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A Forward-Looking Stochastic Fleet Model for Analysing the Impact of Uncertainty on Light-Duty Vehicles Fuel Use and Emissions

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Abstract

Transport policy research seeks to predict and substantially reduce the future transport-related greenhouse gas emissions and fuel consumption to prevent negative climate change impacts and protect the environment. However, making such predictions is made difficult due to the uncertainties associated with the anticipated developments of the technology and fuel situation in road transportation, which determine the total fuel use and emissions of the future light-duty vehicle fleet. These include uncertainties in the performance of future vehicles, fuels' emissions, availability of alternative fuels, demand, as well as market deployment of new technologies and fuels. This paper develops a methodology that quantifies the impact of uncertainty on the U.S. transport-related fuel use and emissions by introducing a stochastic technology and fleet assessment model that takes detailed technological and demand inputs. This model stochastically calculates the probability density functions for fuel use and emissions over time by propagating and calculating the effect of input uncertainties throughout fleet calculations. The fleet turn over is tracked based on the calendar year, vehicle model year, the market penetration rate of advanced technologies and fuels, and the scrappage rate of vehicles on the road. Full life-cycle emissions of fuels are projected and tracked in this model. Three carefully chosen illustrative examples are assessed using the developed methodology in this paper. The results show the probability distribution of the total light-duty vehicle fleet fuel use and emissions out to year 2050, including the mean, mode, standard deviation, spread, and confidence interval of these outputs in the near to long term. The major contributors to the fleet fuel use and emissions are also identified and ranked. These include vehicle scrappage rate, new vehicle sales, emphasis on reducing fuel consumption, and fuel consumption of naturally aspirated spark ignition vehicles. The major contributing variables and uncertainties to fuel use and emissions change over the time period 2020 to 2050. The findings in this paper show that uncertainties in the future fleet fuel use and emissions are significant and need to be taken into consideration when choosing amongst alternative fuel and emissions reduction pathways, in the light of their possible consequences.

Keywords: Stochastic modelling, decision theory, numerical decision making, transport GHG emissions and fuel use, light-duty vehicle fleet, uncertainty, STEP

1 Introduction

Light-duty vehicles are responsible for about 44% of the total U.S. and 10% of the world oil consumption (Davis, 2007). There are about 240 million light-duty vehicles (LDV) in the U.S., which consists of about 40% cars and 60% pick-up trucks, SUVs, and vans. The total fuel consumption from LDVs was about 528 billion litre in 2005 (Davis, 2007, Transportation, 2008). LDVs produced 1,260 million metric tons of CO_2 emissions in 2005, which account for 22% of the total U.S. GHG emissions with an estimated growth rate of 1.3% per year (EIA, 2007). Road-transport fuel consumption and emissions have become an important issue on the nation's policy agenda with ever increasing concerns about impacts of climate change and energy security issues.

The U.S. Corporate Average Fuel Economy (CAFE) program has enforced fuel economy standards on light duty vehicles for more than forty years. The new regulations have mandated a significant increase in fuel economy for an average vehicle to 34.1 miles per gallon (MPG) by 2016 (Davis, 2007). Stricter regulations are also under consideration for the mid and longer term. The automotive industry is expected to play an important role in reducing the total fleet fuel use though technology improvements. While most automakers claim to be taking action to reduce their carbon footprint and energy consumption, whether voluntarily or under regulatory pressure, the anticipated result of these actions is unknown due to a number of uncertainties. Such uncertainties include performance of future vehicles, emissions and availability of alternative fuels, demand, and market deployment of new technologies.

In an effort to get a better picture of what the future of road transportation might look like, various vehicle fleet models have been developed and employed in scenario analysis. 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 development 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. Therefore, merely averaging and summing up those effects, without proper stochastic modelling of the vehicle fleet risks misrepresenting the likely future impacts of policy choices. Accordingly, this paper develops a stochastic fleet model that quantifies the impact of uncertainty on the U.S. light-duty vehicle fleet fuel use and GHG emissions. This model provides a mathematical framework to help decision makers choose among a set of alternatives, given not only their "average" outcome but the full spectrum of possible consequences given the uncertainties in the inputs.

In some fields, such as climate change, the distinction between deterministic scenario analysis and stochastic modeling has been clearly established: major analyses used in IPCC assessments are based on probabilistic studies (M.L. Parry, 2001, M.L. Parry, 2007). However, in the transport sector the distinction remains somewhat 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's 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 the decision maker with a more complete picture showing the range of possible outcomes and the probability associated with each outcome, given a chosen fuel 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 a significant practical importance as policy makers are restricted to choose one pathway that best addresses their objectives, and 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 introduces a stochastic technology and fleet assessment framework, STEP (Stochastic Transport Emissions Policy Model), which determines 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. The significance of the results in the context of emissions mitigation and transport policy planning are discussed.

2 Literature Review

This work builds on the vehicle fleet modelling literature in transport research and stochastic modelling techniques in the climate change literature. This study makes a methodological contribution in transport research literature and provides a policy tool to help decision makers in the transport sector analyze the future of light-duty vehicle fleet given real-world uncertainties.

2.1 U.S. Vehicle Fleet Models

A number of fleet models have been designed in the past few years to explore the future of road transport in the U.S. using scenario analysis. Some of the prominent studies include the MIT fleet model by Bandivadekar et al, LEVERS model by Yang et al , fleet scenarios by Greene and Plotkin 2011 study, NEMS model by Morrow et al , and the CGE-MARKAL Hybrid Model by Schafer and Jacoby (Bandivadekar, 2008, Yang, 2009, David L. Greene. Howard H. Baker, 2011, Morrow, 2010, Schäfer A., 2006, McCollum, 2009). The studies by Marrow, and Schafer et al are pursued in a macro-economic context, whereas the MIT model, LEVERS, and Plotkin et al are based on bottom-up technology and fuel models developed to examine in detail the fleet turn over, demand, and technology improvements and deployment, and their impact on the total fuel consumption and emissions in the next couple of decades. A number of models with engineering and technological details have also been developed by the Argonne National Laboratory, including the GREET, Autonomie, PSAT, GC Tool, and VISION(R. Vijayagopal, 2011, Argonne, 2010). These models have been drawn upon in various analyses pursued by the U.S. Department of Energy, U.S. Department of Transport, automotive industry, and academic researchers to better understand the impact of proposed CAFE standards on the future fleet and the automakers.

2.2 Stochastic Modelling

Stochastic modelling is widely used in climate change research. A number of integrated assessment models (IAM) have been developed worldwide to investigate the impact of uncertainty in climate change policy making. These include DICE by Nordhaus (1994), PAGE (1993) by Hope et al, ICAM by Dowlatabadi and Morgan (1993, 1995), SLICE by Kelly and Kolstad (1997a), AS/ExM by Lempert , MIT (1994), and FUND by Tol et al (1995) (Nordhaus, 1994, Hope C, 1993, Dowlatabadi, 1993, Morgan, 1995, David L. Kelly, 1998, MIT, 1994, R. Tol, 1995, R.J. Lempert, 1994, R. Mendelsohn, 1994). Some of the prominent IAMs have been cited in assessments for stochastic cost benefit analysis of various climate polices. Examples include the PAGE2002 mode, which was used in the Stern Review and the Working Group II report of the IPCC Fourth Assessment (M.L. Parry, 2001, M.L. Parry, 2007). IAMs are considered the only credible method for cost benefit analysis of climate change mitigation policies given the uncertainties in climate change science and economics (Stern, 2007). These models inform policy makers of the range of possible outcomes of their decisions using stochastic modelling and numerical decision making.

