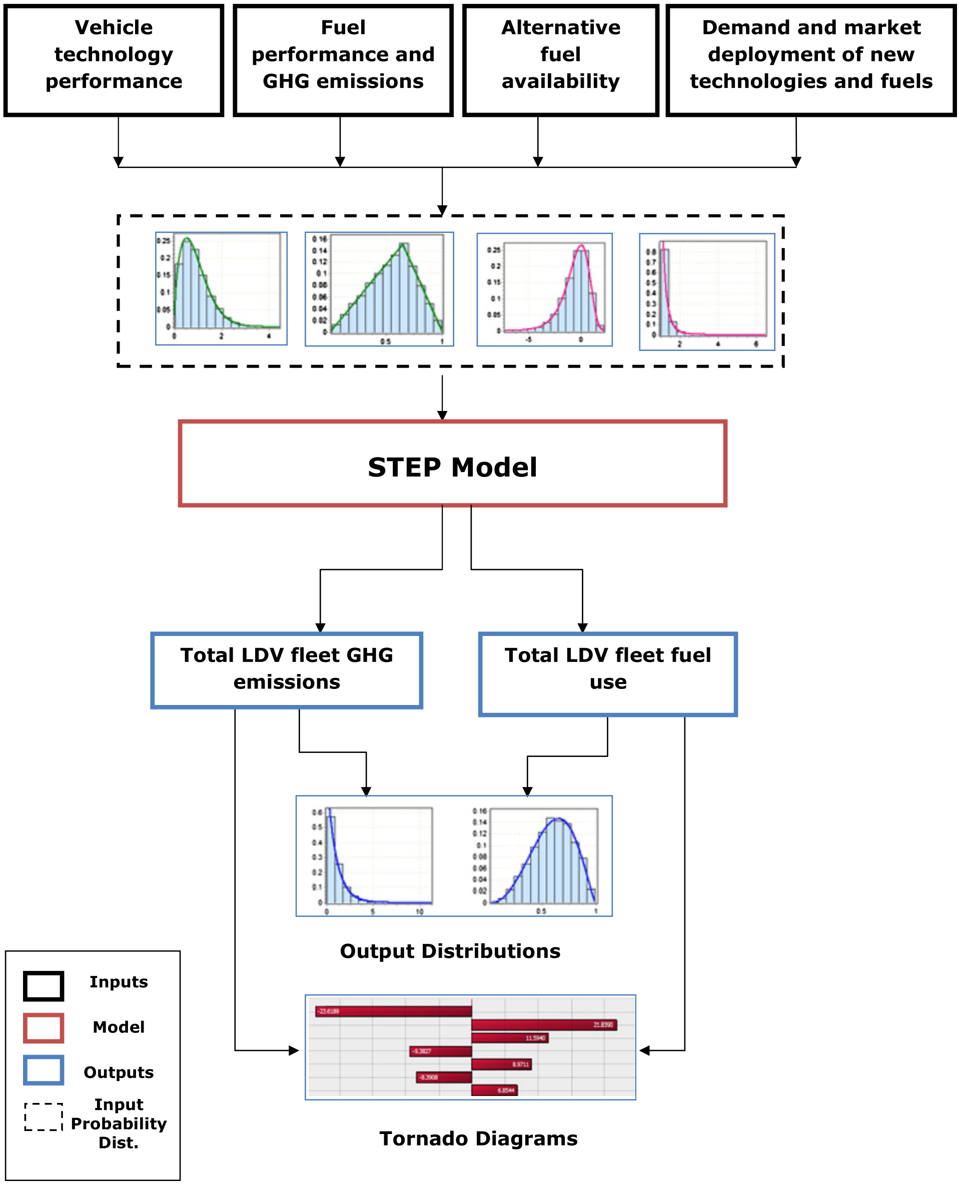

Fig. 1. STEP model overview.

3.1. Data: estimation of input parameters

This section describes the inputs to the model for a pathway with a relatively ambitious emissions reduction target, with realistic uncertainty bounds, which are then used to calculate the results presented in Section 4. These input values represent a sensible and ambitious pathway that results in significant fuel and emissions reduction with realistic uncertainty bounds, and are used as default values for STEP. They are chosen based on historical data, available relevant literature, MIT Sloan Automotive Laboratory's engine-in-vehicle engineering analysis and engine simulations, expert judgment, and internal consistency.

Although the reduction targets for 2030 and beyond used here are ambitious, this model can be used with any set of inputs, should other experts wish to explore the uncertainty in the outputs given a different set of input probability distributions based on their subjective stochastic assessments of the future LDV fleet. This is in fact the very reason for proposing a model that can take uncertain inputs and do more than present the results as predictions of the future. This model cab thus be used to provide a more complete and realistic picture of future characteristics of light-duty vehicle fleet fuel use and emissions given real-world uncertainties.

The most important inputs are shown in Table 1; the following sections describe why these input values were chosen. Refer to Appendix A for the complete list of input parameters.

3.1.1. Vehicle demand

The annual sales of LDVs from year 1970 to 2007 data were obtained from the US Environmental Protection Agency database (EPA, 2009b). These figures include all 4-wheeled vehicles weighing less than 3865 kg (8500 lbs) (Bandivadekar et al., 2008; EPA, 2009b). The impact of the recent recession in the US on the automobile sales is also taken into account using short-term forecasts of the US market (Polk, 2009). Historical data are used in the model up to the present date, and the equations explained the author's methodology paper (Bastani et al., 2011) are used to interpolate and extrapolate data over time using the model inputs in year 2030.

The following Fig. 2, from Cheah's work shows that historically scrappage follows sales with some delay (Cheah, 2010). History shows that scrappage rate has stayed at around 80% in the US (GmbH, 2005). A constant, but uncertain, future scrappage rate is thus used here as an input to the model.

The US Bureau of the Census estimate that population growth will fall from 0.9% to 0.75% per year by 2040 (Bureau, 2007). The mean vehicle sales here is assumed to be in tandem with the mean population growth rate of 0.8% per year (Bandivadekar et al., 2008; Bandivadekar, 2008). The resultant forecasted vehicle sales using this assumption compare well with The Polk Company and the Federal Highway Administration estimates (Davis, 2007; Polk, 2009; Cheah, 2010) The number of vehicles in operation in the model does not exceed the estimated vehicle ownership saturation level (850 vehicles per 1000 people), determined based on income and population density (Dargay et al., 2007; Bureau, 2008). Fig. 3 shows a range of data from the literature that have informed the vehicle sales input into STEP.

Vehicle life is significantly uncertain (Bandivadekar et al., 2008). This uncertainty is due to a number of factors including: the reliability of new vehicle technology, economic factors that could result in consumers keeping their cars for a longer or shorter period of time, technology developments which could result in vehicles becoming more durable and reliable, as well as higher safety provisions as a result of new regulations and scrappage policies. These factors also have an effect on the scrappage rate of older vehicles.

The vehicle median life can be calculated using three methods described in the literature (Bandivadekar, 2008). These methods include using a logistic function to estimate the vehicle's survival rate; using a Weibull distribution; and using

Table 1
Important inputs into STEP.

Parameter	Min	Mode	Max	Mean	STD	Coefficient of Variation (CoV)	Values in 2010
Total light vehicles Sales in 2030 ['000]	9387	18,403	23,000	16,930	2827	17%	11,500
Future scrappage rate (2011+)	65%	80%	105%	83%	8%	10%	80%
% Sales HEV in 2030	3%	10%	17%	10%	3%	30%	3%
% Sales PHEV in 2030	1%	5%	9%	5%	2%	35%	0%
% Sales BEV in 2030	0%	4%	8%	4%	2%	40%	0%
VKT-annual-growth (2006–2020)	0.26%	0.50%	0.74%	0.50%	0.10%	20%	0.50%
VKT-annual-growth (2030+)	−0.40%	0.00%	0.40%	0.00%	0.16%	N/A	N/A
ERFC Cars	40%	80%	100%	73%	12%	17%	50%
% Blend cellulosic ethanol in 2030	4%	14%	24%	14%	4%	30%	0%
% Electricity from clean sources in 2030	30%	50%	75%	52%	9%	18%	29%
Cellulosic Ethanol WTW in 2030 [gCO_2/MJ]	6	8	14	9	2	18%	10
Gasoline WTW in 2030 [gCO_2/MJ]	81	92	103	92	5	5%	92
Electricity WTW in 2030 [gCO_2/kW h]	376	970	1376	908	205	23%	1078
FC-r NA-SI cars in 2030 (Relative fuel consumption)	0.44	0.70	0.96	0.702	0.105	15%	1.00
FC-r NA-SI LT in 2030 (Relative fuel consumption)	0.45	0.71	0.98	0.714	0.107	15%	1.00

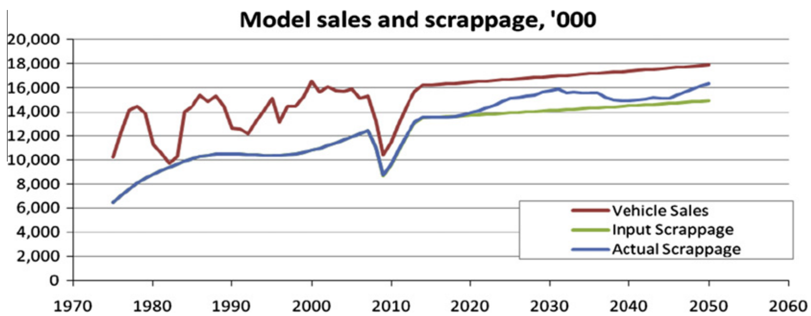

Fig. 2. US passenger vehicle sales and scrappage, 1975–2050.

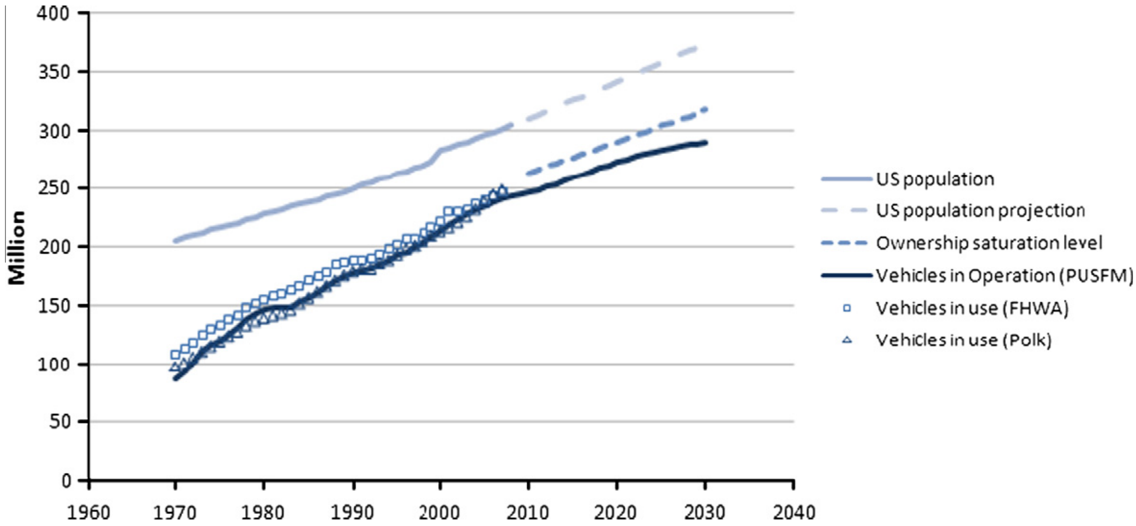

Fig. 3. Estimates informing STEP total sales input.

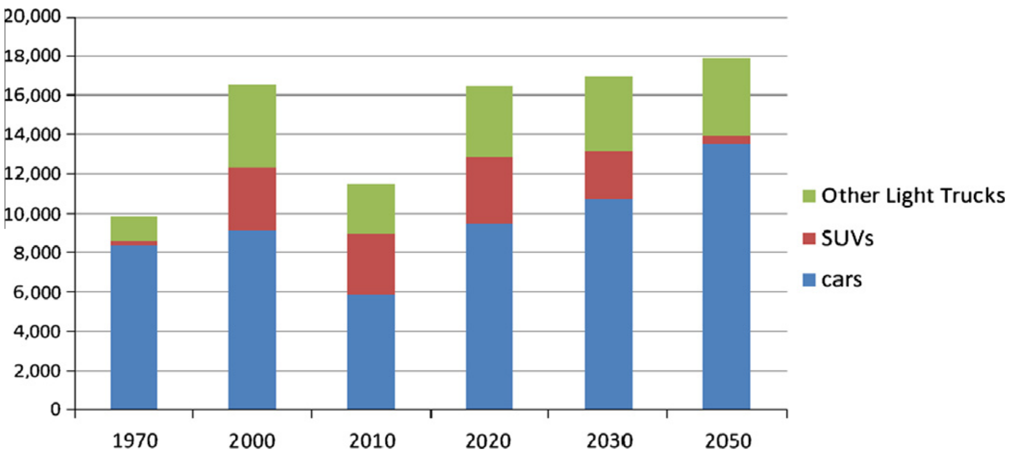

Fig. 4. Mean input values for vehicle segment shares 1970–2050.

"engineering" and "Cyclical" Scrappage rate (Greene and Chen, 1981; Libertiny, 1993; Greenspan and Cohen, 1999). The logistics curve derived by Bandivadekar et al. is used in this model to determine the median life for vehicles using several data sources (Greene and Chen, 1981; Libertiny, 1993; Greenspan and Cohen, 1999; NHTSA, 2006; Bandivadekar et al., 2008). The vehicle retirement is in tandem with the median vehicle life (Bandivadekar et al., 2008; Bandivadekar, 2008).

The model also keeps track of different segments of the LDV market – small cars, SUVs, and other light trucks (such as pick-up trucks) – to allow vehicle segment shift and downsizing of vehicles in the future. Historical data shows a change in the share of light trucks versus cars and SUVs; and that the increase in the sales of light trucks has slowed down during the past few years (Heavenrich, 2006; EIA, 2007a). The market share of light trucks in the US is the largest and the share of small cars is the smallest compared to the rest of the world, which in turn indicates a large potential for the fleet downsizing in the US (Cheah, 2010; Gibson, 2000) The market share of other light trucks (pick-up trucks) has been constant at about 22% historically, and is kept constant in this model. The downsizing potential thus comes from the shift to lighter weight vehicles and segment shift from SUVs and vans to cars. The mode of inputs describing the LDV segmentation is displayed in Fig. 4 below.

Literature data are used to inform the mode value for the total vehicle sales and future scrappage rate as described. The range of data in the literature and literature simulation and regression models (Eg. demand models by Train) (Lave, 1979; Train, 1980b) are then used as an indicative measure of uncertainty in these variables, and to inform the process of probability elicitation. Finally, weighting and ranking of the inputs qualitatively as well as elicitation techniques (Morgan and Henrion, 1990; Bastani et al., 2011) were used with prominent experts in the field to determine a set of plausible minimum and maximum values for the total vehicle sales and future scrappage rate variables as shown in Table 2. This is an iterative process through which a set of sensible and self-consistent distributions are chosen for the input variables.

Table 2
Vehicle demand input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
Total light vehicles sales in 2030	9387	18,403	23,000	16,930	11,500
Future scrappage rate (2011+)	65%	80%	105%	83%	80%
% Car (vs. light trucks)	45%	65%	80%	63%	51%

3.1.2. Travel patterns

The modal vehicle kilometres travelled (VKT) data is obtained from Oak Ridge National Laboratory's TEDB and is different for cars, SUVs, and OLTs, as shown in Fig. 5 (Bandivadekar et al., 2008). It is assumed here that the VKT of cars decreases as they age, as shown in Fig. 6. VKT changes with a number of parameters such as growth in the highway infrastructure, gasoline prices, income growth, and demographic trends. The mode annual growth rate of VKT is set to decrease over time, from 0.5% (for 2006–2020) to 0.25% (for 2020–2030) and to 0.1% from 2030 onwards. The different growth rates in time periods chosen here reflect the change in travelling demand growth dynamics in the short, mid, and long term (Bandivadekar et al., 2008; Greene and Rathi, 1990; NRC, 2002). Figs. 5 and 6 show the mean inputs into the model. The minimum and maximum values for these inputs are chosen following the probability elicitation process described earlier in Section 3, and were informed by literature data and travel demand simulation and regression models, such as the work of Train and Mannering in this area (Mannering et al., 1981; Lohrer, 1983; Mannering, 1983; Mannering and Winston, 1980). The VKT growth rates here are chosen to reflect the possibility of a decrease in travel demand. These values are summarized in Table 3.

3.1.3. Well-to-wheel emissions

Gasoline, diesel, cellulosic and corn ethanol, bio-diesel, hydrogen, tar sand, and electricity are the sources of energy taken into account in STEP. The full life-cycle emissions of these fuels are obtained from industry data and existing literature; such as: GREET, 2007 data; Groode and Heywood, 2008; Kromer and Heywood, 2007; McCulloch and Francis, 2005 and recent EPA studies (CONCAWE, 2007; GREET, 2007; Groode and Heywood, 2008; Kromer and Heywood, 2007; McCulloch and Francis, 2005; EPA, 2010, 2009a). The WTW emissions in year 2030 are uncertain inputs and are interpolated and extrapolated over time (Bastani et al., 2011). The WTW emissions factors change over time to account for refinery processes and vehicle efficiency improvements. As explained in previous sections, literature data are used to inform the mode values chosen here, and probability elicitation techniques and literature simulations, including the GREET model, have informed the inputs range. The values are summarized in Table 4.

Substantial but achievable changes on the energy supply side are assumed here. For instance, the average grid electricity emissions is assumed to reduce its mean significantly (by almost a factor of four by 2050), and the amount of fuel coming from sources such as tar sands grows substantially by 2050.

A weighted average electricity emissions factor is used here, based on the contribution from renewable and conventional sources, the current grid emissions, as well as the seasonal and day and night time variability in electricity emissions (De Sisternes, 2010; EPA, 2010; Elgowainy et al., 2009). This factor also changes over time to account for better integration of renewable sources into the grid and implementation of ideas such as "smart" grid and "micro-grids". These WTW emissions factors of various fuel sources are then used to calculate the total life-cycle GHG emissions of the on-road light duty vehicle fleet.