2.3 Regulations Modelling

The U.S. government uses a number of models to support the rule making process for the CAFE program (DOT, 2010). Some of these models draw upon the detailed technological simulations developed by Argonne National Laboratory, and others include the U.S. DOT CAFE model (Argonne, 2010, NHTSA, 2009). These models are used to investigate, using scenario analysis, the impact of the proposed fuel economy standards on the fleet fuel use and emissions reduction in the short and long term.

3 The Model

This section describes the methodology and structure of the STEP model.

3.1 Methodology

The model uses similar techniques to those developed for Integrated Assessment Modelling to provide a forward looking numerical framework to explore the impact of uncertainty on the future U.S. light-duty vehicle fleet fuel use and emissions. Numerical modelling is used to help decision making by calculating outputs based on the user's degree of belief about the likely values of the input variables. A probability distribution is thus assigned to input variables based on "up-to-date knowledge" in the engineering and LDV markets (Lindley, 1985). This model stochastically calculates the probability density functions for GHG emissions and fuel use outputs over time by propagating and calculating the effects of input uncertainties throughout fleet calculations. Figure 1 shows an overview of the Stochastic Transport Emissions Policy Model stochastic (STEP). The fleet turn over is tracked based on the calendar year, vehicle model year, the market penetration rate of advanced technologies and fuels, and scrappage rate of vehicles on the road. The fuel economy of each powertrain as well as the Well-to-Tank (WTT) and Tank-to-Wheel (TTW) efficiencies of conventional and alternative fuels are tracked to account for the full life-cycle GHG emissions of fuels. Vehicle weight reduction impact is further taken into account through powertrain fuel consumption improvements over time. The main features of the STEP model are described in section 3.2 and the equations details can be found in the Appendix.

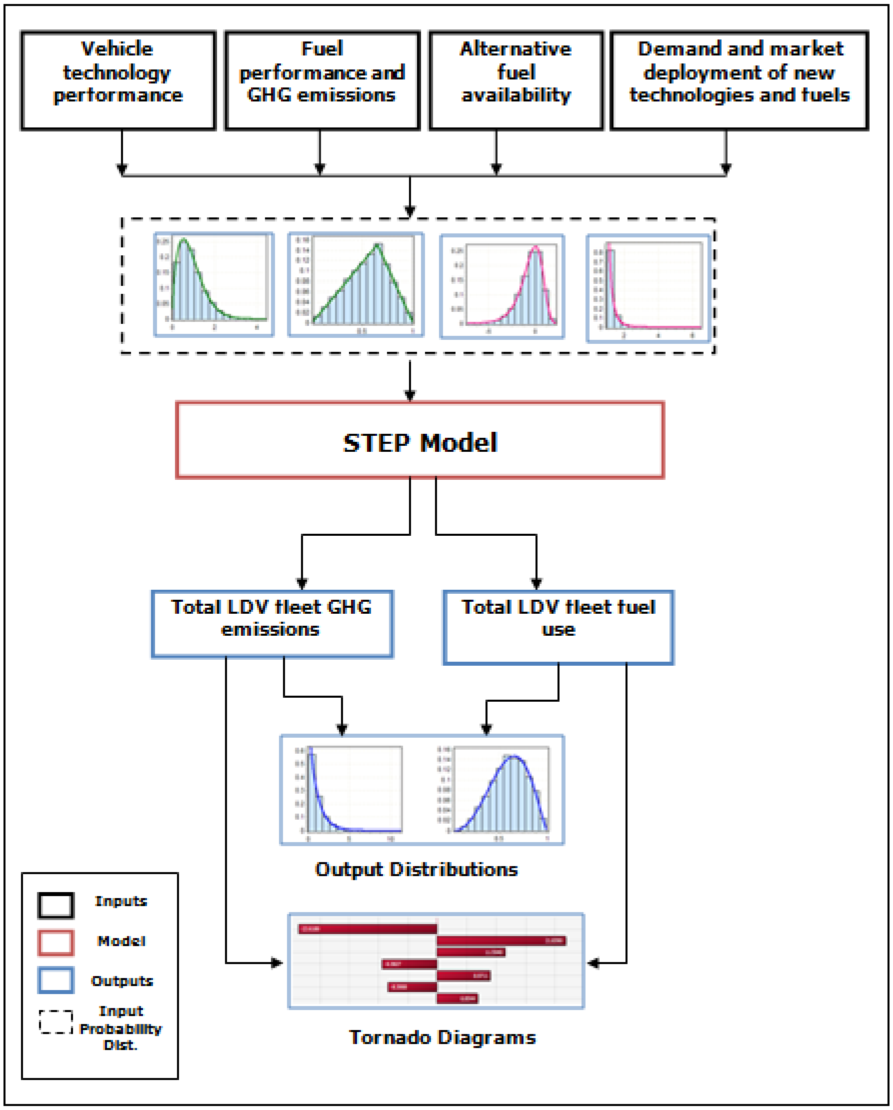

Figure 1-STEP Model Overview

The basic calculation logic that is used to compute the fleet fuel use and emissions here follows the MIT fleet calculations logic (Bandivadekar, 2008) which allows sensible and robust tracking of bottom-up details that characterize the fleet. Data is drawn from various sources, including the Transportation Energy Data Book (TEDB) (Davis, 2007), EPA Light-Duty Automotive Technology and Fuel Economy Trends report (Heavenrich, 2006), and the U.S. Department of Transportation report (compiled by NHTSA for CAFE compliance) (NHTSA, 2008) , to calculate fleet fuel use and life-cycle GHG emissions.

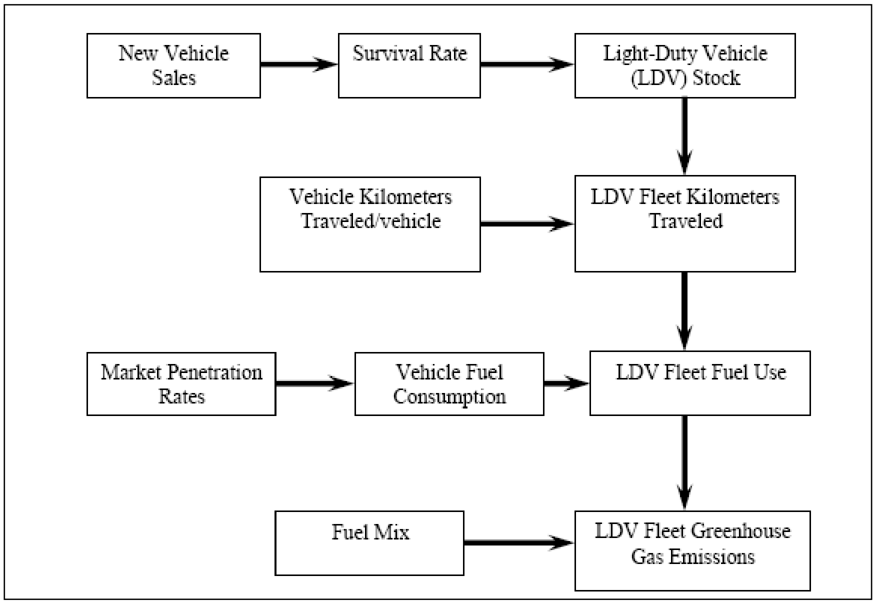

Figure 2-Fuel use and GHG emissions calculations logic

As Figure 1shows the uncertainties in the inputs are captured as a set of probability distributions and fed into the STEP model. The model then uses Latin Hypercube Sampling (an advanced form of Monte Carlo simulation) to calculate the outputs, fuel use and emissions, as a stochastic distribution over time out to year 2050. Typically the model is run 10,000 times. Values are randomly sampled from input distributions in each run and the outputs are calculated based on the aggregated result of these runs. The most influential contributors to the outputs are also identified and ranked using multivariate linear regression and displayed as tornado diagrams. These analyses thus identify what drives the uncertainties in the outputs to inform priorities in transport policy making under uncertainty.

This methodology adopts a decision theory framework. Decision theory 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 identified by Tversky and Kahneman leading to predictable biases (Tversky, 1974). For instance, anchoring leads to a bias in the uncertainty range by the experts, which are likely to be stated as narrower than can be justified by the experts' knowledge (Tversky, 1974, Alpert, 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 (Morgan, 1990, Henrion, 1991). These techniques, which are well-established in climate change modelling (M. Granger Morgan, 2009), involve interactions with prominent experts in the field. 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 similarly completed in consultation with the expert (Morgan, 1990).

Figure 3 illustrates the logic of the methodology for determining the inputs for STEP . A survey of US road transport literature shows a number of different underlying assumptions used in exploring technological and fuel development, demand, and market deployment rates. We suggest that the wide range in these differing assumptions is indicative of the underlying uncertainty in the variables. Further, a number of engineering and vehicle simulations and market behavioural models are used here to inform the uncertainty in the input variables. Finally, ranked and weighted screening of inputs is used to inform preliminary judgements on the possible ranges of each input variable. The probability elicitation techniques, mentioned earlier (Henrion, 1991, Morgan, 1990) are then used with experts in the field to determine a realistic set of input distributions, discussed in the authors' 2011 study (Bastani, 2011).

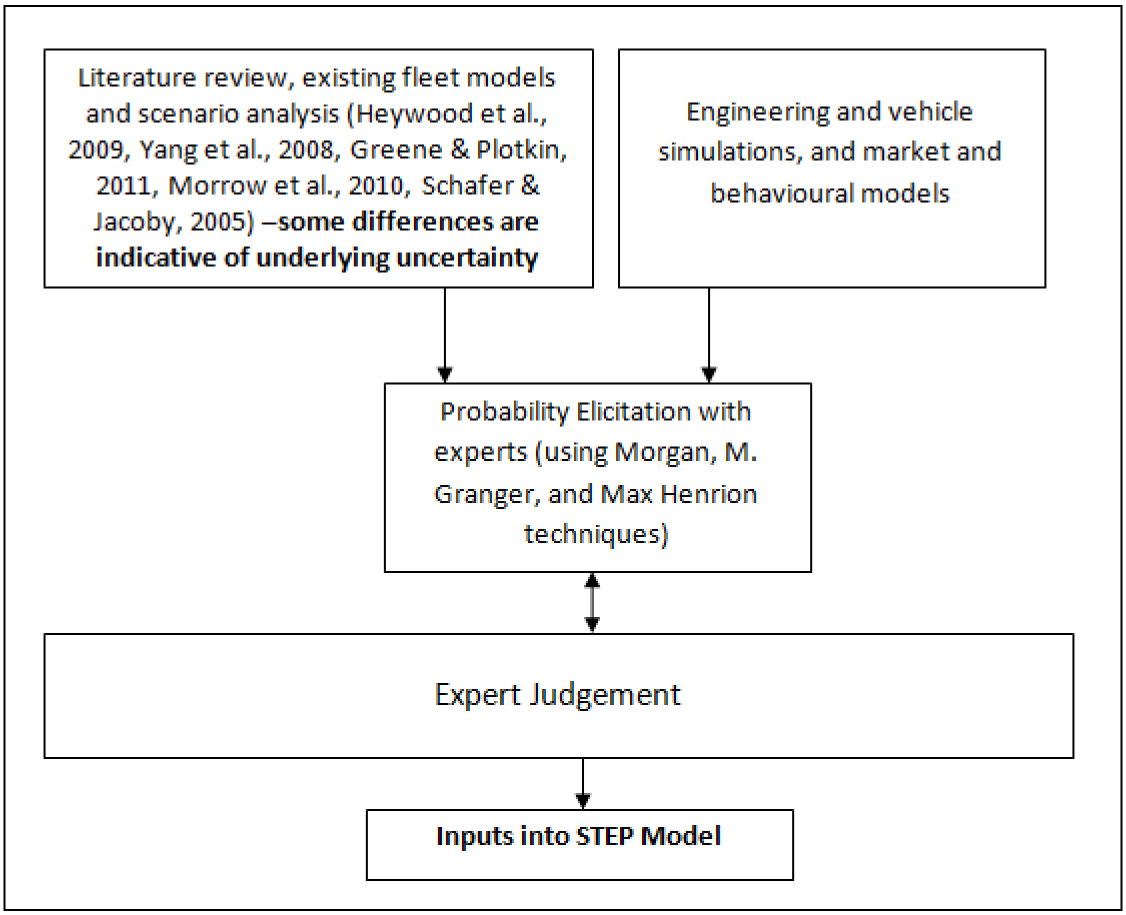

Figure 3- Process for determining the inputs probability distributions

This methodology therefore contributes to closing the gap between a snap shot analysis of future road transport using discrete deterministic scenarios, and a more complete picture of the future vehicle fleet characteristics given uncertainties, using a stochastic model that shows the probability distribution of fuel consumption and emissions over time out to year 2050. Moreover, using the tornado diagrams in this paper, one can answer questions such as: what is the sensitivity of fuel use and emissions to their major contributors, given technological and fuel uncertainties in the near to long term? Which factors are dominant in determining the outputs and how do they change over time? Given technological and behavioural uncertainties, is a 5% change in vehicle kilometres travelled more or less important than a 15% change in average fuel economy standards? And many more questions with important practical implications.

3.2 Model Set-up

The model assumptions and some of the key equations are described in this section. The model is set up such that the ranges for most of the inputs are specified at year 2030 and data are interpolated and extrapolated before and after that date. 2030 was chosen since it is not too far out in time that useful judgements cannot be made, but it is also far enough in time such that significant changes can be reasonably expected. The uncertainty in the inputs is propagated throughout the data points in the model out to year 2050 as described in the following sections. Input distributions are represented as triangular distributions, defined by a maximum, most likely, and minimum value. Refer to the Appendix for the complete list of equations, parameters, and the symbols used to represent the input and output variables. The equation numbers used in this section refer to the numbering used in the Appendix.

3.2.1 Computing Vehicle Stock

The share of vehicles in the market is captured as percentage of sales in each year. The share of conventional NA-SI engines in the market is not specified directly but is calculated as the residual not covered by the percentage of sales of other types of powertrains. An exponential growth function is used to interpolate and extrapolate sales shares, total vehicle sales, and percentage of cars (versus light trucks) from present to 2030 and out to year 2050, as shown in Eqnn 1 below: where TSL is the total vehicle sales, which is an input to the model. The extrapolated values are then checked to ensure the changes are reasonable over time. Year 2009 is used as the base year here. The uncertainty in the sales shares, total sales, and percentage of cars is propagated over time using similar equations to Eqn 1, where both the mode and the range are extrapolated out to year 2050. These numbers are not to be taken as forecasts but as conditional projections into the future.

$$TLS(i) = TLS(2009) * \exp[(\ln(TSL(2030)/TSL(2009))/(21)) * (i - 2009)];\ i = 2010\text{-}2050 \quad [mil] \qquad \text{Eqn (1)}$$

Market segmentation is also tracked, to allow for a shift between cars and light trucks over time using equation 4 below, where PCAR represents the percentage of cars (versus light trucks) in the sales share in year i.

$$TLS\text{-}SEG1(i) = PCAR(i) * TLS(i) \qquad [mil] \qquad \text{Eqn (4)}$$

The future scrappage rate input is then used to keep track of the number of cars removed in each calendar year. This is then used to calculate the on road vehicle stock, using the number of surviving cars based on model year (from 1960 onwards) and the calendar year. Refer to equations 5-10 described in the Appendix .