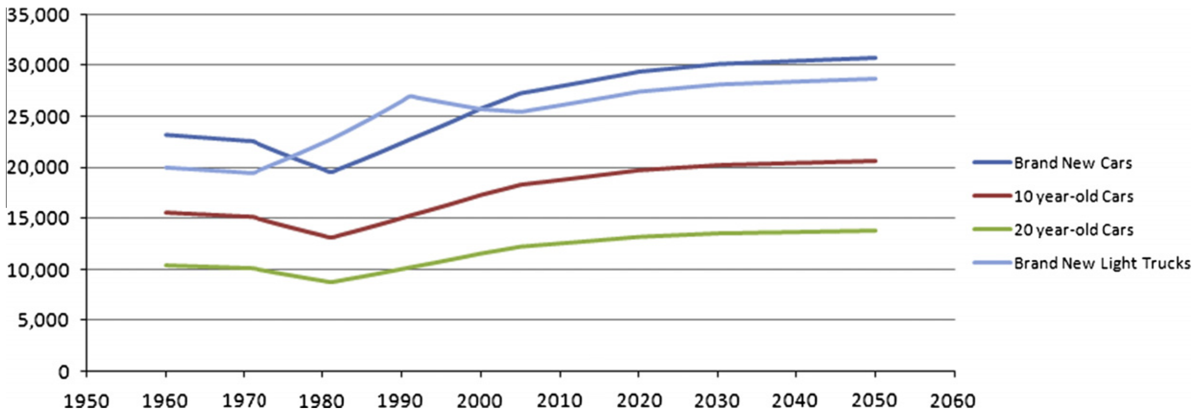

Fig. 5. Mean input values for VKT [km] of cars and light trucks over 1970–2050.

3.1.4. Alternative energy source availability

The availability of alternative energy sources such as bio-fuels, electricity, and tar sands is tracked in STEP to assess the impact of these fuels on the total GHG emissions in the next couple of decades. A number of studies have estimated the amount of available biomass in the USA, such as the study by DOE which suggests hundreds of million of tons of biomass will be available, produced in a sustainable manner (DOE, 2005). BP estimates that 10–30% of global transportation fuel can be supplied by bio-fuel by 2030 (Ellerbusch, 2008). A General Motors and Sandia National Laboratory study estimated that 60 billion gallons of ethanol can replace conventional fuel by 2030 (Sandia National Labs, 2008; Melillo et al., 2009a). Studies also warn about possible environmental damage (Melillo et al., 2009a,b). Logistics issues and the economics of bio-fuels are further considered limiting factors to market share of these fuels in the next couple of decades (UC-Davis, 2008; Reilly and Paltsev, 2009).

In this study, electricity and biofuels are modelled to have a dirty component (coal/ corn ethanol), a clean component (renewable electricity/cellulosic biomass), and average GHG emission components. The use of tar sands fuels is also assumed to grow over time. IEA data show the current electricity supply mix in the US, which includes nuclear, solar, hydro, wind, coal, oil, and gas: 30% was generated from clean sources in 2010 (IEA, 2009). The average US grid emissions were about 700 g/kW h in 2009 (IEA, 2009). The 2007 EIA Annual Energy Outlook estimates little improvement in the average grid emissions from now to 2030 (EIA, 2007a). As new power plants come online, a modest improvement in average grid emissions is

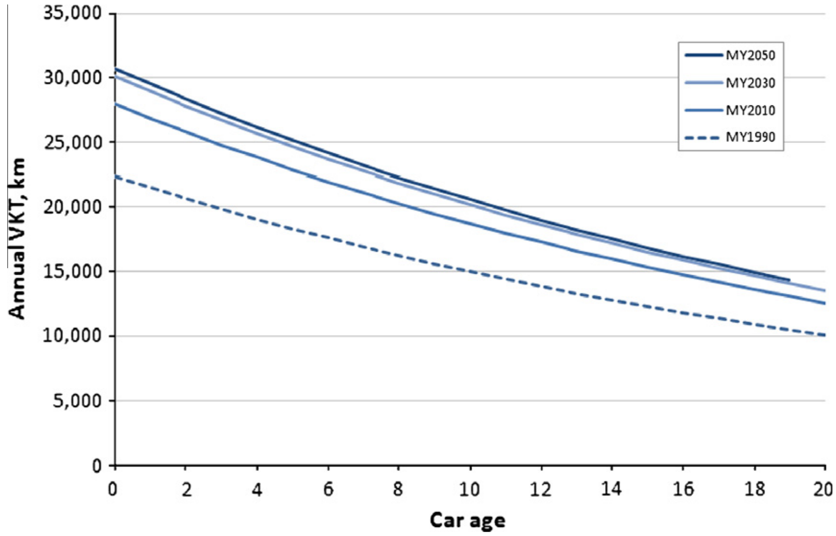

Fig. 6. Mean input values for annual VKT driven by different model year cars.

Table 3
Travel demand input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
VKT-annual-growth (2006–2020) (%)	0.26	0.50	0.74	0.50	0.50
VKT-annual-growth (2020–2030) (%)	0.07	0.25	0.43	0.25	N.A
VKT-annual-growth (2030+) (%)	−0.40	0.00	0.40	0.00	N.A

Table 4
WTW input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
Ethanol WTW in 2030	6	8	14	9	10
Com ethanol WTW in 2030	60	69	90	73	77
Gasoline WTW in 2030	SI	92	103	92	92
Diesel WTW in 2030	82	94	106	94	94
Bio-diesel WTW in 2030	56	89	122	89	S9
Conventional electricity WTW in 2030 [gCO/kW h]	376	970	1376	90S	1078
Hydrogen WTW in 2030	93	123	1376	123	137
Tar sands WTW in 2030	92	105	113	105	109

estimated (Kromer and Heywood, 2007). The current electricity consumption is about 3700 billion kilowatt hours and is estimated to grow to 5200 billion kilowatt hours by 2035 (EIA, 2007a). The average grid emissions depend on initial marginal load, seasonal variability, integration of clean sources into the grid, and grid management, for example using smart grid algorithms. Proper integration and management of the grid is thus necessary for the potential of cleaner electricity to be realized in reducing transport GHG emissions in the next couple of decades.

Tar sands or oil sands is another source of energy taken into account here. Canadian Association of Petroleum Producers (CAAP) estimates there are more than a total of 175 billion barrels recoverable oil. In 2006, 1.2 million barrels per day of tar sand was recovered from Canadian reserves (CAAP, 2006). CAAP estimates oil sands production to increase to 4 million barrels per day by 2020. The Canadian Energy Research Institute estimates this to increase to 6 million barrels per day by 2030 (O&GJ, 2006). The Energy Information Administration's International Energy Outlook 2007 estimates 1.9–4.4 million barrels per day from Canadian reserves in 2030 (EIA, 2007a). Its is assumed here that available tar sand fuels replaces gasoline and diesel equally. Similar to previous sections, these data from the literature have informed the mean values for the inputs to the model as shown in Fig. 7 below. The blend of cellulosic and corn ethanol are shown as a percentage of the total gasoline fuel demand, and the tar sands percentage corresponds to the share of combined diesel and gasoline that tar sands will replace. Percentage clean electricity shows the share of total electricity demand that will be produced using renewable sources. Further, the bio-diesel share is shown as a percentage of the total diesel fuel demand. The distribution of these input variables is also summarized in Table 5.

3.1.5. Market deployment

Market deployment rates of advanced powertrains are very uncertain due to a number of factors such as infrastructure needs, consumer preferences, gasoline prices, incentives for adopting an alternative vehicle and so forth. A number of forecasts have been made both by the automotive industry and other independent studies to estimate the market share of various powertrains in the US in the mid and longer term (Sullivan, 2008; Omotoso, 2008; UBS, 2007; Solheim, 2008; Ulrich, 2008; Volkswagen, 2010). Several discrete choice models have also been developed to find the relation between vehicle attributes and consumer preference such as the work of Greene and Train in this area. (Train, 2007, 1980a; Xinyu Cao, 2004; Grreene, 2001; Brownstone et al., 1994). These have informed the mode values chosen for the inputs here, as shown in Fig. 8. Aggregated and disaggregated vehicle demand models have also been developed which take into account both vehicle

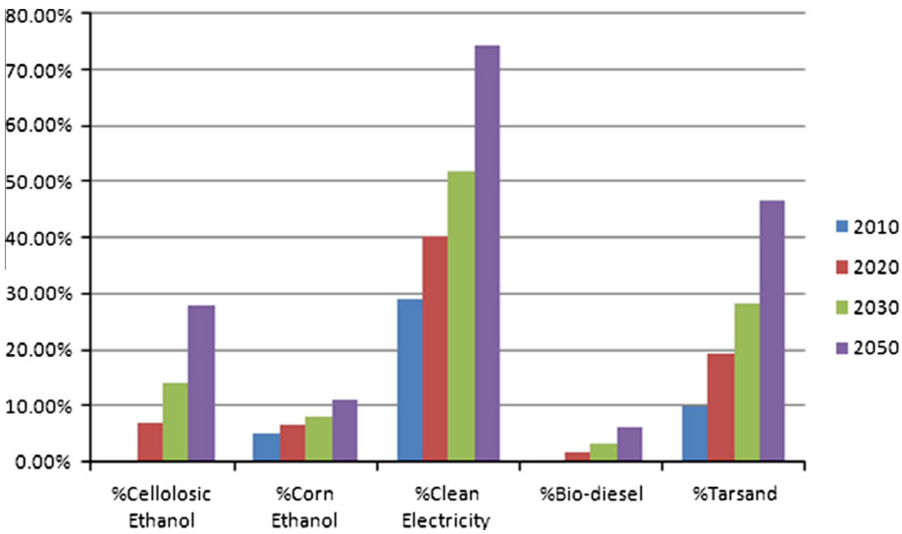

Fig. 7. % Alternative energy source mean input values 2010–2050.

Table 5
Alternative fuel input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
% Blend cellulosic ethanol in 2030	4	14	24	14	0
% Blend com ethanol in 2030	2	8	14	8	5
% Electricity from clean sources in 2030	30	50	75	52	29
% Bio-diesel	1	3	5	3	0
% Tar sands in 2030	15	25	45	28	10

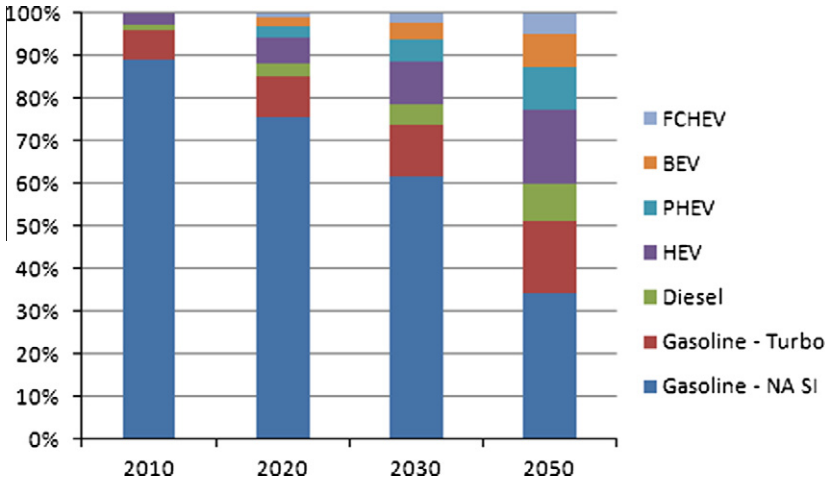

Fig. 8. Powertrain market share mean input values 2010–2050.

Table 6
Sales share input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
% Sales gasoline-turbo in 2030	6	12	18	12	7
% Sales diesel in 2030	1	5	9	5	1
% Sales HEV in 2030	3	10	17	10	3
% Sales PHEV in 2030	1	5	9	5	0
% Sales BEV in 2030	0	4	8	4	0
% Sales FCHEV in 2030	0	2	5	2	0

attributes and other variables such as availability of fuel stations (disaggregate models), to predict market deployment of alternative powertrains (Xinyu Cao, 2004; Grreene, 2001; Brownstone et al., 1994). Similar to previous sections, probability elicitation with experts, based on a combination of these forecasts, literature-based data, market models, and confidential automaker's data, have informed the input probability distributions summarized in Table 6.

A higher ratio of turbo sales might be plausible in the mid-term. This ratio will be conditioned on regulatory push and consumer acceptance of driving characteristics, especially as vehicles are further downsized and problems such as turbo lag becomes more evident. However, higher penetration of turbo vehicles, since the differences between an improved naturally-aspirated vehicle and turbo is about 10% and lowers over time, would not have much of an effect on the results shown here.

3.1.6. Fuel economy

The measure used in this model is fuel consumption, the inverse of fuel economy, expressed in L/100 km. Vehicle fuel use is calculated from the ERFC (Emphasis on Reducing Fuel Consumption) and the powertrain's relative fuel consumption (2008 NA-SI is the base). ERFC measures the degree to which weight reduction and technological powertrain improvements are used to reduce vehicle fuel use. ERFC is defined as the actual fuel consumption reduction realized, divided by the fuel consumption reduction achievable if size and performance are kept constant; it is reported as a percentage. At 100% ERFC, all the technological improvements are used to reduce fuel use while vehicle acceleration capability and size are kept constant. At 0% ERFC, the fuel consumption stays the same because all technological improvements have been offset by performance gains (faster acceleration time) and negligible weight reduction (Fig. 12). Using vehicle simulations, with a program called Advisor, ERFC is related to the relative fuel consumption of vehicles (compared to the reference fuel consumption of NA-SI in 2008) (Cheah et al., 2009; Kasseris and Heywood, 2007). Using relative fuel consumption and ERFC, the fuel use of each powertrain can then be calculated (Bastani et al., 2011). Thus the impact of performance variation and weight reduction are both captured in the ERFC measure as shown in Fig. 9. Historical data shows an increase in performance and weight of the vehicles (Fig. 10) which corresponds to the decline of ERFC (Cheah, 2010; EPA, 2009b). Thus, the trade offs between fuel economy, performance, and weight have been included in the analysis.

ERFC has varied historically as shown in Fig. 11. ERFC was historically highest and above 100% before the 1985 oil crises. It then declined and remained low for several years before rising again in the past few years as a result of tighter regulatory emphasis on fuel economy improvements, as shown in Fig. 11. The history in this area has been steadily increasing performance and weight, and ERFC has been below 50%.

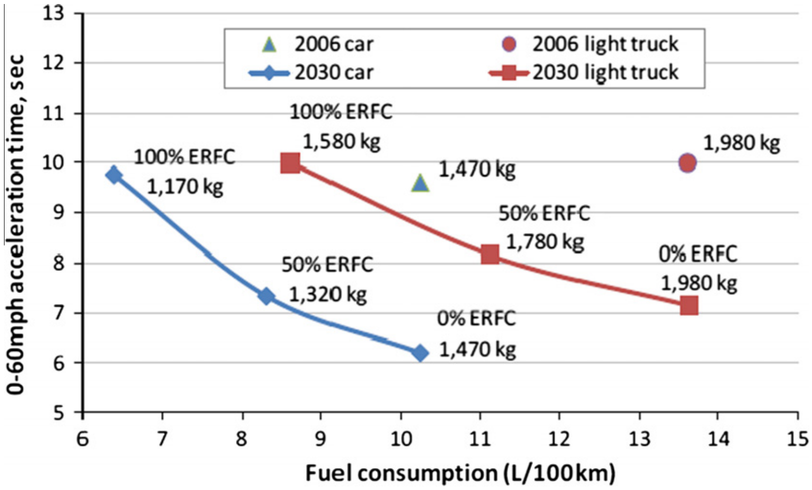

Fig. 9. Trade off between acceleration performance, weight, and fuel consumption (Cheah, 2010).

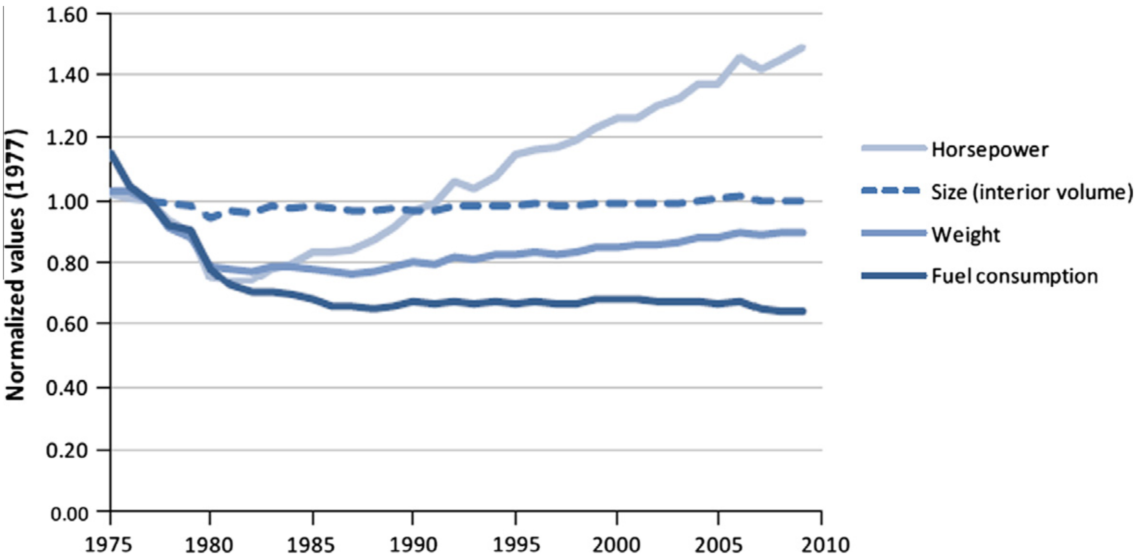

Fig. 10. Average US vehicle characteristics (Cheah, 2010).

Though not explicitly stated, there is vehicle weight reduction involved in the calculations here: it is coupled into the ERFC value as described above. An average weight reduction of about 10% by 2030, and an average of 20% reduction, by 2050, has been built into the ERFC values chosen in this study. These weight reductions occur through downsizing, use of light-weight materials, and vehicle redesign. These couple through ERFC as this parameter trades off performance increase, vehicle size and weight, and fuel consumption. An EPA correction factor is further used here to correct laboratory fuel economy measurements for highway and city driving conditions (Bandivadekar et al., 2008; EPA, 2009b). Similar to previous sections, the input mode values chosen here are based on literature data and are shown in Fig. 13 and Fig. 14 for the relative fuel consumption of different powertrains. It is assumed here that the fuel consumption reduction rate slows down over time as the easier modifications are expected to be done earlier in time. A number of forecasts including EPA, DOE, EIA, as well as vehicle simulations (including Advisor simulation work by Cheah et al.) have been used in the probability elicitation process to inform the probability distribution of inputs summarized in Table 7 (DOT, 2010; EIA, 2007b; EPA, 2006, 2007; Cheah et al., 2009; Kasseris and Heywood, 2007; Cheah, 2010; Mannering and Sinha, 1979).

The fuel consumption values shown below for each specific powertrain technology are for the average car or light truck sold in a given year. New technologies that have only penetrated into some of the new vehicles are multiplied by a weighting number less than one. Also, only a fraction of the new cars have the latest technology. Because the production run for each vehicle model design in about five years, the technology in the average engine and vehicle sold is about three years old. Also,

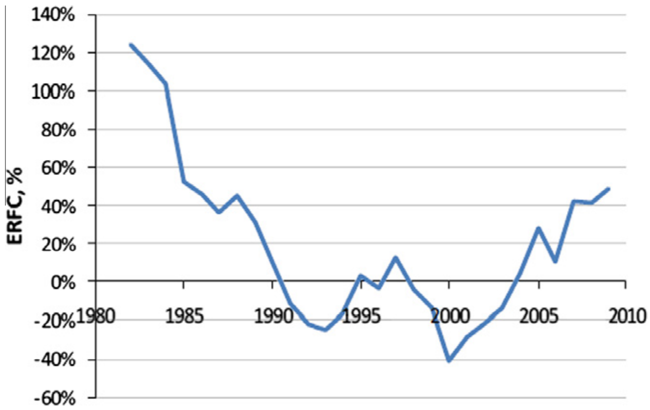

Fig. 11. ERFC of average new US vehicle (MacKenzie, 2009).

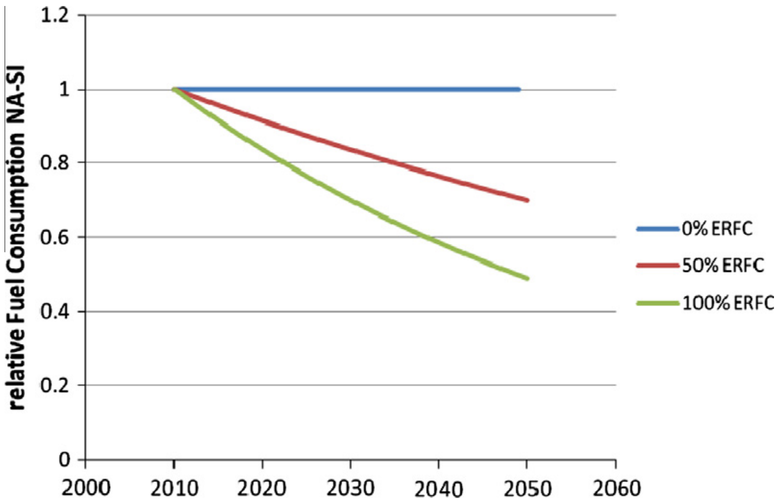

Fig. 12. Relative fuel consumption of NA-SI powertrain at varying ERFC (simplified FC-relative-ERFC map).

any performance and size increases that occur degrade fuel consumption significantly, a factor captured in the ERFC parameter. Further, weight reduction must be put in the context of the historical trend of steady weight increases due to response to new regulations, additional features and size increase, for a given model vehicle.

4. Numerical simulation results

This section presents the simulation results from running the model 10,000 times given the inputs described in Section 3.1.

4.1. Transport-related fuel use (near, mid, and long-term)

The following results show the uncertainty profile of the total transport-related fuel consumption in the near, mid, and long term (year 2020, 2030, 2050). These graphs show the total liquid based fuel use, which is reported in billion litres gasoline equivalent.

The results are in the form of probability distribution functions, where the area underneath the graph is equal to 1. The *y*-axis shows the relative probability, adjusted to keep the integral of the graph equal to 1, and has no physical meaning. The statistic summary for each graph is shown on the right hand side of the probability distribution functions. The minimum and maximum values are not meaningful measures as they dependent on the number of runs and thus are not referred to here. Instead, the 1% and 99% percentile values are used here to interpret the range of outcomes. Statistics such as the mean and standard deviation and confidence intervals converge over large number of runs and should be used to interpret the probabilistic results shown here. The results (Fig. 15) show that the fuel consumption in the near term (2020) will be most likely

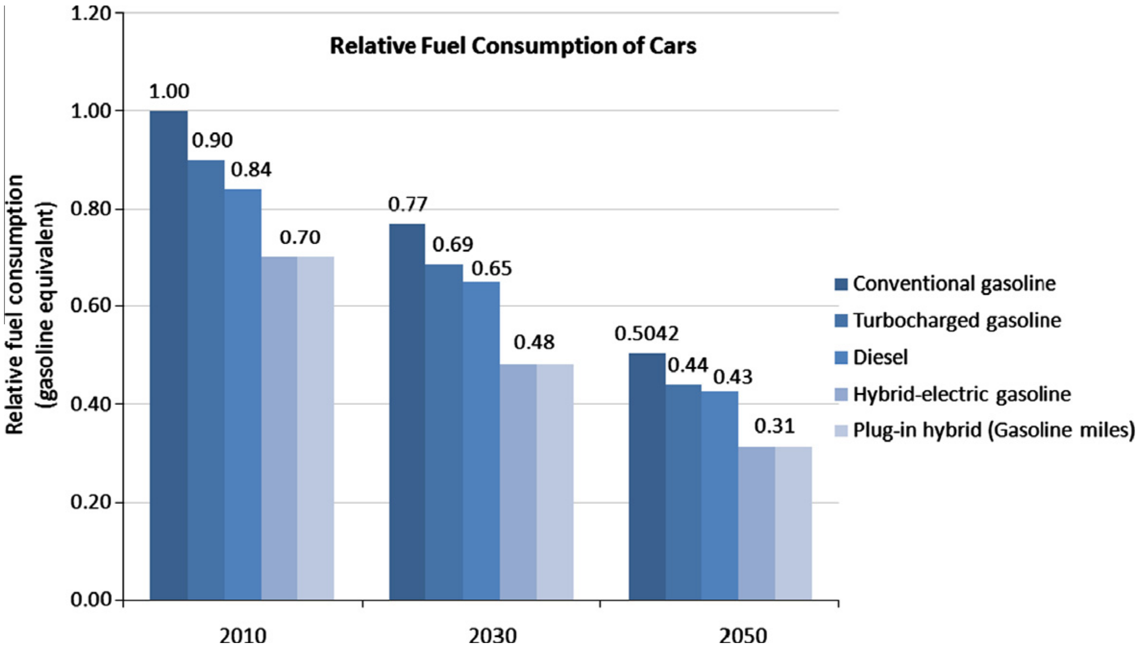

Fig. 13. Relative fuel consumption of cars mean input values 2010–2050.

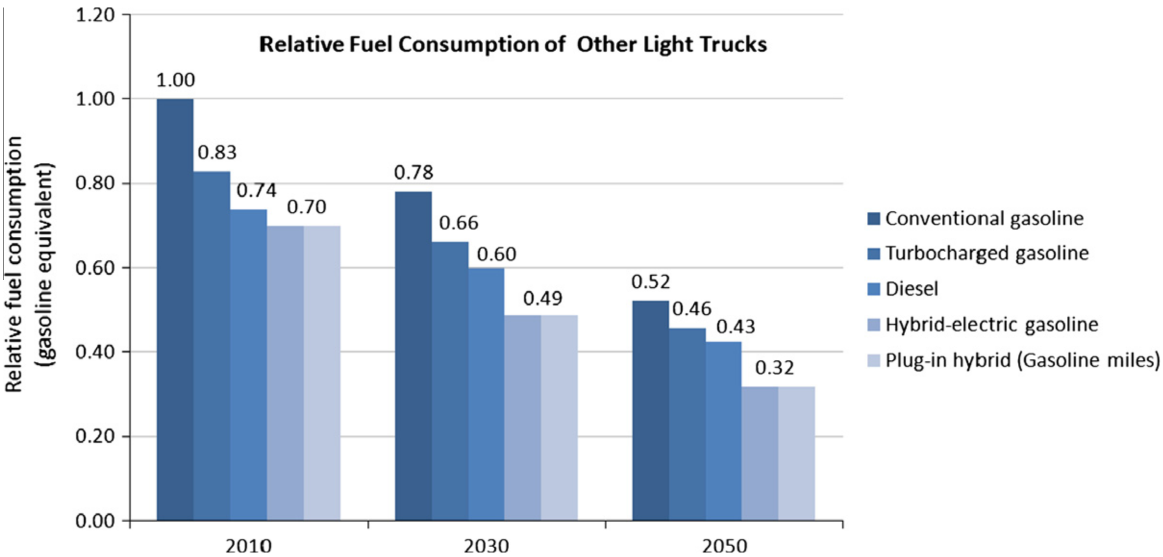

Fig. 14. Relative fuel consumption of light trucks mean input values 2010–2050.

around 540 billion litres (expected value) and could be anywhere between 490 and 590 billion litres (1% and 99% values) respectively (note that the values in this section have been rounded to avoid implying high precision). The standard deviation in year 2020 is about 22 billion litres. The coefficient of variation is about 4% which indicates a low level of uncertainty in the 2020 fuel use. In other words, given the uncertainties in the inputs, the fuel use in 2020 is fairly well known. Moreover, the 90% confidence interval indicates that there is 90% chance the fuel use will be somewhere between 500 and 570 billion litres in 2020, and there is only a 5% chance that fuel reductions below 500 billion litres can be achieved in the short term. The fuel use distribution is asymmetric and negatively skewed in 2020, which means the distribution has a few low values. In other words, there is a slight chance that a large fuel reduction below 470 billion litres would be possible.

Looking ahead into the mid term, the results (Fig. 16) show that there is about a 7% reduction in the expected value of fuel use from 2020 to 2030. It is shown that the fuel use will be most likely about 500 billion litres and could be anywhere between 410 and 600 billion litres. The standard deviation in 2030 is about 40 billion litres, which is higher than 2020, as our

Table 7
Vehicle fuel economy input distribution values into STEP.

Parameter	Min	Mode	Max	Mean	Values in 2010
Emphasis on Reducing Fuel Consumption (ERFC)					
ERFC cars	40%	80%	100%	73%	50%
ERFC light trucks	30%	70%	100%	67%	50%
FC relative in2030					
FC-r NA-SI cars in 2030	0.44	0.70	0.96	0.70	1.00
FC-r Turbo cars in 2030	0.39	0.62	0.85	0.62	0.90
FC-r Diesel cars in 2030	0.37	0.59	0.81	0.59	0.84
FC-r HEV cars in 2030	0.21	0.42	0.63	0.42	0.70
FC-r PHEV cars in 2030	0.21	0.42	0.63	0.42	0.70
FC-r NA-SILT in 2030	0.45	0.71	0.98	0.71	1.00
FC-r Turbo LT in 2030	0.39	0.61	0.83	0.61	0.83
FC-r Diesel LT in 2030	0.35	0.56	0.76	0.56	0.74
FC-r HEV LT in 2030	0.22	0.43	0.63	0.43	0.70
FC-r PHEV LT in 2030					
Electricity use					
PHEV Elec consumption (kWh/100 km) in 2030	12	24	35	24	36
BEVElec consumption (kWh/100 km) in 2030	12	24	36	24	36
FCV Hybrid Electric Energy use (MJ/100 km)	30	115	200	115	115
Utility Factor	30%	48%	66%	48%	N.A
	0.22	0.43	0.63	0.426	0.70

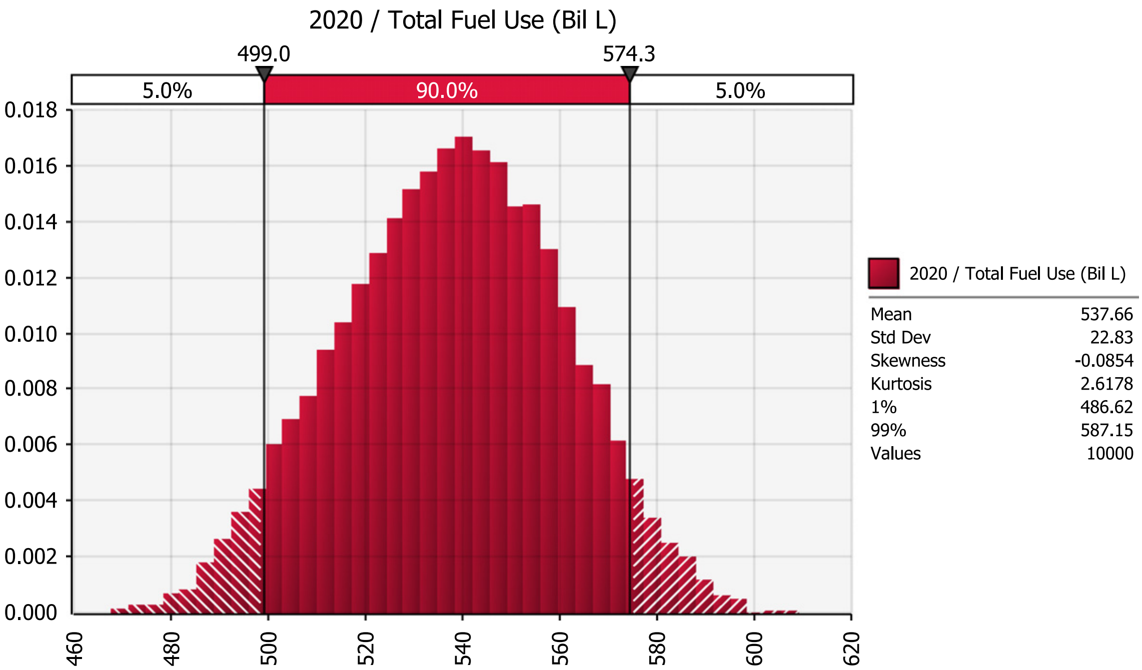

Fig. 15. 2020 US fleet fuel use (billion litres gasoline equivalent/year).

knowledge of fleet behaviour becomes more uncertain as we move into the future. The coefficient of variation is about 10% which indicates a medium level of uncertainty in the fuel use in mid term. Furthermore, the 90% confidence interval indicates that there is a 90% chance that fuel use will lie somewhere between 430 and 560 billion litres, with only 5% chance that fuel use would be lower than 430 billion litres. There is also a small chance that fuel use would exceed 560 billion litres in the mid term. The fuel distribution in 2030 is asymmetric and positively skewed, which indicates the distribution has a few high values. In other words there is a slight chance that the fuel use exceeds our expectations and is above 600 billion litres.

In 2050, the mean results (Fig. 17) show around a 35% reduction in fuel use from 2020 levels. Fuel use will be most likely around 350 billion litres in 2050 and could lie anywhere between 200 and 580. The standard deviation is about 84 billion litres, which is quiet large and indicates that the outcomes are spread over a larger range in 2050. The coefficient of variation is about 24%, which indicates a relatively high level of uncertainty in 2050 fuel use. As shown in the probability density func-

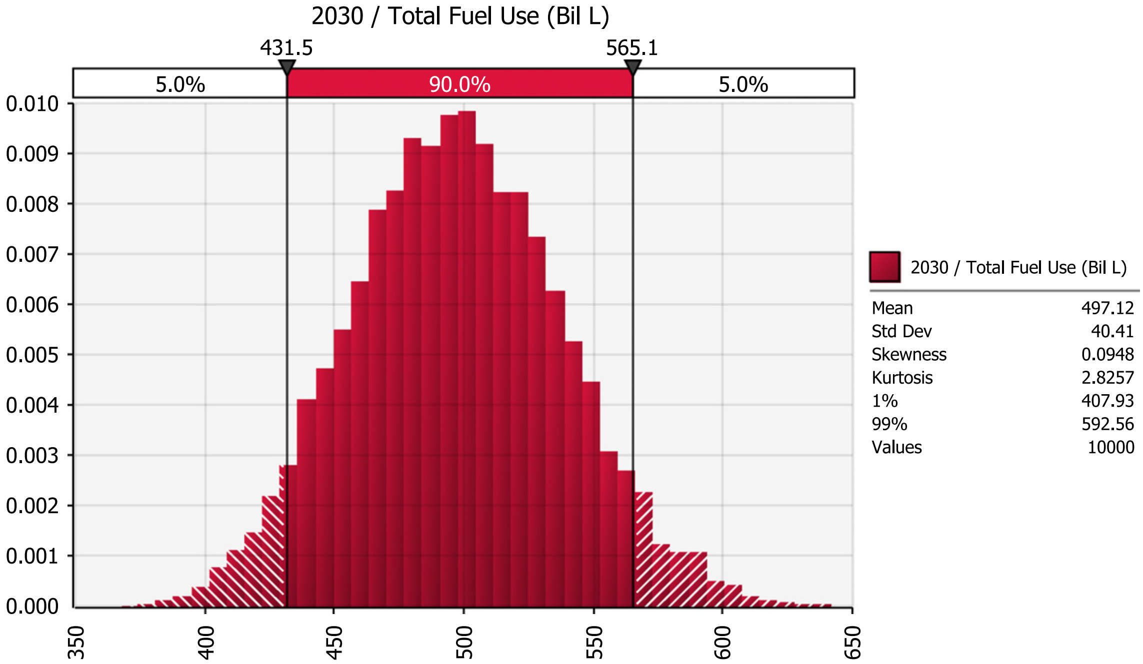

Fig. 16. 2030 US fleet fuel use (billion litres gasoline equivalent/year).

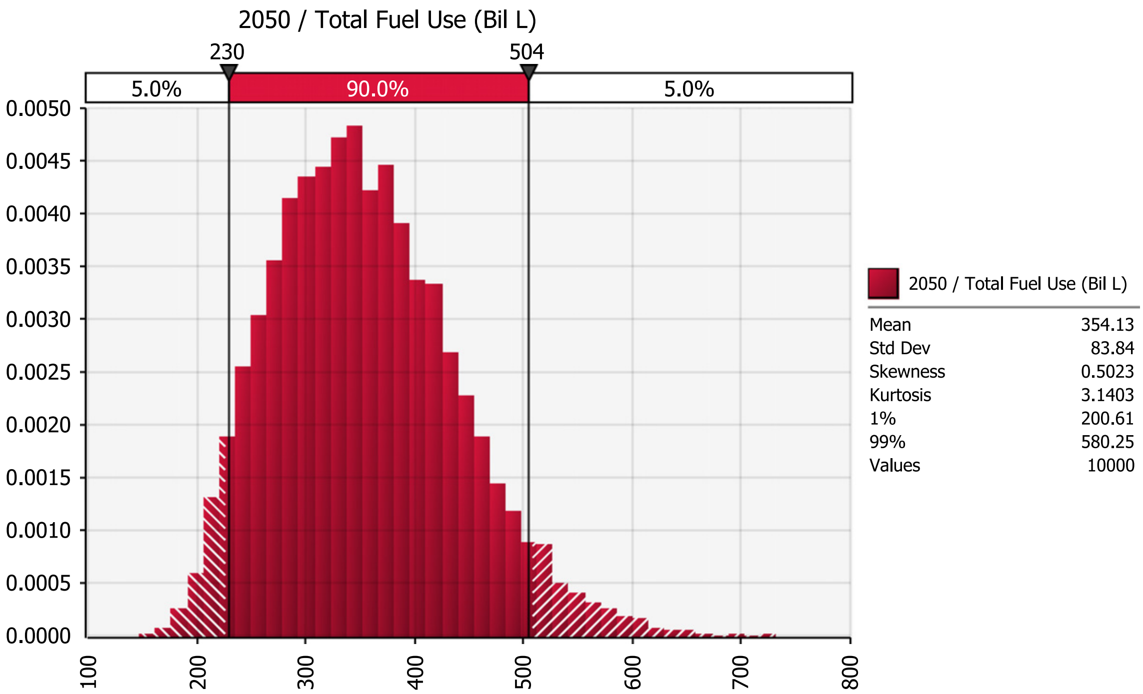

Fig. 17. 2050 US fleet fuel use (billion litres gasoline equivalent/year).

tions below, the uncertainty spread grows over time, as expected. The increase in the coefficient of variation is non-linear over time. Moreover, the results show that there is a 90% chance that fuel use will lie between 230 and 500 in 2050, with only 5% chance of achieving a reduction lower than 230 billion litres. There is also a small risk that fuel use would exceed 500 billion litres in 2050. The fuel use distribution is highly asymmetric in 2050, and is positively skewed. This indicates that the distribution has a long right hand tail, which means there is a possibility that fuel use could highly exceed our expected value in 2050. Finally, the *r* results could also be used to determine the probability of achieving a reduction target, for instance, there is about a 10% probability in 2050 that fuel use can be reduced to 250 billion litres or half the 2030 expected value. Alternatively, in 2030, for example, there is a 60% chance of achieving a 5% fuel use reduction from the 2020 expected level. Similarly, all these probability density function can be used to determine the probability of achieving a target over time. Cumulative probability functions, such as that shown in Fig. 18, could also be used to determine the probability of achieving a target or lower values given a chosen pathway at any given point in time out to year 2050.