The same sets of calculations are performed for all segments of the LDV market (cars, SUVs, and OLTs), and the details of each segment are kept track of separately until the very last calculations to compute the total fuel use and GHG emissions. This in turn allows segment specific analyses.

3.2.2 Computing Vehicle Kilometres Travelled and Fuel Consumption

VKT is calculated using annual growth rates, which vary in different periods of time, and is based on the vehicle's model year. It is assumed that VKT of vehicles decline with age, in other words, older cars travel less. Equations 12 and 13 below describe how VKT is kept track of over time, based on the vehicle model year. The uncertainty in the VKT variable is propagated over time through the growth rate as shown in Eqn 13.

$VKT(i, MY_{h,} VA) = VKT(i, MY_h, VA-1) * \exp(MYDC*VA)$;

$VA=1\text{-}60, i=2006\text{-}2050; h=1960=2050$ [km] Eqn(12)

$VKT(i, MY_h) = (1+VKT\text{-}G_r)* VKT(i-1, MY_h); r=1\text{-}3; i=2006\text{-}2050; h=1960=2050$ [km] Eqn (13)

Fuel consumption is the inverse of the well-known measure of fuel economy and is measured in Litres/100km. Fuel consumption of Cars, SUVs, and OLTs, and different powertrains are kept track of separately. A correction factor has been used to take into account the difference between laboratory fuel economy measurements and highway driving conditions, as explained in section 3.4.

Fuel consumption is calculated based on a measure called Emphasis on Reducing Fuel Consumption (ERFC), which takes a value between 0 and 1, and is defined as the percentage of the actual FC reduction realized to total FC reduction possible with constant size and performance (Cheah, 2009, Bandivadekar, 2008). ERFC of cars and light trucks in year 2030 are specified as inputs to the model and are described using an exponential relation over time, as shown in Eqn 15 below. The uncertainty in the future vehicles' fuel consumption is thus propagated through ERFC, as described in Eqn 15, as well as their relative fuel consumption over time.

$ERFC_u(i) = ERFC_u(2009) * \exp[(\ln(ERFC_u(2030)/ ERFC_u(2009))/(21))*(i - 2009)]$;

$i=2010\text{-}2050; u=1,2$ [ ] Eqn (15)

The relative fuel consumption of each powertrain (relative to a NA-SI conventional engine in 2008) is then used to calculate the vehicle fuel use over time. The relative fuel consumption is a function of ERFC as described earlier. The relative fuel consumption of each powertrain at 100% ERFC is also described over time with an exponential curve similar to that described in Eqn 14. The relative fuel consumption of different powertrains in 2030 at 100% ERFC level is also input into the model. The actual fuel consumption of each powertrain in each year is then calculated based on the ERFC in that year as well as the relative fuel consumption of that powertrain in the same year, multiplied by the fuel consumption of the base vehicle (2008 NA-SI). ERFC is used here to account for weight savings and changes in the performance of vehicles over time.

The relative fuel consumption for PHEV used in this paper is for the miles these vehicles travel on gasoline engine. Their electricity consumption is then calculated using their electricity use per kilometres travelled on the battery, treated the same way as BEVs. The utility factor is used to calculate the number of kilometres PHEVs travel on gasoline versus electricity (Eq 14). For FCVs, we keep track of the energy consumption per 100 km, which is then used to calculate the total FCV life-cycle energy use based on its associated VKT.

3.2.3 Computing Total Fuel use and Life-cycle GHG Emissions

The fuel consumption for each powertrain and each calendar year is kept track of separately and then summed up in the last step to calculate the total fuel use in billion litre gasoline equivalent per year. The total fuel consumption is calculated using equations 19 and 23 below, and includes all liquid based fuels. This excludes electricity primary fuel use; life-cycle energy use from electricity is included in the energy graphs discussed in section 4.5.

$FU_m(i) = \sum FC\text{-}SEG_k(i) * VKT(i, MY_h) * VS(i); i,h=1960\text{-}2050; m=1\text{-}4, k=1\text{-}3$ [Bil L] Eqn (19)

$FU\text{-}t(i) = \sum FU_m(i); i=1960\text{-}2050; m=1,2$ [Bil L] Eqn (23)

The volume of alternative fuels is calculated based on the blend percentage. It is assumed that total available tarsand will be split equally in replacing diesel and gasoline. Total fuel consumption is reported in billion litre gasoline equivalent and is adjusted for different fuel energy densities. The total energy consumption is calculated using fuel volumes and fuel energy densities based on Eqn 24 below, which also includes the electricity total life-cycle energy consumption.

$EC(i)= \sum[FU_a (i) * FD_a] + FU\text{-}E(i)*FD_{3;}$ $i=1960\text{-}2050;\ a=4\text{-}10$ [MJ] Eqn (24)

WTW coefficients are described using an exponential curve over time shown in equation 25 below, as it is assumed here that the WTW emissions will improve over time due to better raw material processing and more efficient use on the vehicle. The GHG emissions are then calculated using life-cycle WTW emissions and the fuel use based on equation 26 below, and summed up to represent the total life-cycle emissions from the fleet in Mt CO_2 equivalent per year. For electricity, the WTW emissions represent the grid average emissions. This is calculated, as shown in Eqn 26 below, based on the percentage of electricity that comes from renewable clean sources (which is an input to the model) as well as the WTW of conventional electricity (coal and natural gas based), which is also an input to the model. The uncertainty in the life-cycle emissions are thus propagated through WTW coefficients and alternative fuel use over time following equations 25 and 26 below.

$WTW_d\ (i)= WTW_d\ (2009) * \exp [\ (\ln(WTW_d\ (2030)/\ WTW_d\ (2009))/(21))*(i - 2009)];$

$i=2010\text{-}2050;\ d=1\text{-}8$ [gCO_2 eqv/MJ, g/kWh] Eqn (25)

$WTW\text{-}E\ (i)= (1\text{-}PCS\text{-}5(i))*\ WTW\text{-}EC+\ PSC\text{-}5(i)*WTW\text{-}EC;\ i=2010\text{-}2050$ [gCO_2 eqv/kWh] Eqn(26)

$WTW\text{-}t\ (i)= \sum\ WTW_d\ (i) * FU_p;\ i=2008\text{-}2050;\ d=1\text{-}6;\ p=1\text{-}8$ [Mt CO_2 eqv] Eqn(27)

3.3 Methodological Illustrative Examples

Three illustrative examples are carefully chosen here to demonstrate the methodology. The inputs are first ranked based on their level of uncertainty and then grouped in very low, low, medium, and high uncertainty categories. The rankings are chosen to be representative and sensible but are for demonstration purposes only to allow readers to understand the methodology without getting into detailed consideration of why a certain range and mode is used for each input. Refer to the authors' 2011 study which covers those details for a realistic technology and fuel development pathway (Bastani, 2011). Table 1 below shows the ranking chosen for these examples. The inputs are represented by triangular distributions and the min, mode, and max values are shown in the table below.