4.2. Transport-related emissions (near, mid, and long-term)

The following results show the uncertainty profile of the total full life-cycle transport-related emissions in the near, mid, and long term (year 2020, 2030, 2050). The total GHG emissions are reported in Mt CO_2 equivalent. The results (Fig. 19) show that the life-cycle emissions in the near term (2020) will be most likely around 1580 Mt CO_2 equivalent (expected value) and could be anywhere between 1380 and17,600 Mt CO_2 equivalent. The standard deviation in year 2020 is about 80 Mt CO_2 equivalent. The coefficient of variation is about 5% which indicates a low level of uncertainty in the 2020 emissions. In other words, given the uncertainties in the input, the emissions in 2020 are fairly well known. Moreover, the 90% confidence interval indicates that there is a 90% chance that the emissions will be somewhere between 1450 and 1710 Mt CO_2 equivalent in 2020, and there is only a 5% chance that emissions reductions below 1450 Mt CO_2 equivalent could be achieved in the short term. The emissions distribution is asymmetric and positively skewed in 2020, which means the distribution has a few extremely high values. In other words, there is a slight chance that emissions could exceed our expectations and be higher than 1800 Mt CO_2.

Looking ahead into the mid term, the results (Fig. 20) show that there is a 14% reduction in the expected value of emissions from 2020 to 2030. Emissions will be most likely about 1360 Mt CO_2 equivalent and could be anywhere between 1070 and 16,800 Mt CO_2 equivalent. The standard deviation in 2030 is about 130 Mt CO_2 equivalent, which is higher than 2020, as our knowledge of fleet behaviour becomes more uncertain as we move into the future. The coefficient of variation is about 10% which indicates a medium level of uncertainty in the emissions in mid term. Furthermore, the 90% confidence interval indicates that there is a 90% chance that emissions will lie somewhere between 1150 and 1590 Mt CO_2 equivalent, with only 5% chance that emissions would be lower than 1150 Mt CO_2 equivalent. There is also a small chance that emissions would exceed 1590 Mt CO_2 equivalent in the mid term. The emissions distribution in 2030 is asymmetric and positively skewed, which indicates that the distribution has a few high values. In other words there is a slight chance that the emissions could exceed our expectations and be above 1850 Mt CO_2 equivalent.

In 2050, the mean results (Fig. 21) show around a 47% reduction in emissions from 2020 levels. GHG emissions will be most likely around 850 Mt CO_2 equivalent in 2050 and could lie anywhere between 440 and 1450 Mt CO_2 equivalent. The standard deviation is about 225 Mt CO_2 equivalent, which is quite large and indicates that the outcomes are spread over

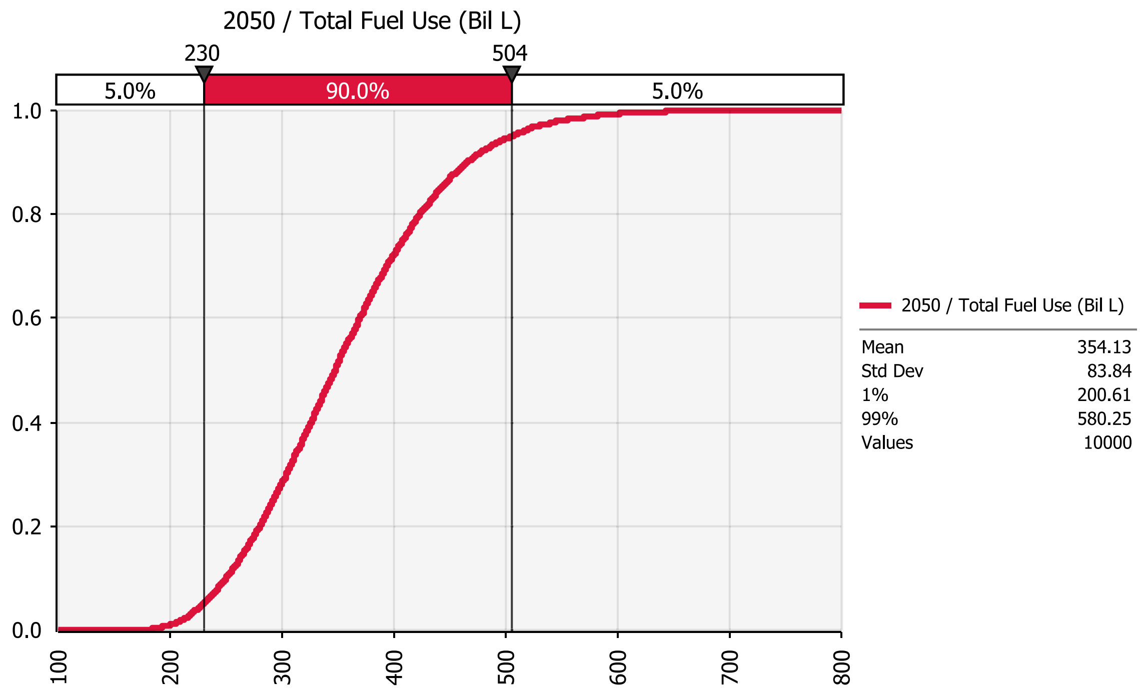

Fig. 18. 2050 US fleet fuel use (billion litres gasoline equivalent/year) cumulative probability function.

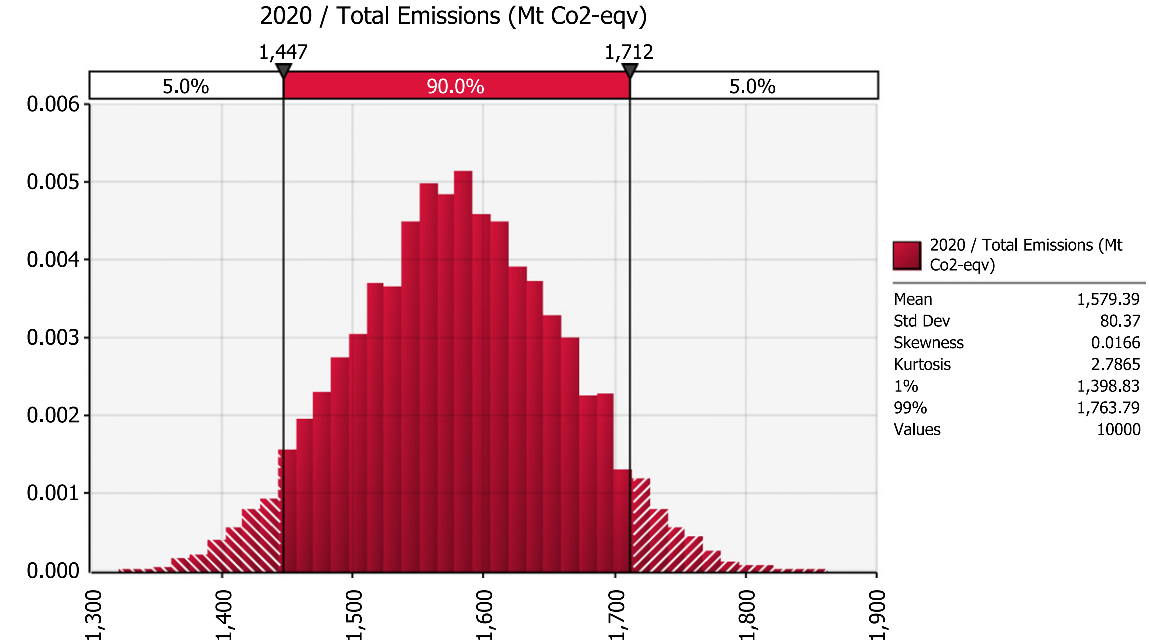

Fig. 19. 2020 US fleet GHG emissions (Mt CO2 equivalent/year).

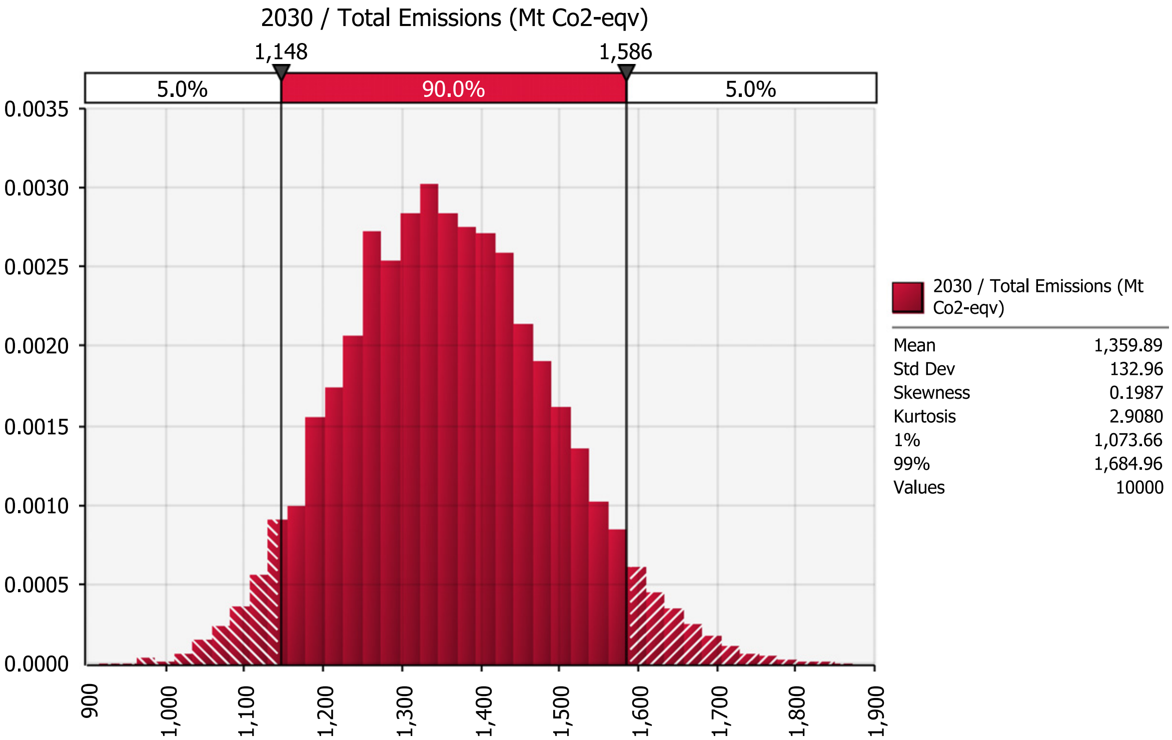

Fig. 20. 2030 US fleet GHG emissions (Mt CO_2 equivalent/year).

a larger range in 2050. The coefficient of variation is about 27%, which indicates a relatively high level of uncertainty in 2050 emissions. As shown in the probability density functions below, the uncertainty spread grows over time, as expected. The increase in the coefficient of variation is non-linear over time. Moreover, the results show that there is a 90% chance that emissions will lie between 520 and 1260 Mt CO_2 equivalent in the long term, with only a 5% chance of achieving a reduction

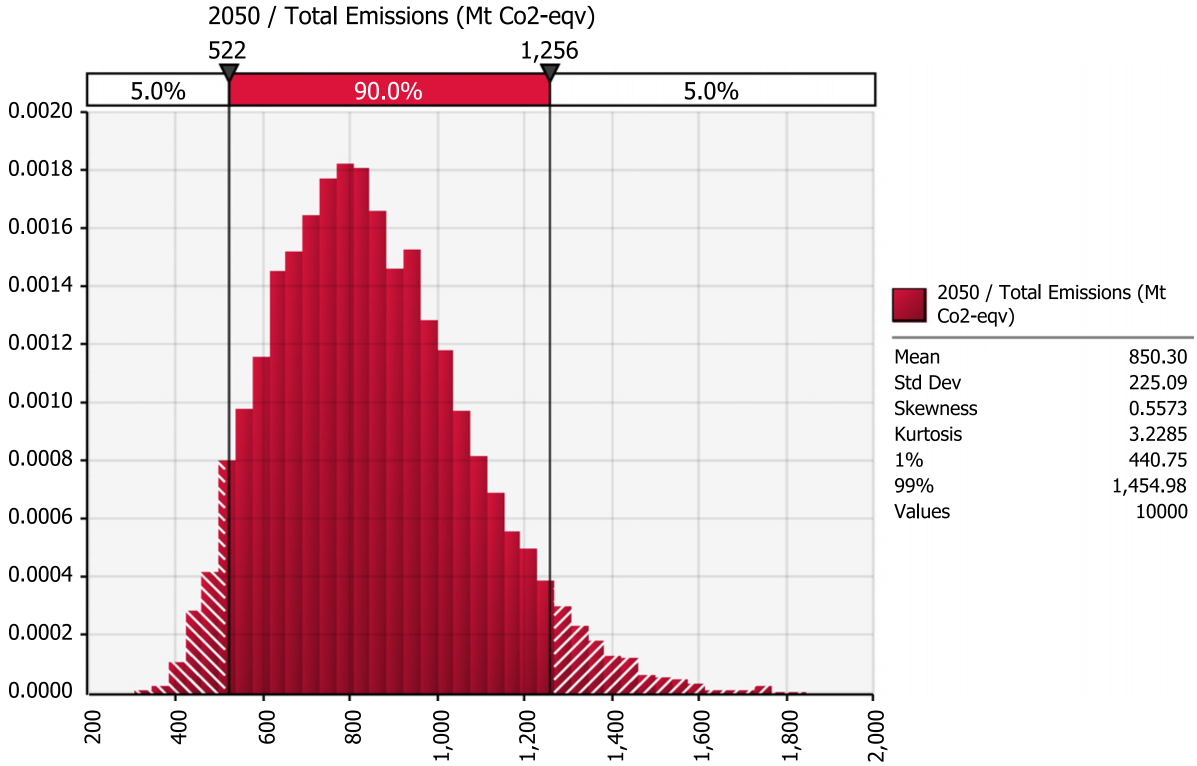

Fig. 21. 2050 US fleet GHG emissions (Mt CO_2 equivalent/year).

lower than 520 Mt CO_2 equivalent. There is also a small risk that emissions could exceed 1260 Mt CO_2 equivalent in 2050. The emissions distribution is highly asymmetric in 2050, and is positively skewed. This indicates that the distribution has a long right hand tail, which means that there is a possibility that emissions could significantly exceed our expected value in 2050. In other words, there is a chance that GHG emissions could be much worse than expected.

4.3. Fuel use major Influences (near, mid, and long term)

The following tornado graphs show the major contributors to total transport-related fuel consumption over time, and ranks them based on their relative importance. These graphs are developed using ranked linear regression analysis of the inputs and outputs, using data from 10,000 simulation runs. The labels on the *y*-axis indicate the major influencing factors, and the numbers on the bar in front of each parameter, along the *x*-axis, shows by how much (in billion litres of gasoline equivalent) the total fuel consumption would increase with a one standard deviation increase in the input shown on the *y*-axis. Refer to Appendix A for a complete list of inputs and statistics (including input standard deviation values).

In year 2020, for instance, if the scrappage rate is increased by one standard deviation (i.e. 8%), the total transport fuel use decreases by about 20 Billion litres of gasoline equivalent. The changes in the output shown on these tornado graphs is a result of the net effect of the influence of each input in determining the final output, as well as the underlying uncertainty in each input. As shown in Fig. 23, in 2030, for example, if the relative fuel consumption of NA-SI cars is increased by one standard deviation (i.e. 0.1), the total fuel use will be increase by 13 billion litres. Further the direction in which the outputs are impacted by the inputs should be noted. For example, as shown in Figs. 22–24 below, an increase in scrappage rate decreases the fuel consumption, due to faster fleet turn over, and an increase in VKT growth increases fuel consumption, due to increase in travelling. Further, an increase in the relative fuel consumption of NA-SI cars increases fuel use due to reduced fuel economy, while an increase in the BEV sales reduces fuel use, due to electricity replacing fuel. All the directional effects of the inputs on the total fuel use, shown in Figs. 22–24, are as expected.

These tornado graphs are "Mapped Regression Values", which means the outputs are scaled to the unit of fuel use (billion litres) to describe the impact of each parameter on the output in absolute terms. These graphs thus indicate which parameters are most important in determining total fuel use in the near to long term. These graphs also show that the major influencing parameters change dynamically over time, as the uncertainty profile and dynamics of interaction between various influencing forces change.

As shown in Figs. 22–24, the scrappage rate is the most influential parameter in determining total fuel use in the short and mid term, and one of the major contributors in the long term This is because the scrappage rate directly controls the size of the fleet and thus the technology turn over. Therefore, the higher the scrappage rate, the faster old and inefficient vehicles are replaced by new improved vehicles with higher fuel economy. Furthermore, the mid term VKT annual growth is influ-

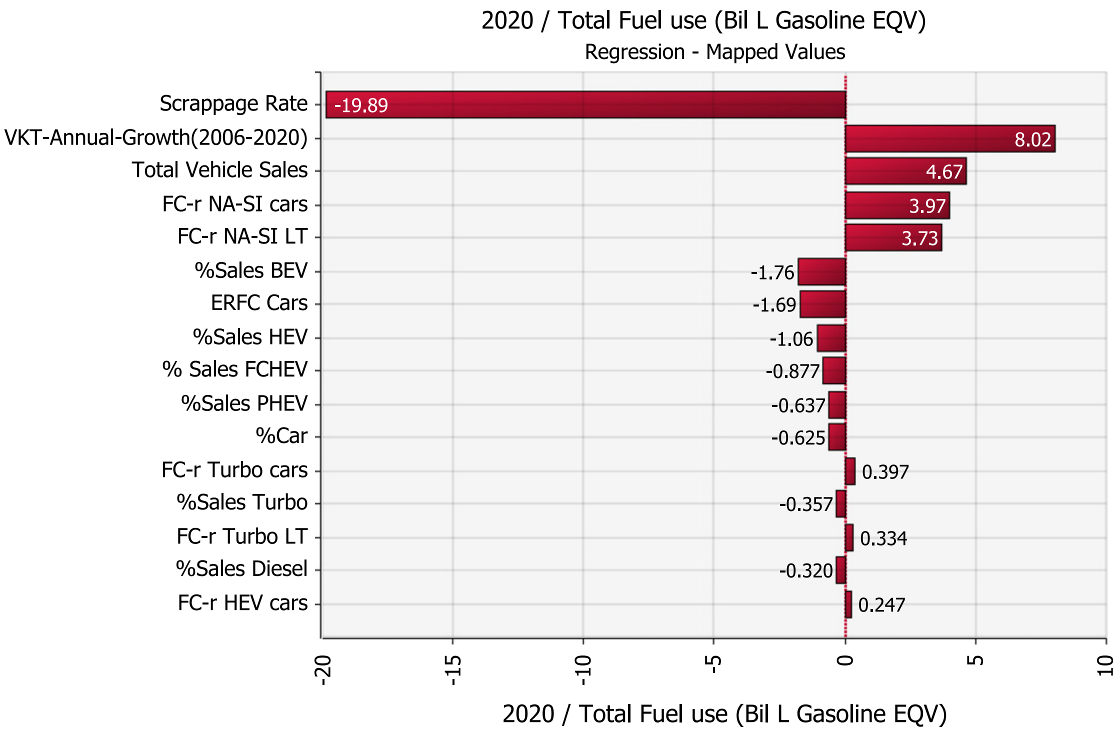

Fig. 22. 2020 US fleet fuel use ranked major influences (billion litres gasoline equivalent/year) under uncertainty.

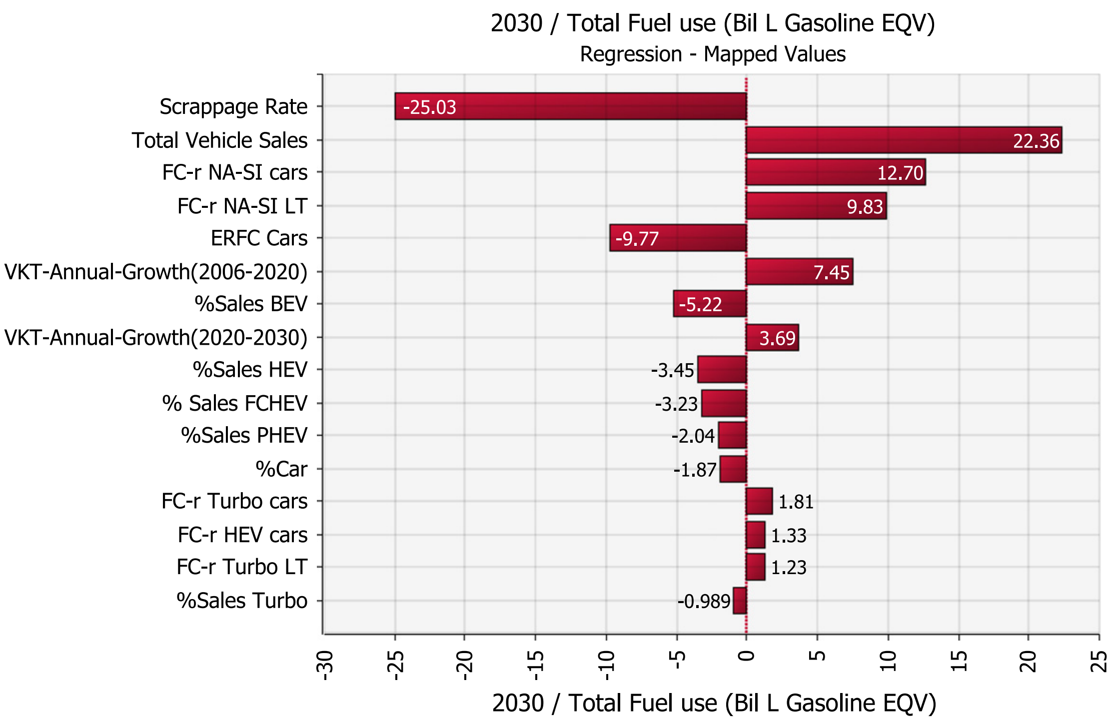

Fig. 23. 2030 US fleet fuel use ranked major influences (billion litres gasoline equivalent/year) under uncertainty.

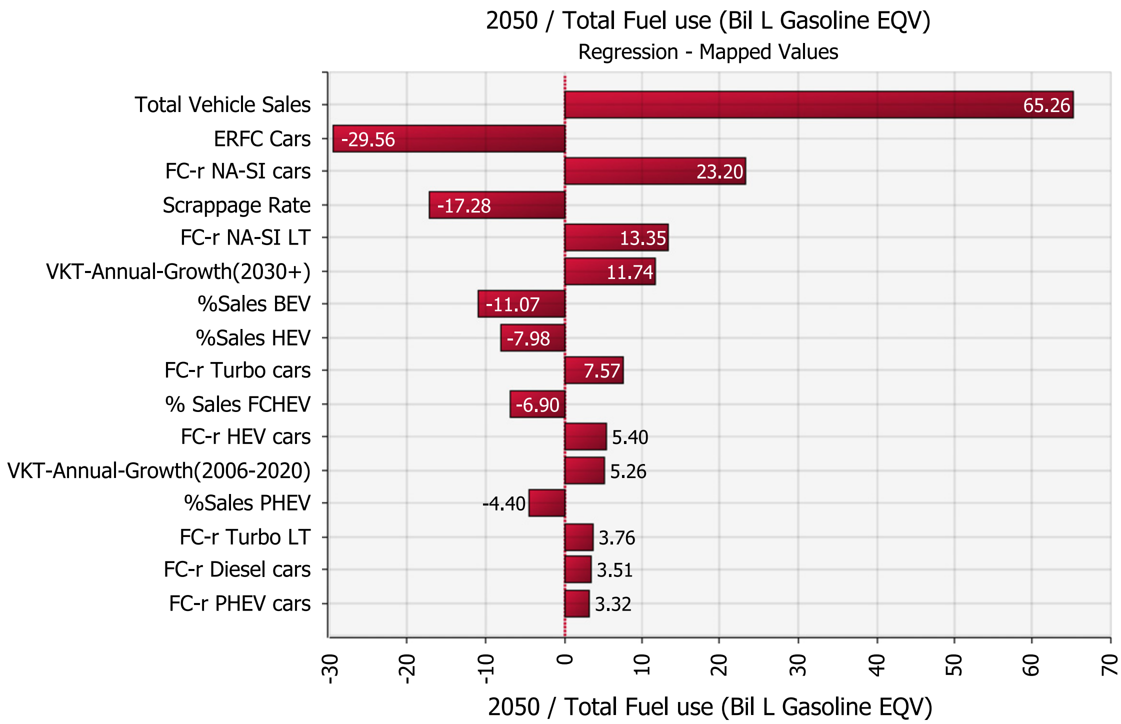

Fig. 24. 2050 US fleet fuel use ranked major influences (billion litres gasoline equivalent/year) under uncertainty.

ential in the mid and short term, while the long-term VKT annual growth is more important in year 2050, Also, the VKT annual growth is relatively more important in the near term than the mid and long terms. This could be attributed to the lower fuel economy of vehicles in the near term, and thus the higher impact of the kilometres travelled by these less efficient vehicles. Moreover, the ERFC of cars becomes more important in the long term, as the emphasis on reducing fuel consumption becomes higher (lower vehicle weight and less emphasis on vehicle performance increase), and thus technological improvements are used to increase vehicles' fuel economy.

The total vehicle sales becomes more influential over time, and is the most important contributor to fuel use in 2050. This is attributed to the fact that vehicle sales has a direct impact on the growth of the vehicle fleet over time. In 2050, one standard deviation (i.e. 2,800,000 vehicles) increase in the total vehicle sales increases fuel use by 65 billion litres. Further, the ERFC of cars becomes the second most influential parameter in 2050, that is, if ERFC is increased by 12% the total fuel use will be decreased by about 30 billion litres. The relative fuel consumption of NA-SI vehicles also becomes influential in 2050, where an increase of 0.1 in the relative NA-SI fuel consumption results in a 24 billion litre increase in the total fleet fuel use. Similarly, the relative fuel consumption of light trucks (SUVs and pick-up trucks) becomes a more important factor in determining the total fleet fuel use over time. Finally, the relative fuel consumption of NA-SI gasoline cars stays dominant in the mid and long term, but the fuel consumption of turbo-SI and diesel also become more important over time as their market share increases.

The market share of BEVs and HEVs become more influential over time. This could be attributed to technology improvements over time and the growing market share of these vehicles in the market. In 2050, one standard deviation increase in the BEV sales share (i.e. 2% increase) in the car market results in 11 billion litres decrease in total fuel use. This indicates the large potential of alternative vehicles in reducing the total US fleet fuel use in the mid and long term.

4.4. GHG emissions major influences (near, mid, and long-term)

Similar to the previous section, the following tornado graphs show the major contributors to the total transport-related emissions over time and ranks them based on their relative importance under uncertainty. As in the last section, the labels on the *y*-axis indicate the major influencing factors, and the numbers on the bar in front of each parameter, along the *x*-axis, shows by how much (in Mt CO_2 equivalent) the total GHG emissions would increase with a one standard deviation increase in the input shown on the *y*-axis. Refer to Appendix A for a complete list of inputs and statistics (including input standard deviation values).

In year 2020, for instance, if the scrappage rate is increased by one standard deviation (i.e. 8%), the total transport emissions decreases by about 59 Mt CO_2 equivalent. As shown in Fig. 26, in 2030, for example, if the gasoline WTW is increased by one standard deviation (i.e. 5 gCO_2/MJ), the GHG emissions will be increased by 45 Mt CO_2 equivalent. In 2020, for example, a

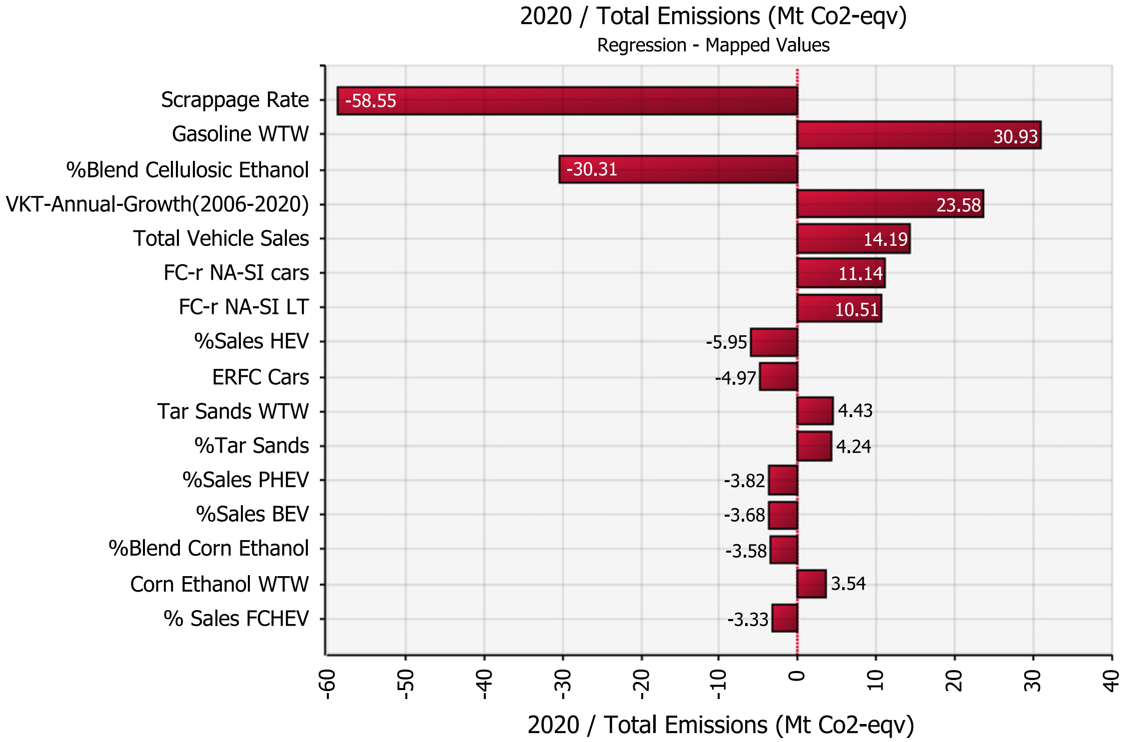

fig. 25. 2020 us fleet GHG emissions ranked major influences (Mt CO_2 equivalent/year) under uncertainty.

one standard deviation increase in the annual VKT growth rate in the near term (i.e. by 0.1%) results in an increase of 24 Mt CO_2 equivalent in the total fleet life-cycle emissions.

As shown in Figs. 25 and 26, the scrappage rate is the most influential parameter in determining the total emissions in the short and mid term. Though still important in the long term, scrappage rate is not as influential in 2050 compared to the

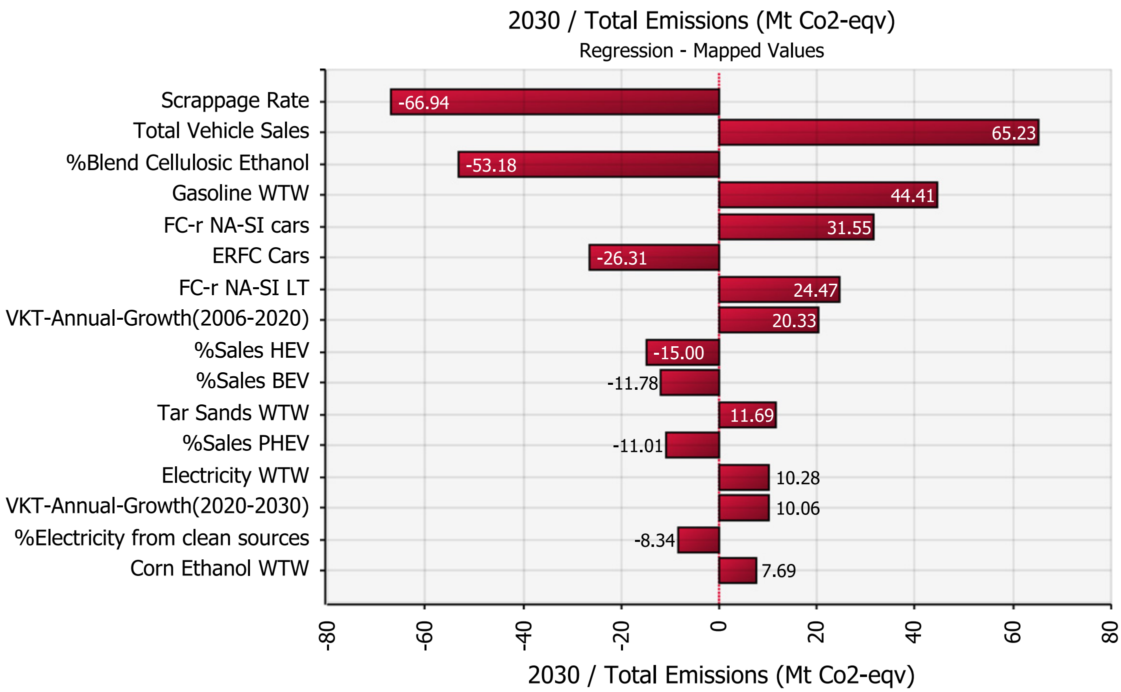

Fig. 26. 2030 US fleet GHG emissions ranked major influences (Mt CO_2 equivalent/year) under uncertainty.

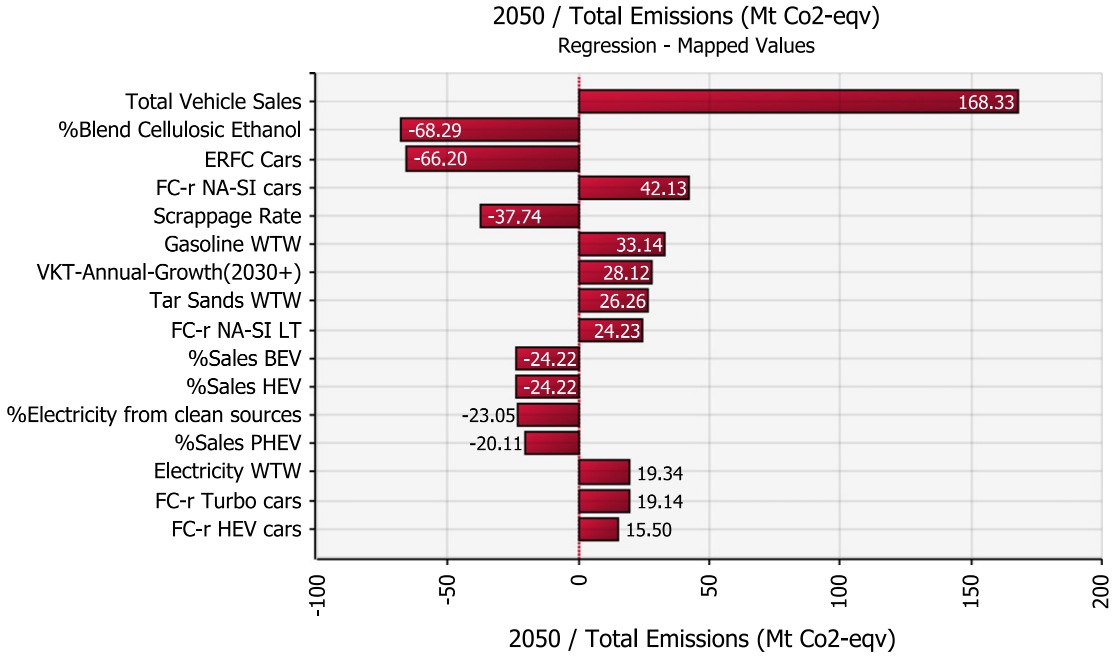

Fig. 27. 2050 US fleet GHG emissions ranked major influences (Mt CO_2 equivalent/year) under uncertainty.

nearer term (Fig. 27). This could be attributed to the fact that scrappage rate directly controls the size of the fleet and thus the technology turn over, in addition to the fact that, fuels become less emissions intensive over time. Therefore, the higher the scrappage rate, the faster are old and inefficient vehicles replaced by new improved vehicles with higher fuel economy, using fuels that have a much cleaner life-cycle. Moreover, the WTW of gasoline is most influential in the near term and becomes less and less important over time, as other types of fuels replace gasoline and as their process of fuel making and the raw material become cleaner, making fuels less emissions intensive. The percentage cellulosic ethanol blend is one of the most influential parameters in the near to long term, this is due to the high level of uncertainty in the development of this fuel, due to technological challenges and the economics of this fuel, and its extremely low emissions compared to conventional fuels. This also indicates cellulosic ethanol's large potential in contributing to large emissions reduction in 2030 and beyond.

Furthermore, the near term VKT annual growth (2006–2020) becomes influential in the short-mid term, while the long-term VKT annual growth (2030+) becomes important in year 2050 (Fig. 27). Also, the VKT annual growth is relatively more important in the near term than in the mid and long terms. This is because of the lower fuel economy of vehicles and dirtier fuels in the near term, and thus of the higher impact of the kilometres travelled by these less efficient vehicles. Moreover, the ERFC of cars becomes more important in the long term, as the emphasis on reducing fuel consumption becomes higher (lower vehicle weight and less emphasis on vehicle performance increase), and thus technological improvements are used to increase vehicles' fuel economy.