The measure used in this model is the inverse of fuel economy, which is the vehicle fuel consumption in L/100km. Vehicle fuel use is calculated from ERFC (Emphasis on Reducing Fuel Consumption) and powertrain's relative fuel consumption. ERFC measures the degree to which weight savings and technological 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, and is reported as a percentage (DOT, 2010). At 100% ERFC all the technological improvements are used to reduce fuel consumption while power and weight are kept constant. At 0% ERFC, the fuel consumption stays the same because all technological improvements have been offset by performance gains (power and faster acceleration time, and added weight). Though not explicitly stated, weight reduction is taken into account in these calculations through its coupling with ERFC.

Parameter	Min	Mode	Max	Mean	STD	Uncertainty Level	Values in 2010
Total light vehicles Sales in 2030 [‘000]	16,149	18,403	20,657	18,403	920	Low	11,500
Future Scrappage Rate(2011+)	60%	80%	100%	80%	8%	Medium	80%
%Sales HEV in 2030	5%	10%	15%	10%	2%	High	3%
% Sales PHEV in 2030	3%	5%	7%	5%	1%	High	0%
%Sales BEV in 2030	2%	4%	6%	4%	1%	High	0%
VKT-Annual-Growth(2006-2020)	0.38%	0.50%	0.62%	0.50%	0.05%	Medium	0.50%
VKT-Annual-Growth(2020-2030)	0.13%	0.25%	0.37%	0.25%	0.05%	High	N/A
VKT-Annual-Growth(2030+)	-0.20%	0.00%	0.20%	0.00%	0.08%	High	N/A
Emphasis on Reducing Fuel Consumption (ERFC)							
ERFC Cars	60%	80%	100%	80%	8%	Medium	50%
ERFC Light Trucks	53%	70%	87%	70%	7%	Medium	50%
Fuels and Energy Sources							Value in 2010
%blend cellulosic ethanol in 2030	7%	14%	21%	14%	3%	High	0%
%blend corn ethanol in 2030	4%	8%	12%	8%	2%	High	5%
%electricity from clean sources in 2030	38%	50%	62%	50%	5%	Medium	29%
%bio-diesel	2%	3%	4%	3%	0%	Medium	0%
%tarsand in 2030	13%	25%	37%	25%	5%	High	10%
WTW Coefficients[gCO_2 eqv/MJ]							
Cellulosic Ethanol WTW in 2030	4	8	12	8	2	High	10
Corn Ethanol WTW in 2030	52	69	86	69	7	Medium	77
Gasoline WTW in 2030	86	92	98	92	2	Very Low	92
Diesel WTW in 2030	88	94	100	94	2	Very Low	94
Bio-Diesel WTW in 2030	67	89	111	89	9	Medium	89
Conventional ElectricityWTW in 2030 [gCO_2/kWh]	495	970	1445	970	194	High	1078
Hydrogen WTW in 2030	93	123	1445	123	12	Medium	137
TarSand WTW in 2030	99	105	111	105	3	Very Low	109
Electricity Use							
PHEV Elec consumption (kWh/100km) in 2030	12	24	35	24	5	High	36
BEV Elec consumption (kWh/100km) in 2030	12	24	36	24	5	High	36
FCV Hybrid Electric Energy use (MJ/100km)	59	115	171	115	23	High	115
Utility Factor	24%	48%	72%	48%	10%	High	N/A
FC Relative in 2030							
FC-r NA-SI cars in 2030	0.53	0.70	0.87	0.7	0.07	Medium	1.00
FC-r Turbo cars in 2030	0.47	0.62	0.77	0.62	0.06	Medium	0.90

FC-r Diesel cars in 2030	0.45	0.59	0.73	0.59	0.059	Medium	0.84
FC-r HEV cars in 2030	0.21	0.42	0.63	0.42	0.084	High	0.70
FC-r PHEV cars in 2030	0.21	0.42	0.63	0.42	0.084	High	0.70
FC-r NA-SI LT in 2030	0.54	0.71	0.89	0.714	0.071	Medium	1.00
FC-r Turbo LT in 2030	0.46	0.61	0.76	0.609	0.06	Medium	0.83
FC-r Diesel LT in 2030	0.42	0.56	0.69	0.555	0.056	Medium	0.74
FC-r HEV LT in 2030	0.22	0.43	0.63	0.426001	0.085	High	0.70
FC-r PHEV LT in 2030	0.22	0.43	0.63	0.426	0.085	High	0.70

Table 1-Ranked Input List for example A

Then three illustrative examples are simulated using these ranked categories, with very low, low, medium, and high categories representing the spread (standard deviation/mean) set to 2.5%, 5%,10%,15% respectively in example A, ; to 5%, 10%,20%,30% in example B; and to 10%, 20%40%,60% in example C. These illustrative examples are chosen as simplified examples where the mode is kept constant and the spread is doubled to give readers a better sense of how the integrated impact of uncertainty on the outputs changes as the level of uncertainty is increased, with a consistent set of inputs. These examples also confirm the internal validity of the results. The simulation results for these examples are presented in the next section.

3.4 Numerical Simulation Results

This section presents the simulation results from running the model 10,000 times given the inputs described in section 3.3 for illustrative examples A,B, and C with different levels of uncertainty.

3.4.1 Illustrative Example A

The following graphs (Figure 4,Figure 5, Figure 6, Figure 7) show the simulation results from running the model with the inputs shown in Table 1 above and with spread (standard deviation/mean) for very low uncertainty set to 2.5%, low uncertainty to 5%, medium to 10% and high uncertainty to 20%. The results here show the total fuel consumption and emissions in 2030 and 2050.

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. For instance, in year 2030 (Figure 4), the fuel consumption will be most likely around 510 billion litres gasoline equivalent, but could be anywhere between 450 and 590 billion litres (note that the values are rounded here to avoid implying high precision). The standard deviation shows the spread of the outcome. In example A, for example, in year 2030, the standard deviation is 31 billion litres, which shows how much variation there is from the mean value (expected value). A small standard deviation shows that the outcomes are expected to vary in a range close to the mean value and a large standard deviation shows that the outcomes are spread out over a large range of values. The ratio of the standard deviation to the mean, also called the coefficient of variation or unitized risk, is a normalized measure of dispersion of a probability distribution, and is the measure we use here to discuss the uncertainty in the outcomes. The coefficient of variation of fleet fuel use in example A in year 2030 is about 6% and in year 2050 is about 11%. As expected, the level of uncertainty in the outcome increases over time, as our knowledge of the future declines. The coefficient of variation in this example is relatively low, which is consistent with the relatively low uncertainties in the inputs. The measure “values” on the right side of the probability density functions show the number of times the model is run using Latin Hypercube sampling.. 10000 runs is chosen here because the standard error of the mean can then be conveniently calculated by dividing the standard deviation by 100, which is about 0.3 billion litres for the 2030 fleet fuel use in this case. In other words, if we run the model another 10000 runs, there is about a 95% chance that we will find a mean value within 0.6 billion litres of the 510 billion litres expected value found here. Moreover, the interval shown above the graphs is the 90% confidence interval which indicates the reliability of the shown estimates. For instance, in example A, in year 2030, there is a 90% chance that the fuel consumption estimates will be somewhere between 470 to 570 billion litres. That is, there is only a 10% risk that fuel consumption will exceed 570 or be below 470 billion litres. These types of information are significant for policy makers, for example, when deciding which emissions pathways to choose based on an accepted level of risk associated with the outcomes not matching what they expect.

The probability distribution outcomes below can be used to determine any level of confidence interval based on the readers’ interest; the 90% interval is only shown here as an example. Further, different percentile values can also be read from the following graphs; for instance, Figure 4 shows the 5% percentile for 2030 fuel use, which means there is 5% chance of fuel consumption falling below 470 billion litres in year 2030 in this example. Different percentiles and quartiles of interest can be similarly inferred from these PDF functions.

Another measure of interest is the outcome skewness, which is a measure of asymmetry. In 2030 fleet fuel use in example A, the skewness is small which means the outcome is relatively symmetric. In year 2050, the skewness is larger and is a positive number, which means the outcome distribution has a longer right hand tail compared to the left side, which means the distribution has a few high values. In contrast, when skewness is negative the distribution has a longer left tail and has a few low values. Even though the input distributions were chosen symmetrically for this example, the outputs are not always symmetric. This is due to the interactions among variables, described in the equations earlier, and is yet another reason for having to develop a proper stochastic model to be able to examine the impact of uncertainties in the input on the outcome. Finally, Kurtosis is another useful measure which indicates the level “peakedness” and heavy tails in a probability distribution. In other words, higher Kurtosis indicates that the spread is due to a few extreme deviations as opposed to frequent modest deviations. This could be used to determine what the source of uncertainty is in the outcomes. In year 2050 in example A (Figure 5), for example, the Kurtosis is low which means the spread in the fuel consumption comes from frequent modest deviation and the distribution has a more rounded peak and shorter thinner tails. Similarly, Figure 6 and Figure 7 can be read using the most likely, range, spread, coefficient of variance, confidence intervals, and such to interpret the emissions distribution results from illustrative example A. In year 2030 (Figure 6), for instance, the fleet GHG emissions will be most likely around 1400 Mt CO_2 equivalent, but could be anywhere between 1190 and 1640 Mt CO_2 equivalent. The standard deviation of GHG emissions is about 97 and 117 Mt CO_2 equivalent in years 2030 and 2050, respectively. The emissions distributions are also positively skewed with a few higher extreme values with very low probabilities.

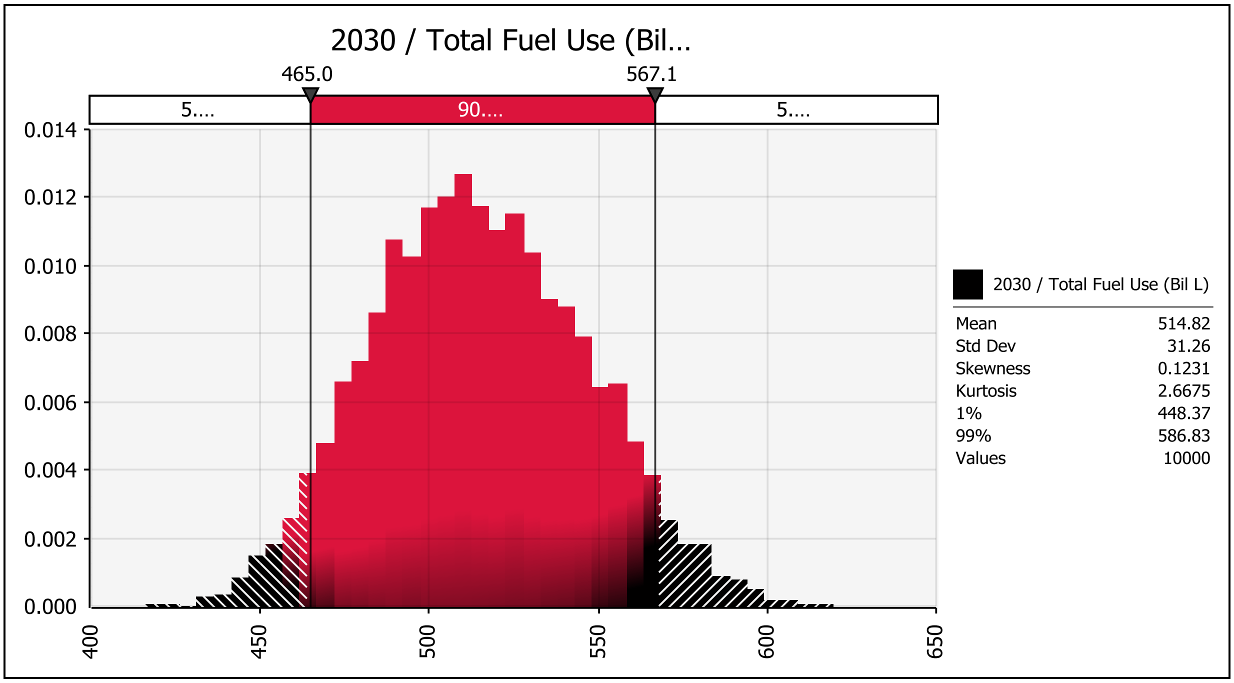

Figure 4-2030 U.S. Fleet fuel use [Bil L gasoline eqv/year] : Illustrative Example A Results

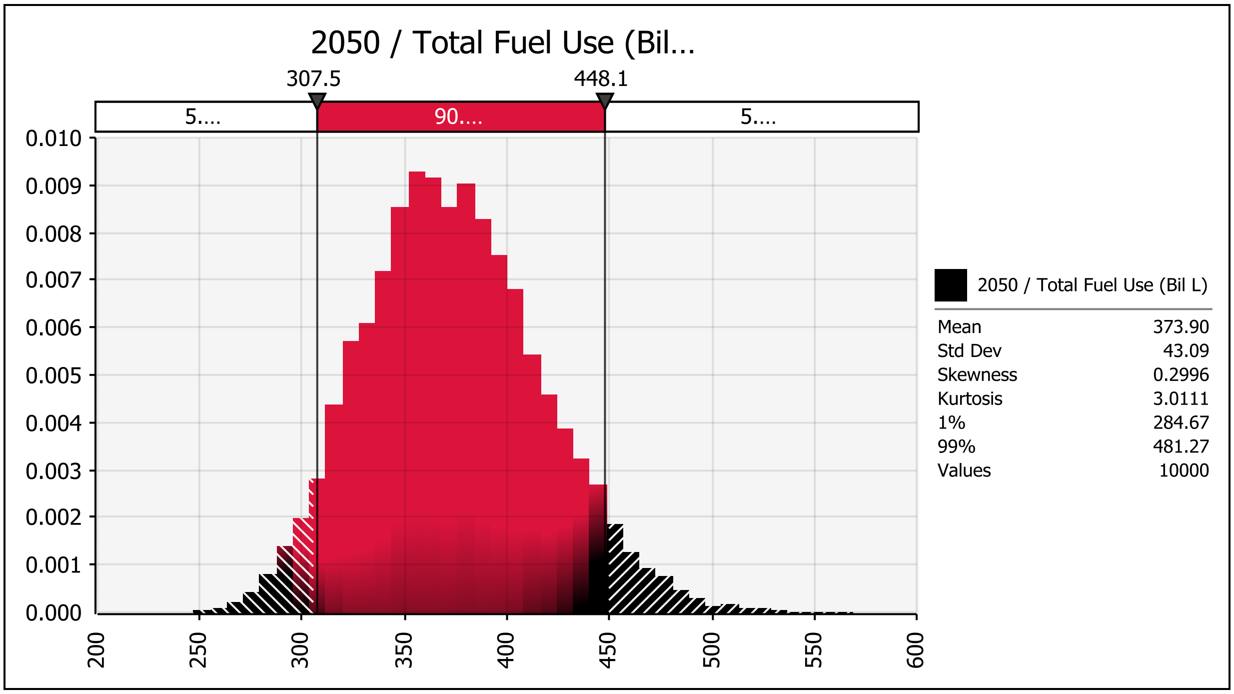

Figure 5-2050 U.S. Fleet fuel use [Bil L gasoline eqv/year]: Illustrative Example A Results