The total vehicle sales becomes more influential over time, and is the most important contributor to GHG emissions in 2050, as was the case with fuel use and described in previous section. This is attributed to the fact that vehicle sales has a direct impact on the growth of the vehicle fleet over time. In 2050, one standard deviation (i.e. 2800,000 vehicles) increase in the total vehicle sales increases the total fleet emissions by 167 Mt CO_2 equivalent (Fig. 27). Further, the ERFC of cars becomes the third most influential parameter in 2050, that is, if ERFC is increase by 12% the total emissions will be decreased by about 67 Mt CO_2 equivalent. The relative fuel consumption of NA-SI vehicles also becomes influential in 2050, where an increase of 0.1 in the relative NA-SI fuel consumption results in 43 Mt CO_2 equivalent increase in the total fleet GHG emissions. The relative fuel consumption of NA-SI gasoline cars stays dominant throughout the time, but the fuel consumption of turbo-SI and HEVs become more important in the longer term, as their market share increases.

The market share of BEVs, HEVs, and PHEVs become more influential over time This could be attributed to battery technology improvements over time, the growing market share of these vehicles in the market, and greening of the electricity grid. In year 2050, one standard deviation increase in the BEV sales share (i.e. 2% increase) in the car market results in a 24 Mt CO_2 equivalent decrease in total fleet emissions. This indicates the large potential of alternative vehicles in reducing the total US fleet GHG emissions in the mid and long term.

The WTW of tar sands becomes more important over time, as this fuel starts to replace a higher volume of conventional fuels. In 2050, for example, one standard deviation increase in tar sands WTW (i.e. 5 gCO_2/MJ increase) would result in about 27 Mt CO_2 equivalent increases in life-cycle fleet emissions. The WTW of electricity and the percentage of renewable energy fed into the gird become more important in the long term, as the market share of BEVs and PHEVs increase and thus the greening of the grid plays a more influential role. In 2050, for instance, a one standard deviation increase (i.e. 205 gCO_2/kW h increase) in conventional electricity WTW (i.e. coal and natural gas based electricity) results in 19 Mt CO_2 equivalent increase in the emissions. Moreover, a standard deviation increase (i.e. 9% increase) in the percentage of electricity produced from clean sources decreases the fleet GHG emissions by about 22 Mt CO_2 equivalent. The potential of clean electricity can thus be more fully realized as electrification increases over time.

4.5. Emissions and fuel consumption uncertainty-time plots

The following graphs in Figs. 28 and 29 show the evolution of the fleet fuel use and GHG emissions over time. These figures show the range of possible fuel use and emissions outcomes at any point out to year 2050. From these graphs, one can determine what the probability of achieving a target is, in this case given the pathway chosen in this paper. The mean curve shown on Figs. 28 and 29 show the expected reduction that can be achieved over time, given the pathway chosen in this paper. The 95% and 5% dotted lines bound the range of outcomes that could be expected with 90% confidence and the 75% and 25% dotted lines bound the range of outcomes that could be expected with 50% confidence. In other words, there is a 90% chance that the fuel use would be somewhere between the outer dotted lines, shown on Fig. 28, out to year 2050. As shown in these results, the uncertainty in the fleet fuel use and GHG emissions is significant and grows considerably over time.

The following graph (Fig. 30) shows the uncertainty (spread/mean) of GHG emissions and fuel consumption over time, where spread is defined as two Standard-deviations. This plot (Fig. 30) shows that the uncertainty in both emissions and fuel use grow over time, and reach approximately 50% for both fuel use and emissions in 2050. This is expected as uncertainty in our knowledge of the future also increases as we look ahead in time.

4.6. Life-cycle energy consumption

The following graphs show the probability distribution for the life-cycle energy consumption of the fleet in 2050. The energy results include the full life-cycle energy consumption from all fuels including electricity and hydrogen, as well as the primary fuel used to generate electricity. The coefficient of variation is about 24% in 2050, and is similar to that of fuel use that year. Fig. 31 shows that the energy consumption will be somewhere between 7.5 and 17 Exajoules with a 90% confidence level, and will be expected to be around 12 Exajoules in 2050. The distribution is positively skewed and thus there is a chance that the energy consumption could be much higher than expected. The ranked major influences on energy consumption are shown in Fig. 32. The major influences are similar to that of fuel use in 2050; however, the ranking is different. For instance, the sales share of BEVs is relatively less important that HEVs in determining the total energy consumption than in fuel use in 2050. This is because the use of BEVs results in replacing liquid-based fuel by electricity, which means a significant change in the fuel use volume; however, BEVs still use energy to move and hence their less significant impact on life-cycle energy use Moreover, the growth of travel demand in the mid term becomes relatively more important than light truck fuel consumption. This can be attributed to the fact that LT fuel consumption only affects the fuel use directly, while the VKT demand affects the amount of energy needed for both conventional and alternative powertrain vehicles.

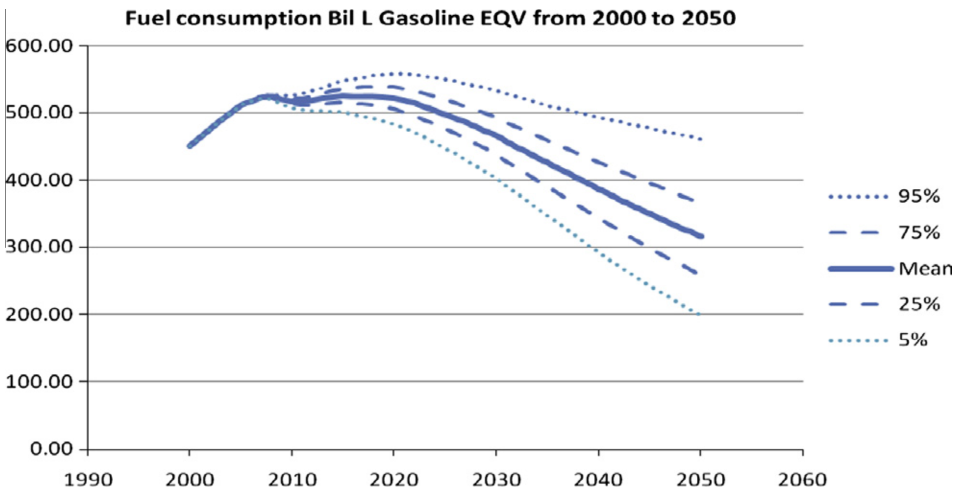

Fig. 28. US fleet fuel use (billion litres gasoline equivalent/year) over time out to 2050.

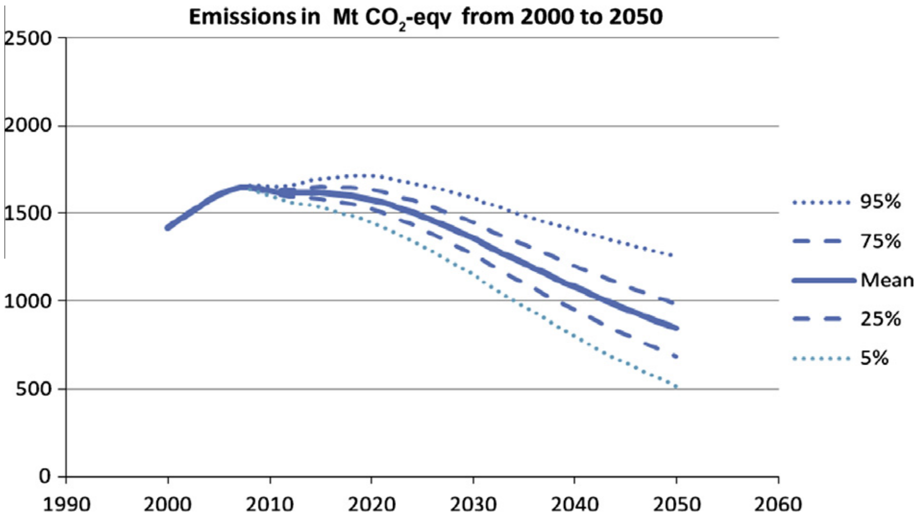

Fig. 29. US fleet GHG emissions (Mt CO_2 equivalent/year) over time out to 2050.

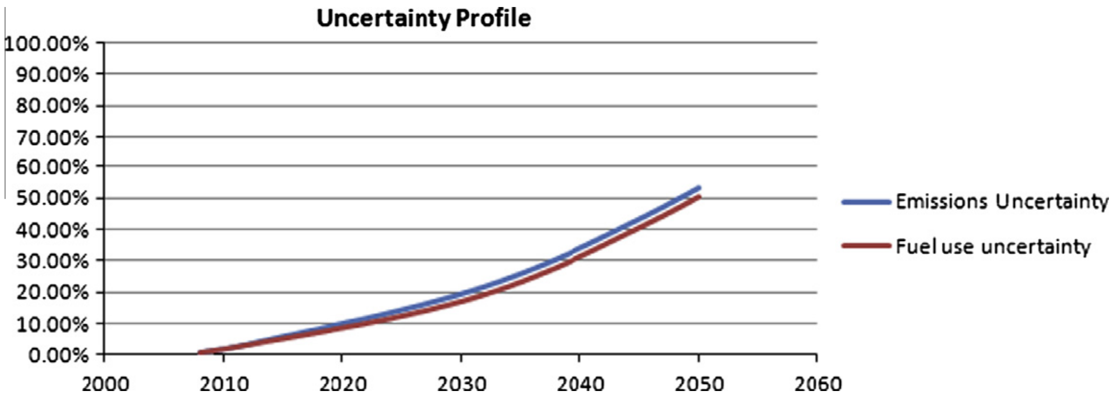

Fig. 30. Uncertainty–time plot for US fleet GHG emissions and fuel use based on two standard deviation/mean.

5. Fleet behaviour

The following section describes the fleet behaviour, given the pathway chosen in this paper. The graphs in this section are based on the mean input values of various distributions, and are presented here as a complementary set of results. The input values in this study are chosen to reflect sensible projections into the future so that the results could be interpreted in a real world sense. Very few robust and detailed analyses out to 2050 have been done to date; therefore, the authors provide this section to describe one example of the fleet behaviour out to the year 2050, given the pathway chosen here.

Fig. 33 shows the fuel consumption (L/100 km) for an average future vehicle, calculated using a weighted average based on the powertrain shares in the fleet for each year out to 2050. Gasoline NA-SI remains as a dominant powertrain in the future, even with the rather aggressive positive electrification explored here. Fig. 34 shows the share of alternative powertrain sales as a percentage of total market share over the next couple of decades. The fuel consumption of the fleet is then shown in Fig. 35, by LDV segment. The fuel use in the car segment stays dominant over the next few decades; however, a shift between cars and SUVs can be seen in Fig. 35, as a result of downsizing efforts. The fuel use in all segments is also reduced over time due to a higher emphasis on fuel consumption reduction, for example, through weight savings, and reduced vehicle fuel consumption due to improved technologies. Fig. 36 shows the fleet fuel consumption by powertrain. The fuel use from NA-SI is largest and stays dominant over time. The life-cycle GHG emissions are shown in Fig. 37, where emissions from gasoline are substantially reduced over time, while the share of emissions from alternative fuel sources such as tar sand and corn ethanol is increased over time. The emissions from electricity do not increase significantly over time due to an increase in the share of electricity produced from renewable sources and greening of the grid.

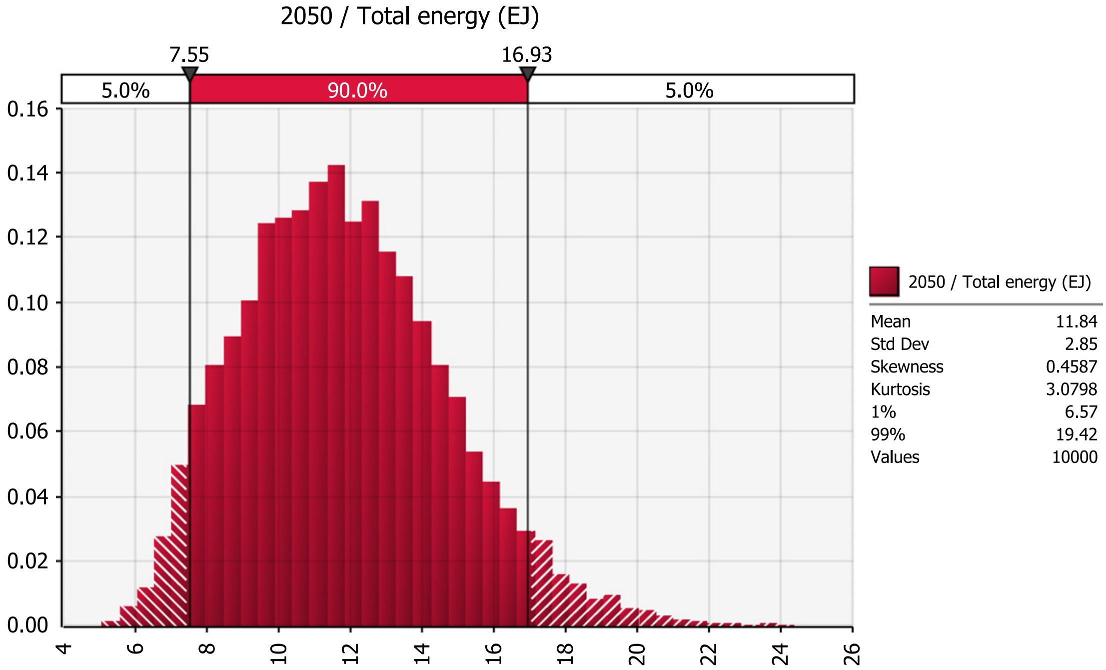

Fig. 31. 2050 US fleet life-cycle energy consumption (EJ/year).

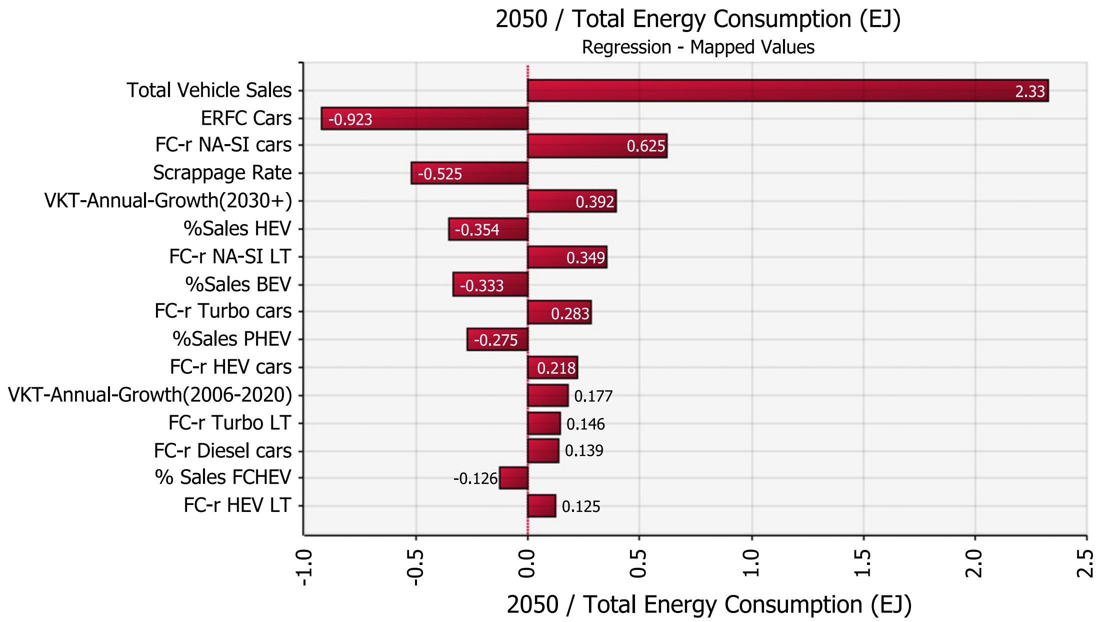

Fig. 32. 2050 US fleet life-cycle energy consumption ranked major influences (EJ/year) under uncertainty.

6. Comparison with earlier work

The following graph in Fig. 38 overlays the fuel use results from this paper with a number of scenarios explored in previous studies such as the MIT model (Bandivadekar et al., 2008), Greene et al. (2011), Yang et al. (2009) and the DOE and AEO forecasts. The minimum, maximum, 5%, 25%, 75%, and 95% results from STEP are also shown in this figure. The deterministic scenarios shown here, drawn from the literature, do not agree on what the future of fuel consumption would look like, due to their different sets of chosen assumptions, model logics, and policy pathways. The deficiencies of scenario analysis are thus self-evident from this graph, as it is not possible for the reader to assign a probability to any of these pathways or prioritize

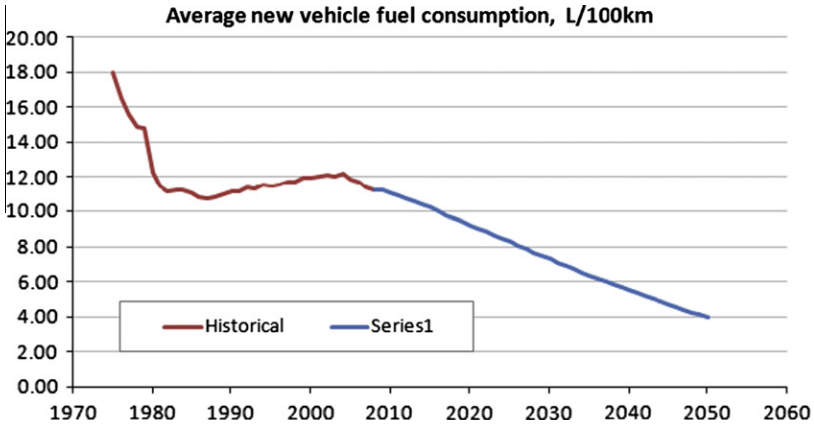

Fig. 33. Average new vehicle mean fuel consumption (L/100 km) out to 2050.

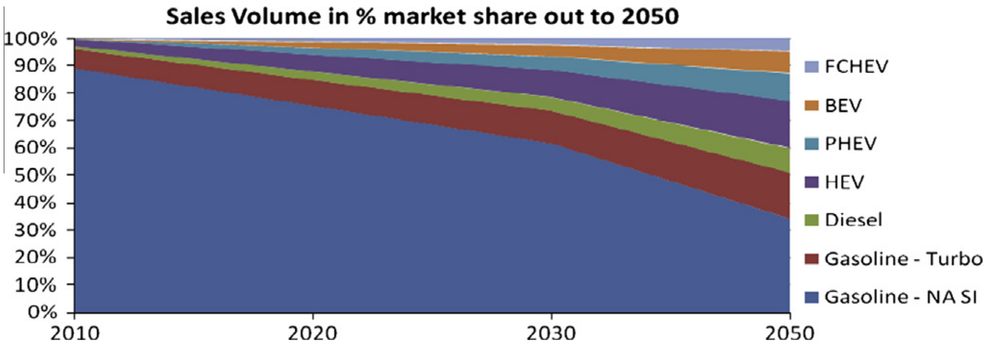

Fig. 34. Mean new vehicle sales market share out to 2050.

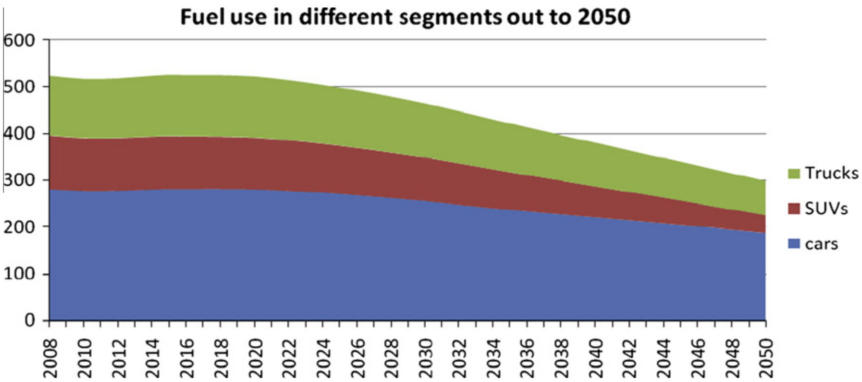

Fig. 35. Mean fuel use in billion litre gasoline equivalent by LDV segment out to 2050.

amongst them. The methodology adopted in STEP, as described in this paper, however, can be seen to offer a way not only to show possible pathways for reducing fuel use and emissions in the future, but also to provide the reader with the range of possible outcomes from such pathways and their associated probabilities. Such results can then be used to compute the probability of achieving a target following a certain pathway. In other words, different policy pathways, including the ones explored by Greene, and Yang et al. in previous studies, can be input into STEP to show the range of possible outcomes that those pathways could result in, as well as the probability associated with those outcomes. This would then allow proper probabilistic comparison amongst policy pathways and thus assist decision makers to choose between them based on their consequences and the probability of achieving certain targets.

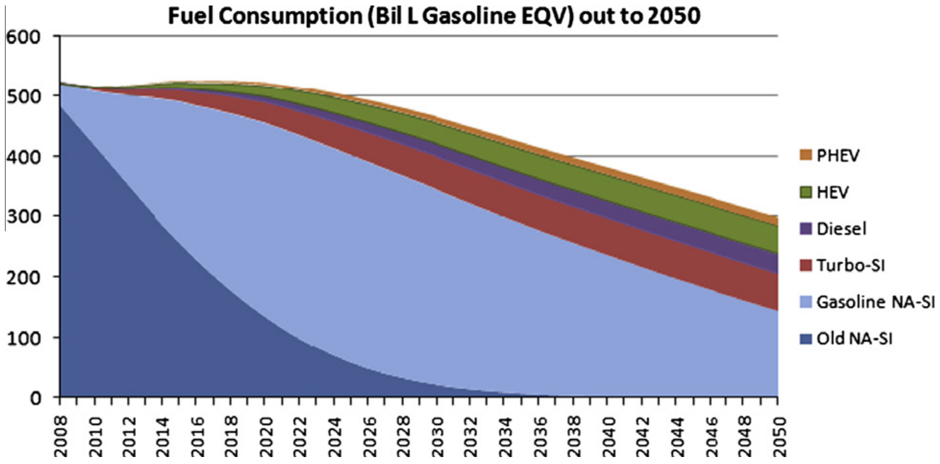

Fig. 36. Mean fuel use (billion litres gasoline equivalent) by powertrain type out to 2050.

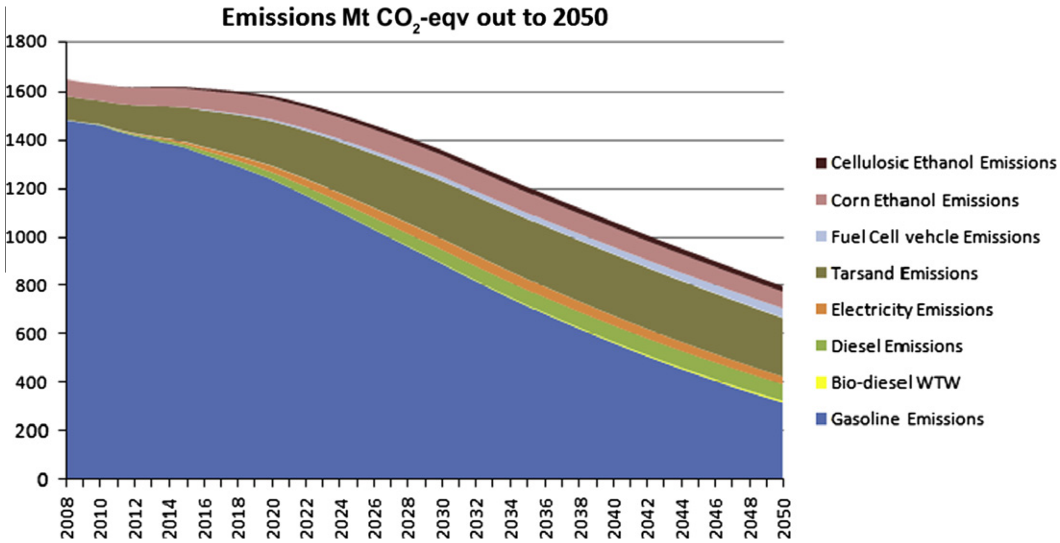

Fig. 37. Mean life-cycle GHG emissions (Mt CO_2 equivalent) by fuel type out to 2050.

7. Discussion and concluding remarks

This paper quantifies the impact of uncertainties on the total US fleet fuel use and GHG emissions, resulted from a pathway of steadily improving vehicle fuel efficiency technology, reduced vehicle size and weight, and the deployment of alternative vehicles and clean energy sources out to 2050. This work also identifies and ranks the major influences on future fuel use and emissions under uncertainty and over time. This relatively aggressive pathway reduces fleet fuel use and GHG emissions to about half of their maximum level (of 2010–2020) by 2050. The results show that the uncertainties are significant in the mid and long term. Therefore, an understanding of the probability distributions of the outputs given a chosen particular pathway is essential, to be able to understand the full range of future possibilities and their associated probabilities. This in turn provides policy makers with a more complete picture of what the consequences of their decisions are in the light of their associated risks, and allows decision makers to analyze the impact of new policies in one space consistently while accounting for the uncertainties in the inputs.

The probability distributions provided in this paper further quantify the range of possible outcomes, using measures such as: 1% and 99% values, as well as the spread, different confidence intervals, and the coefficient of variation in each outcome, for any given point in time out to 2050. The probability distributions also indicate what the chances are of achieving a certain target; for instance, from the results presented in this paper it can be concluded that there is 45% chance of achieving a 36% reduction below 2008 level fuel use in 2050, and a 51% chance of achieving a 49% reduction below 2008 emissions in 2050.

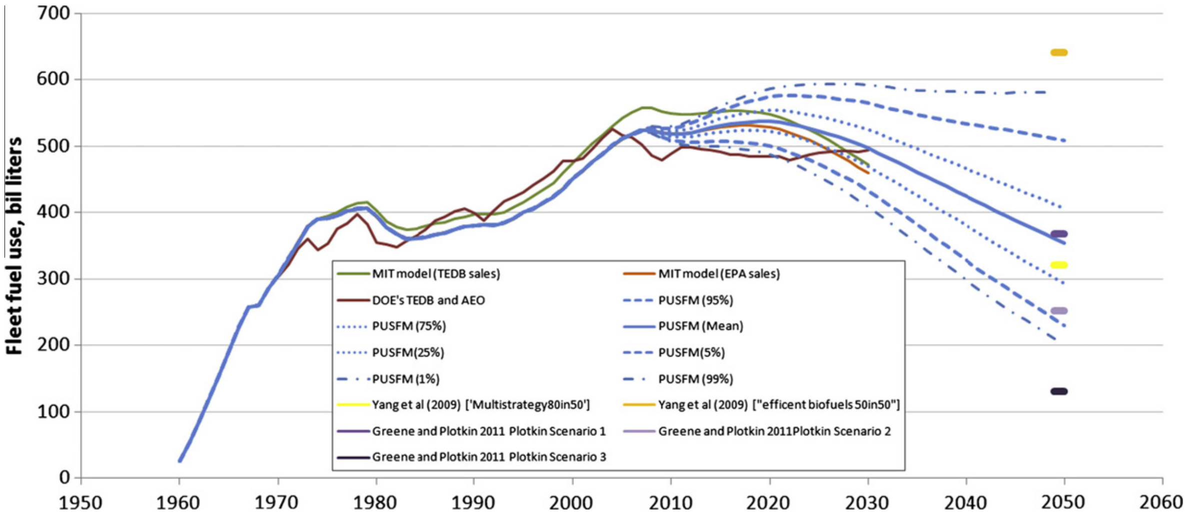

Fig. 38. STEP fleet fuel use results comparison with earlier studies.

Such information clarifies whether the current policies in place can reduce fuel use and emissions with a reasonably high probability, and what the range of possible outcomes look like following current and proposed regulatory plans. Using STEP, key strategies can thus be identified to close the gap between what the current policies are going to achieve in the mid and long term, given future uncertainties, and what it is hoped to achieve in 2030 and beyond.

Further, the results show that the magnitude and uncertainty associated with future scrappage rate, vehicle sales, ERFC, and near and mid term VKT annual growth play an influential role in determining the mid and long term fuel consumption and emissions probability distributions. As well, the results confirm the large potential for reducing emissions using cellulosic ethanol and electricity. The magnitude and ranking of major influences can also inform policy priorities and efforts in better controlling (and thus reducing uncertainty in), and improving certain parameters. Given the revealed importance of future scrappage rate and VKT annual growth rate, for instance, it is recommended that more effort be spent on putting in place effective scrappage policies and travel demand management strategies that control these parameters in the mid-long term. Moreover, the influence of vehicle sales indicates, for example, the importance of having policies in place that regulate sales weighted fuel consumption of vehicles. Finally, the significance of ERFC confirms the need for more efforts to be put into reducing vehicle weight and increasing emphasis on using improved technologies for reducing vehicle fuel consumption.

As shown in the tornado results, the major contributing factors change over time from near to long term. This therefore indicates the need for dynamic policy making, where the focus is changed over time to control and improve the most significant parameters in order to maximize the impact on fuel and emissions reduction. In other words, the tornado diagrams help in policy prioritization both at any given point in time and dynamically over the next few decades.

Furthermore, the relative importance of the major contributors under uncertainty changes based on the type of output in question, whether emissions, fuel use, or energy consumption. In other words, a different set of parameters are most influential based on whether a policy is designed to reduce emissions, fuel use, or energy consumption. Therefore, policy makers should take into account the results from all three outputs in parallel when deciding which areas to focus on.

The identification and ranking of the major influences given real-world uncertainties also allows for prioritization amongst the contributing forces. For instance, the results here show that a 0.1% change in the near term VKT annual growth is twice as effective in increasing the fuel use in 2030, compared to a 0.08% increase in the mid term VKT growth, given the uncertainties associated with VKT demand over time. Furthermore, the results indicate that an 8% increase in future scrappage rate is five times more effective in reducing the fuel use in 2030 compared to a 2% increase in BEV sales, given scrappage policy and BEV sales uncertainties in the future. Such comparisons have real-world implications and can therefore inform the process of decision making and policy prioritization.

The results from this paper demonstrate the effect of uncertainty on the future of fleet wide fuel use and emissions reduction from a carefully constructed pathway that results in significant fuel use and life-cycle GHG emissions reduction in the mid and long term. The results are based on a pathway of steadily improving vehicle fuel efficiency technology, reduced vehicle size and weight, and the deployment of alternative vehicles and clean energy sources. These results show that the impact of uncertainty on the fleet fuel use and GHG emissions is significant, and need to be taken into account when analyzing the future of the light-duty vehicle fleet to inform more robust policy making, given the real world uncertainties in technology development and market behaviour. Quantifying the impact of uncertainty allows decision makers to better understand the consequences of their decisions in the light of their associated risk. This in turn allows decision makers to analyze the impact of new policies while accounting for the uncertainties in the inputs. Further, this study identified the major contributing factors to fleet fuel use and GHG emissions under uncertainty and ranked them in terms of relative influence over time. This therefore indicates the need for dynamic policy making, where the focus is changed over time to control and improve the most significant parameters in order to maximize fuel and GHG emissions reduction. Understanding the probability of achieving certain targets is essential as policy makers and regulatory bodies will be making decisions and setting standards that shape the future of light-duty vehicles over the next several decades, while facing notable uncertainties in technology and market characteristics in the mid to long term. This study offers a quantitative methodology that allows target setting and policy making based on the fleet fuel use and emissions risk distributions over time, and provide a more complete picture of the potential for reducing transport's environmental impacts given real-world uncertainties.

Acknowledgements

The authors wish to acknowledge the support of MIT Sloan Automotive Laboratory, Dr. Matthew Jones at the University of Cambridge, and Dr. Lynette Cheah at MIT.

Table A1
STEP Input List.

Parameter	Min	Mode	Max	Mean	STD	Coefficient of Variation (CoV)	Values in 2010
Total light vehicles sales in 2030 ['000]	9387	18,403	23,000	16,930	2827	17%	11,500
Future scrappage rate (2011+)	65%	80%	105%	83%	8%	10%	80%
% Sales gasoline-turbo in 2030	6%	12%	18%	12%	2%	20%	7%
% Sales diesel in 2030	1%	5%	9%	5%	2%	30%	1%
% Sales HEV in 2030	3%	10%	17%	10%	3%	30%	3%
% Sales PHEV in 2030	1%	5%	9%	5%	2%	35%	0%
% Sales BEV in 2030	0%	4%	8%	4%	2%	40%	0%
% Sales FCHEV in 2030	0%	2%	5%	2%	1%	44%	0%
% car (vs. light trucks)	45%	65%	80%	63%	7%	11%	51%
VKT-annual-growth (2006–2020)	0.26%	0.50%	0.74%	0.50%	0.10%	20%	0.50%
VKT-annual-growth (2020–2030)	0.07%	0.25%	0.43%	0.25%	0.08%	30%	N/A
VKT-annual-growth (2030+)	−0.40%	0.00%	0.40%	0.00%	0.16%	N/A	N/A
Emphasis on Reducing Fuel Consumption (ERFC)							
ERFC cars	40%	80%	100%	73%	12%	17%	50%
ERFC light trucks	30%	70%	100%	67%	14%	22%	50%
Fuels and energy sources							
% Blend cellulosic ethanol in 2030	4%	14%	24%	14%	4%	30%	0%
% Blend corn ethanol in 2030	2%	8%	14%	8%	2%	30%	5%
% Electricity from clean sources in 2030	30%	50%	75%	52%	9%	18%	29%
% Bio-diesel	1%	3%	5%	3%	1%	30%	0%
% Tarsand in 2030	15%	25%	45%	28%	6%	22%	10%
WTW Coefficients [gCO_2 eqv/MJ]							
Ethanol WTW in 2030	6	8	14	9	2	18%	10
Corn ethanol WTW in 2030	60	69	90	73	6	9%	77
Gasoline WTW in 2030	81	92	103	92	5	5%	92
Diesel WTW in 2030	82	94	106	94	5	5%	94
Bio-diesel WTW in 2030	56	89	122	89	13	15%	89
Conventional Electricity WTW in 2030 [gCO_2/kW h]	376	970	1376	908	205	23%	1078
Hydrogen WTW in 2030	93	123	1376	123	12	10%	137
Tar sands WTW in 2030	92	105	118	105	5	5%	109
Electricity use							
PHEV Elec consumption (kWh/100 km) in 2030	12	24	35	24	5	20%	36
BEV Elec consumption (kWh/100 km) in 2030	12	24	36	24	5	20%	36
FCV Hybrid Electric Energy use (MJ/100 km)	30	115	200	115	35	30%	115
Utility factor	30%	48%	66%	48%	7%	15%	N/A
FC relative in 2030							
FC-r NA-SI cars in 2030	0.44	0.70	0.96	0.70	0.105	15%	1.00
FC-r Turbo cars in 2030	0.39	0.62	0.85	0.62	0.093	15%	0.90
FC-r Diesel cars in 2030	0.37	0.59	0.81	0.59	0.088	15%	0.84
FC-r HEV cars in 2030	0.21	0.42	0.63	0.42	0.084	20%	0.70
FC-r PHEV cars in 2030 (gasoline miles)	0.21	0.42	0.63	0.42	0.084	20%	0.70
FC-r NA-SI LT in 2030	0.45	0.71	0.98	0.71	0.107	15%	1.00
FC-r Turbo LT in 2030	0.39	0.61	0.83	0.61	0.091	15%	0.83
FC-r Diesel LT in 2030	0.35	0.56	0.76	0.56	0.083	15%	0.74
FC-r HEV LT in 2030	0.22	0.43	0.63	0.43	0.085	20%	0.70
FC-r PHEV LT in 2030 (gasoline miles)	0.22	0.43	0.63	0.43	0.085	20%	0.70

Appendix A

See Table A1.