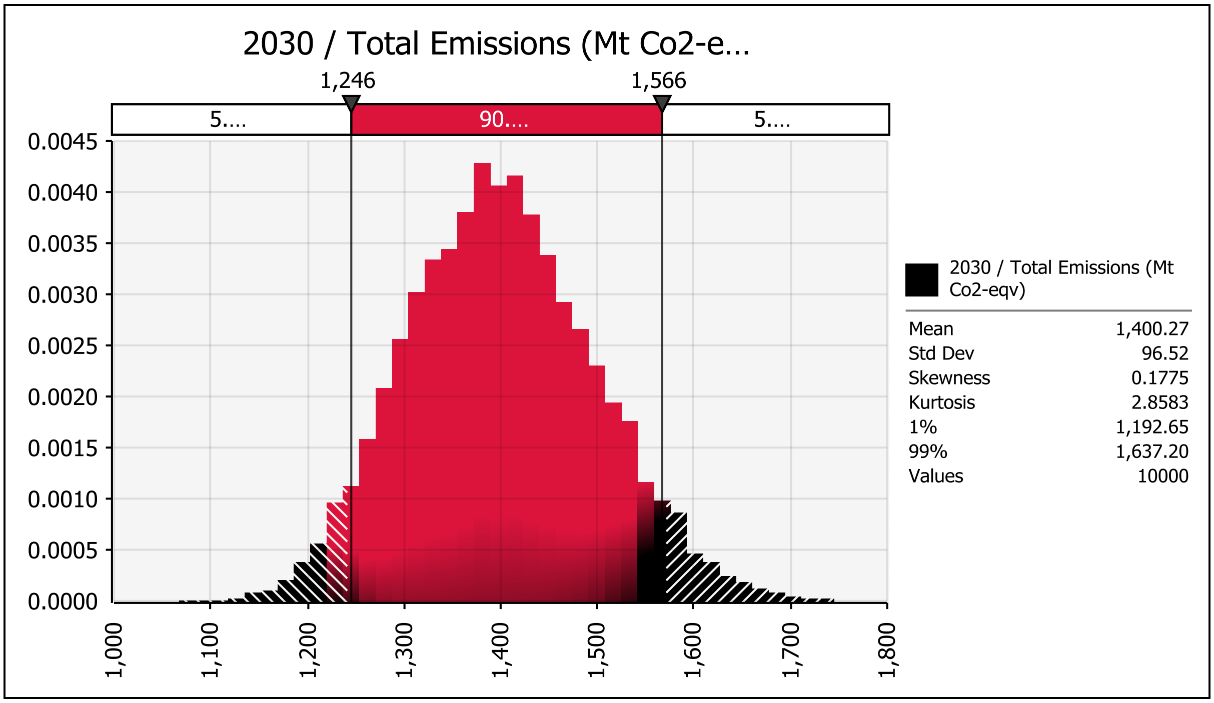

Figure 6-2030 U.S. Fleet GHG emissions [Mt CO_2 eqv/year]: Illustrative Example A Results

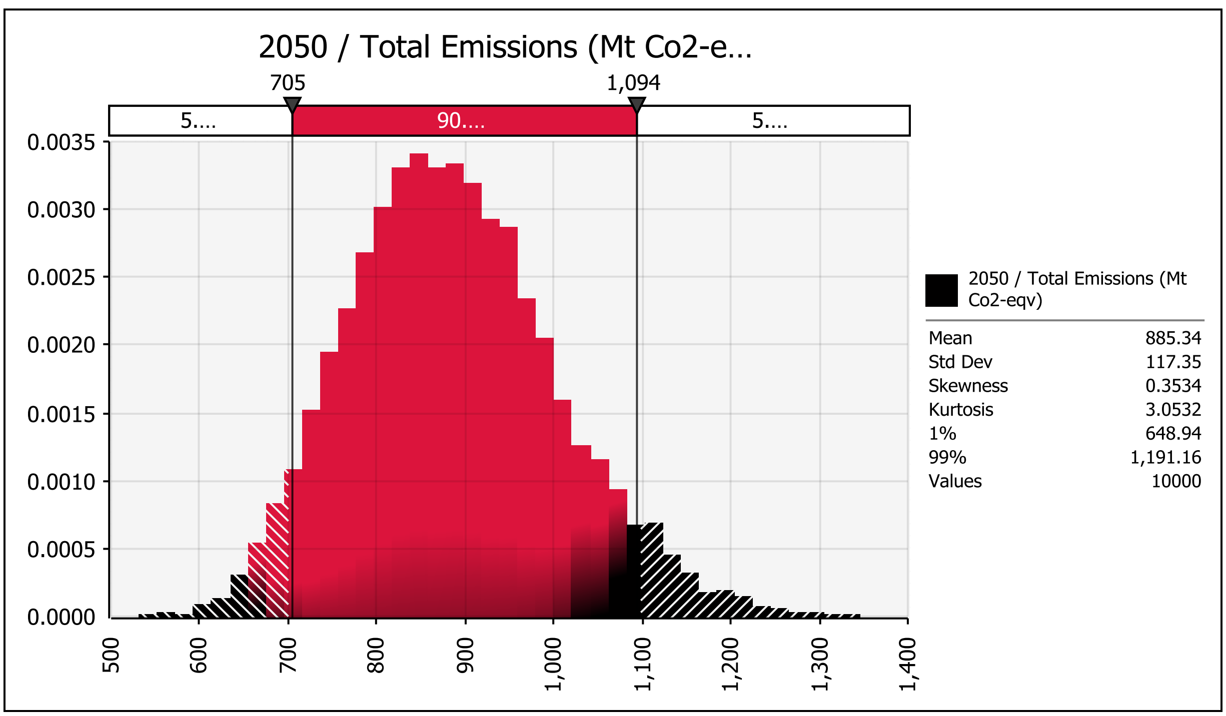

Figure 7-2050 U.S. Fleet GHG emissions [Mt CO_2 eqv/year]:: Illustrative Example A Results

3.4.2 Illustrative Example B

The following graphs (Figure 8 and Figure 9) show the simulation results from running the model with the mode inputs shown in Table 1 above and with coefficient of variation for very low uncertainty as 5%, low uncertainty as 10%, medium as 20% and high uncertainty as 30%. The results here show the fuel consumption and emissions in 2050 (Figure 8 and Figure 9). Similar statistical information can be inferred from these graphs, as explained in section 3.3.1. The mean value stays about the same as that of example A here, since the mode of the inputs have been kept the same. The mean is not exactly the same though due to asymmetry in the output. The spread is now larger in example B, as expected since the uncertainty levels in inputs have been increased. The outputs are also more asymmetrical, with a higher positive skewness and thus a longer right hand tail, which means there is a chance of the fleet fuel use having a much higher value. Even though the inputs are symmetrically chosen here, the outputs are visibly asymmetric. This further confirms that simple averaging and summing up of the effects from the inputs is not sufficient to understand the uncertainty impact on the outputs, and underlines the need for a stochastic model such as the one described in this paper.