References

Abrantes, P.A.L., Wardman, Mark R., 2011. Meta-analysis of UK values of travel time: an update. Transportation Research Part A: Policy and Practice 45, 1–17.
Alpert, W., Raiffa, H., 1969. A progress report on the training of probability assessors.
Bandivadekar, A.P., 2008. Evaluating the Impact of Advanced Vehicle and Fuel Technologies in U.S. Light-Duty Vehicle Fleet. Massachusetts Institute of Technology, Cambridge, Massachusetts.
Bandivadekar, A.P., Cheah, L., Evans, C., Groode, T., Heywood, J., Kasseris, E., Kromer, M., Weiss, M., 2008. Reducing the fuel use and greenhouse gas emissions of the US vehicle fleet. Energy Policy 36, 2754–2760.
Bass, P., Donoso, Pedro, Munizaga, Marcela, 2011. A model to assess public transport demand stability. Transportation Research Part A: Policy and Practice 45, 755–764.
Bastani, P., Heywood, J.B., Hope, C., 2011. A forward-looking stochastic fleet assesment model for analyzing the impact of uncertainty on light-duty vehicles fuel use and emissions. Working Paper No. 1106. University of Cambridge, Cambridge, United Kingdom.
Brownstone, David, Bunch, David S., Golob, Thomas F., 1994. A demand forecasting system for clean-fuel vehicles. UC-Davis, CA.
Buehler, R., 2011a. Determinants of transport mode choice: a comparison of Germany and the USA. Journal of Transport Geography 19, 644–657.
Buehler, R., Pucher, John, 2011b. Making public transport financially sustainable. Transport Policy 18, 126–138.
BUREAU, U.S.C., 2007. Annual Capital Expenditures. US Department of Commerce. ACE-05.
BUREAU, U.S.C., 2008. Table 1. Projections of the Population and Components of Change for the United States: 2010 to 2050 (NP2008-T1).
CAAP, 2006. Canadian Crude Oil Production and Supply Forecast 2006–2020. In: PRODUCERS, C.A.F.P. (Ed.).
Cheah, L.W., 2010. Cars on a Diet: The Material and Energy Impacts of Passenger Vehicle Weight Reduction in the US. Massachusetts Institute of Technology, Cambridge, Massachusetts.
Cheah, L., Evans, C., Bandivadekar, A., Heywood, J.B., 2008. Factor of two: halving the fuel consumption of new U.S. automobiles by 2035. In: Sperling, D.J.S.C., Cannon, J. (Eds.), Chapter 4 in Reducing Climate Impacts in the Transportation Sector. Springer.
Cheah, L.W., Bandivadekar, A.P., Bodek, K.M., Kasseris, E.P., Heywood, J.B., 2009. The trade-off between automobile acceleration performance, weight, and fuel consumption. SAE International Journal of Fuels and Lubricants 1, 771–777.
Concawe, E.A.J., 2007. Well-to-Wheels Report.
Cullinane, S., 1992. Attitudes towards the car in the U.K.: some implications for policies on congestion and the environment. Transportation Research Part A: Policy and Practice, 26.
Dargay, J., Gately, D., Sommer, M., 2007. Vehicle ownership and income growth, worldwide: 1960–2030. The Energy Journal 28, 143–170.
Davis, S.D.S., 2007. Transportation Energy Data Book, 26th ed. Oak Ridge National Laboratory, ORNL-6978.
De Sisternes, F.J., 2010. Plug-in Electric Vehicle Introduction in the EU. Massachusetts Institute of Technology, Cambridge, Massachusetts.
Diana, M., 2012. Measuring the satisfaction of multimodal travelers for local transit services in different urban contexts. Transportation Research Part A: Policy and Practice 46, 1–11.
Doe, U.S., 2005. Biomass as Feedstock for a Bioenergy and Bioproducts Industry: The Technical Feasibility of a BillionTon Annual Supply. In: LAB, O.R.N. (Ed.).
Dot, E.A., 2010. Final Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards. Joint Technical Support Document.
Dowlatabadi, H., 1993. Integrated assessment climate assessment model 2.0, technical documentation. Energy Policy 21, 209–221.
Dowlatabadi, H., Morgan, M.G., 1995. A Model Framework for Integrated Assessment of the Climate Problem. Department of Engineering and Public Policy, Carnegie Mellon University.
EIA, 2007a. Annual Energy Outlook 2007 with Projections to 2030. Energy Information Administration.
EIA, 2007b. Assumptions to the Annual Energy Outlook 2007. Energy Information Administration.
Elgowainy, A.B.A., Wang, M., Molburg, J., Rousseau, A., 2009. Well-to-wheels energy use and greenhouse gas emissions analysis of plug-in hybrid electric vehicles. GREET.
Ellerbusch, S., 2008. BP: Biofuels Could Potentially Account for up to 30% of Global Transportation Fuel by 2030. Green Car Congress.
EPA, 2006. Fuel Economy Labeling of Motor Vehicle Revisions to Improve Calculation of Fuel Economy Estimates. Final Technical Support Document.
EPA, 2007. Light-Duty Automotive Technology and Fuel Economy Trends: 1995 through 2007. <http://www.epa.gov/oms/cert/mpg/fetrends/420r07008.pdf> (accessed).
EPA, 2009a. EPA Lifecycle Analysis of Greenhouse Gas Emissions from Renewable Fuels. <http://www.epa.gov/oms/renewablefuels/420f09024.pdf> (accessed).
EPA, 2009b. Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 through 2009 (Online, Accessed).
EPA, 2010. Smart Grid: Implications and Opportunities for Clean Energy and Greenhouse Gas Emissions Reductions. <http://www.epa.gov/statelocalclimate/documents/pdf/angel_presentation_4-29-2010.pdf> (accessed).
Gibson, T.L., 2000. Life cycle assessment of advanced materials for automotive applications. In: Total Life Cycle Conference and Exposition. SAE International. Detroit, Michigan.
Gmbh, R.B., 2005. Bosch Automotive Handbook. Mass, Bentley Publishers, Cambridge.
Graham-Rowe, E., Skippon, Stephen, Gardner, Benjamin, Abraham, Charles, 2011. Can we reduce car use and, if so, how? A review of available evidence. Transportation Research Part A: Policy and Practice 45, 401–418.
Graham-Rowe, E., Gardner, Benjamin, Abraham, Charles, Skippon, Stephen, Dittmar, Helga, Hutchins, Rebecca, Stannard, Jenny, 2012. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: a qualitative analysis of responses and evaluations. Transportation Research Part A: Policy and Practice 46, 140–153.
Greene, D.L., Chen, C.K., 1981. Scrappage and survival rates of passenger cars and light-trucks in the U.S.: 1966–77. Transportation Research Part A 15, 383–389.
Greene, D. L., Rathi, A., 1990. Alternative Motor Fuel Use Model: Model Theory and Design and User's Guide.
Greene, D.L., Baker, H.H., Plotkin, S.E., 2011. Reducing Greenhouse Gas Emissions from US Transportation Prepared for the Pew Center on Global Climate Change. Argonne National Laboratory.
Greenspan, A., Cohen, D., 1999. Motor vehicle stocks, scrappage, and sales. The Review of Economics and Statistics 81, 369–383.
Greet, 2007. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model. >http://www.transportation.anl.gov/software/GREET/> (accessed).
Groode, T., Heywood, J.B., 2008. Biomass to Ethanol: Potential Production and Environmental Impacts. Massachusetts Institute of Technology Laboratory for Energy and Environment, LFEE 2008-02 RP.
Grreene, D.L., 2001. TAFV Alternative Fuels and Vehicles Choice Model Documentation. US Department of Energy (DOE), Oak Ridge National Laboratory, Oak Ridge, Tennessee.
Habib, K.M.N., 2012. Modeling commuting mode choice jointly with work start time and work duration. Transportation Research Part A: Policy and Practice 46, 33–47.

Habib, K.M.N., Day, Nicholas, Miller, Eric J., 2009. An investigation of commuting trip timing and mode choice in the Greater Toronto Area: application of a joint discrete-continuous model. Transportation Research Part A: Policy and Practice 43, 639–653.

Heavenrich, R., 2006. Light-Duty Automotive Technology and Fuel Economy Trends: 1975 through 2006 (Online) (accessed).

Henrion, M., Breese, John S., Horvitz, Eric J., 1991. Decision analysis and expert systems. AI Magazine 12, 64–91.

Heywood, J.B., Weiss, M.A., Schafer, A., Bassene, S.A., Natarajan, V.K., 2003. The Performance of Future ICE and Fuel Cell Powered Vehicles and their Potential Fleet Impact. MIT Laboratory for Energy and the Environment, Cambridge, Massachusetts.

Hiscock, R., Macintyre, S., Kearns, A., Ellaway, A., 2002. Means of transport and ontological security: do cars provide psycho-social benefits to their users? Transportation Research Part D: Transport and Environment 7, 119–135.

Holstein, S.E.V., 1971. Two techniques for assessment of subjective probability distributions – an experimental study. Acta Psychologica 35, 478–494.

Hope, C., 2006. The Marginal Impact of CO2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern. Integrated Assessment 6.

Hope, C., Wenman, P., Anderson, J., 1993. Policy analysis of the greenhouse effect. Energy Policy 21, 327–338.

IEA, 2009. World Energy Outlook 2009 (Online) (accessed).

Karplus, V.J., Paltsev, Sergey, Reilly, John M., 2010. Prospects for plug-in hybrid electric vehicles in the United States and Japan: a general equilibrium analysis. Transportation Research Part A: Policy and Practice 44, 620–641.

Kasseris, E P., Heywood, J.B., 2007. Comparative analysis of automotive powertrain choices for the Next 25 years. In: SAE World Congress & Exhibition, SAE International, 2007 Detroit, Michigan.

Kelly, David L., Kolstad, Charles D., Schlesinger, Michael E., Andronova, Natalia G., 1998. Learning About Climate Sensitivity from the Instrumental Temperature Record. UCSB Economics Department.

Knittle, C., 2012. Automobiles on steroids: product attribute trade-offs and technological progress in the automobile sector. The American Economic Review.

Kromer, M., Heywood, J.B., 2007. Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet. Massachusetts Institute of Technology Laboratory for Energy and the Environment (LFEE 2007-03 RP).

Kromer, M.A., Heywood, J.B., 2008. A Comparative Assessment of Electric Propulsion Systems in the 2030 US Light-Duty Vehicle Fleet. SAE, World Congress 2008-01-0459.

Lave, K.T., 1979. A disaggregate model of auto-type choice. Transportation Research 13, 1–9.

Lempert, R.J., Schlesinger, M.E., Hammitt, J.K., 1994. The impact of potential abrupt climate changes on near-term policy choices. Climatic Change 26, 351–376.

Libertiny, G.Z., 1993. A New Look at the Service Life Expectancy of Passenger Cars in the United States. SAE.

Lindley, D.V., 1985. Making Decisions. John Wiley and sons, London.

Lohrer, T.A., 1983. Vehicle ownership and usage: an integrated system of disaggregate demand models. In: Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand

Macharis, C., Van Hoeck, Ellen, Pekin, Ethem, Van Lier, Tom, 2010. A decision analysis framework for intermodal transport: comparing fuel price increases and the internalisation of external costs. Transportation Research Part A: Policy and Practice, 44.

Mackenzie, D.W., 2009. Trends and drivers of the performance: fuel economy tradeoff in new automobiles. In: Technology and Policy Program, Engineering Systems Division. Massachusetts Institute of Technology, Cambridge, Mass.

Mannering, F., 1983. An econometric analysis of vehicle use in multivehicle households. Transportation Research 17A, 183–189.

Mannering, F., Sinha, K.C., 1979. Forecasting automobile fleet fuel efficiency. Traffic Quarterly 33, 637–648.

Mannering, F., Winston, C., 1980. Dynamic models of household vehicle ownership and utilization: and empirical analysis. RAND Journal of Economics.

Mannering, F., Harrington, I., 1981. Use of density function and Monte Carlo simulation techniques in the evaluation of policy impacts on travel demand. Transportation Research Record 801, 8–15.

Marshall, S., Banister, David, 2000. Travel reduction strategies: intentions and outcomes. Transportation Research Part A: Policy and Practice 34, 321–338.

Mccollum, D.L., Yang, C., 2009. Achieving deep reductions in US transport greenhouse gas emissions: scenario analysis and policy implications. Energy Policy 37, 5580–5596.

Mcculloch, M., D.N., Francis, E., 2005. Greenhouse Gas Emissions Calculations for the Mackenzie Gas Project. The Pembina Institute.

Melillo, J.M., Gurgel, Angelo C., Kicklighter, David W., Reilly, John M., Cronnin, Timothy W., 2009a. Unintended Environmental Consequences of a Global Biofuels Program. MIT Joint Program on the Science and Policy of Global Change, Cambridge, Mass.

Melillo, J.M., Reilly, J.M., Kicklighter, D.W., Gurgel, A.C., Cronin, T.W., Paltsev, S., Felzer, B.S., Wang, X., Sokolov, A.P., Schlosser, C.A., 2009b. Indirect emissions from biofuels: how important? Science 326, 1397–1399.

Mendelsohn, R., Nordhaus, W., Shaw, D., 1994. The impact of global warming on agriculture, a Ricardian analysis. American Economic Review 84, 753–770.

MIT, 1994. Joint Program on the Science and Technology of Global Climate Change. Massachusetts Institute of Technology, Cambridge, Mass.

Mokhtarian, P.L., Chen, Cynthia, 2004. TTB or not TTB, that is the question: a review and analysis of the empirical literature on travel time (and money) budgets. Transportation Research Part A: Policy and Practice 38, 643–675.

Moore, A.T., Staley, Samuel R., Poole Jr., Robert W., 2010. Special section on climate change and transportation policy: gaps and facts. Transportation Research Part A: Policy and Practice 44, 565–574.

Morgan, M.G., Henrion, Max, 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge.

Morrow, E.A., 2010. Analysis of Policies to Reduce Oil Consumption and Greenhouse-Gas Emissions from the U.S. Transportation Sector.

NHTSA, 2006. Vehicle Survivability and Travel Mileage Schedules. National Highway Traffic Safety Administration (NHTSA).

Nordhaus, W.D., 1994. Managing the Global Commons: The Economics of Climate Change. MIT Press.

NRC, 2002. Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards. National Research Council. National Academy Press.

O&GJ, 2006. Canada's oil sands resource has become the world's hottest hydrocarbon play. Oil & Gas Journal 104, S4–S11.

Omotoso, M., 2008. Alternative powertrain sales forecast. In: Presentation Slides by J.D. Power and Associates, Automotive Forecasting.

Parry, M.L., Canziani, O.F., Palutikof, J.P., Van Der Linden, P.J., Hanson (Eds.), 2001. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

M.L. Parry, Canziani, O. F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E., (Eds.), 2007. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Polk, R.L., 2009. State of the U.S. Light Vehicle Market PolkView.

Reilly, J., Paltsev, S. (Eds.), 2009. Biomass Energy and Competition for Land. Routledge, UK.

Sandia National Labs, G.R.D.C., 2008. 90 Billion Gallon Deployment Study.

Schäfer, A., Jacoby, H.D., 2006. Experiments with a CGE-MARKAL hybrid model. Energy Journal: Hybrid Modeling—Special Issue, 171–178.

Solheim, M., 2008. Diesel Cleans Up Its Act, in Kiplinger's Personal Finance.

Stanley, J.K., Hensher, David A., Loader, Chris, 2011. Road transport and climate change: stepping off the greenhouse gas. Transportation Research Part A: Policy and Practice 45, 1020–1030.

Stradling, S.G., Meadows, M.L., Beatty, S., 2000. Helping drivers out of their cars: integrating transport policy and social psychology for sustainable change. Transport Policy 7, 207–215.

Su, Q., 2010. Travel demand in the US urban areas: a system dynamic panel data approach. Transportation Research Part A: Policy and Practice 44, 110–117.

Sullivan, F., 2008. Diesel Engine Technology – Outlook as Light Vehicle Powerplant in North America. In: PAPER, W. (ed.).

Tal, G., Cohen-Blankshtain, Galit, 2011. Understanding the role of the forecast-maker in overestimation forecasts of policy impacts: the case of Travel Demand Management policies. Transportation Research Part A: Policy and Practice 45, 389–400.

Thompson, K., Schofield, Peter, 2007. An investigation of the relationship between public transport performance and destination satisfaction. Journal of Transport Geography 15, 136–144.

Tol, R.E.A., 1995. The Climate Fund: Some Notions on the Socio-Economic Impacts of Greenhouse Gas Emissions and Emission Reduction in an International Context V.U. Boekhandel/Uitgeverij, Netherlands.

Train, K., 1980a. The potential demand for electric vehicles. Transportation Research 14A, 405–414.

Train, K., 1980b. A structured logit model of auto ownership and mode choice. Review of Economic Studies 47, 357–370.

Train, K.E., Winston, C., 2007. Vehicle choice behavior and the declining market share of U.S. automakers. International Economic Review 48.

Transportation, U.S.D.O., 2008. National Transportation Statistics. Bureau of Transportation Statistics.

Tversky, A.A.K.D., Kahneman, Daniel (Eds.), 1974. Judgement Under Uncertainty: Heuristics and Biases. Cambridge University Press, Cambridge.

Ubs, R.I., 2007. Is diesel set to boom in the US? In: UBS Investment Research, Q-Series: Global Autos Research.

Uc-Davis, 2008. Strategic Assessment of Bienergy Development in the West: Spacial and Supply Curve Development. University of California, Davis.

Ulrich, L., 2008. Diesel Automobiles Clean Up for US Revival. The New York Times.

Volkswagen, 2010. Volkswagen AG. In: Cheah, L.W. (Ed.), Proceedings on the International Conference on Innovative Developments for Lightweight Vehicle Structures. 2009. Wolfsburg, Germany IN: Cars on a Diet: The Material and Energy Impacts of Passenger Vehicle Weight Reduction in the U.S. Massachusetts Institute of Technology, Cambridge, Massachusetts.

Wadud, Z., 2011. Personal tradable carbon permits for road transport: why, why not and who wins? Transportation Research Part A: Policy and Practice 45, 1052–1065.

Winkler, R.L., 1967. The assessment of prior distributions in Bayesian analysis. Journal of the American Statistical Association 62, 776–800.

Wright, C., Egan, J., 2000. De-marketing the car. Transport Policy, 7.

Xinyu Cao, P.L.M., 2004. The Future Demand for Alternative Fuel Passenger Vehicles: A Diffusion of Innovation Approach. UC Davis – Caltrans Air Quality Project, Davis, CA.

Yang, C., Mccollum, D., Mccarthy, R., Leighty, W., 2009. Meeting an 80% reduction in greenhouse gas emissions from transportation by 2050: a case study in California. Transportation Research Part D 14, 147–156.

Glossary

BEV: Battery electric vehicle
BOF: Steelmaking technique using a basic oxygen furnace
CAFE: Corporate Average Fuel Economy
CAR: Sedans and Wagons
CoV: Coefficient of Variation
ERFC: Emphasis on Reducing Fuel Consumption
EPA/USEPA: US Environmental Protection Agency
EV: Electric Vehicle
FCH: Fuel-cell Hybrid
Fuel Consumption (FC): Amount of fuel consumed by a vehicle per unit distance of travel (L/100 km), which is the inverse of the frequently used metric, fuel economy
Fuel Economy (FE): Distance travelled per unit of fuel used (miles per gallon, MPG).
Fuel use: Total fuel used in liters of gasoline-equivalent
GDI: Gasoline Direct-Injection
GHG: Greenhouse gases
GREET: Greenhouse gases, Regulated Emissions, and Energy use in Transportation model by Argonne National Laboratory
HEV: Hybrid-electric vehicle
HCCI: Homogenous Charge Compression Ignition
ICE: Internal combustion engine
LCA: Life-cycle assessment
Light truck: Class of vehicles including sport utility vehicles, vans and pickups weighing less than 8500 lb (gross vehicle weight)
LDV: Light-duty vehicles
MIT: Massachusetts Institute of Technology
MPG: Miles per gallon, units of vehicle fuel economy
MY: Model year of new vehicles
NA-SI: Naturally-aspirated Spark Ignition (versus a turbo or supercharged) engine
NHTSA: US National Highway Traffic Safety Administration
NRC: US National Research Council
OLT: Other Light Trucks (includes pick-up trucks and all trucks that are part of LDVs but not categorized as SUV or cars)
PDF: Probability Density Function
PHEV: Plug-in hybrid electric vehicle
SUV: Sport Utility Vehicle
TEDB: Transportation Energy Data Book published by Davis et al. [2]
TTW: Tank-to-Wheels
Turbo-SI: Turbo charged Spark Ignition engine
VKT: Vehicle kilometres travelled
WTT: Well-to-Tank
WTW: Well-to-Wheels