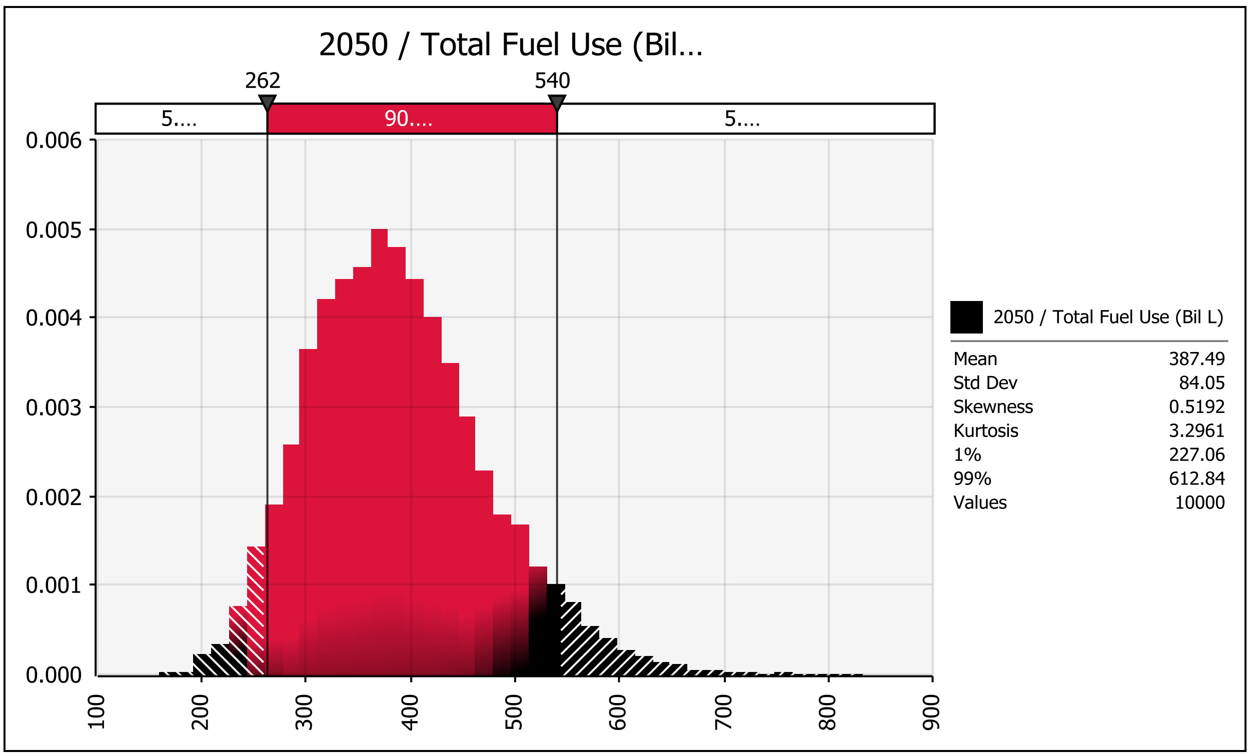

Figure 8-2050 U.S. Fleet fuel use [Bil L gasoline eqv/year]: Illustrative Example B Results

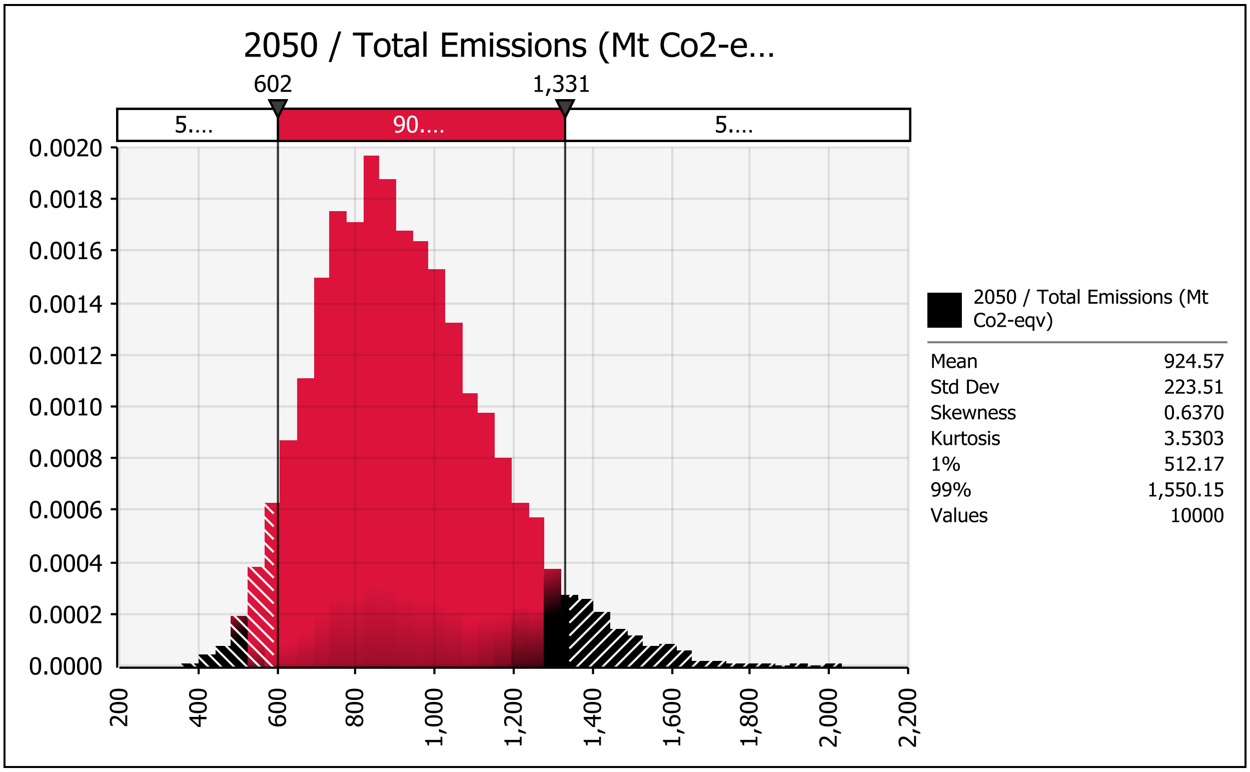

Figure 9-2050 U.S. Fleet GHG emissions [Mt CO_2 eqv/year]:: Illustrative Example B Results

3.4.3 Illustrative Example C

The following graphs (Figure 10and Figure 11) show the simulation results from running the model with the mode inputs shown in Table 1 above and with higher uncertainties as the coefficient of variation is set to 10% for very low uncertainty and20%, 40% , and 60% for low, medium and high levels of uncertainty respectively. The results here show the fuel consumption and emissions in 2050. Similar statistical information can be inferred from these graphs (Figure 10 and Figure 11), as explained in section 3.3.1. The spread in this example is substantially greater than in the previous examples, which is driven by higher uncertainties in the inputs. The level of uncertainty in the inputs has an amplified impact on the output. The outputs are also highly positively skewed with a very long right hand tail, with a relatively symmetric set of inputs, which indicates that there is a chance that the fuel consumption and emissions could be much larger than the expected value (mean) in year 2050.

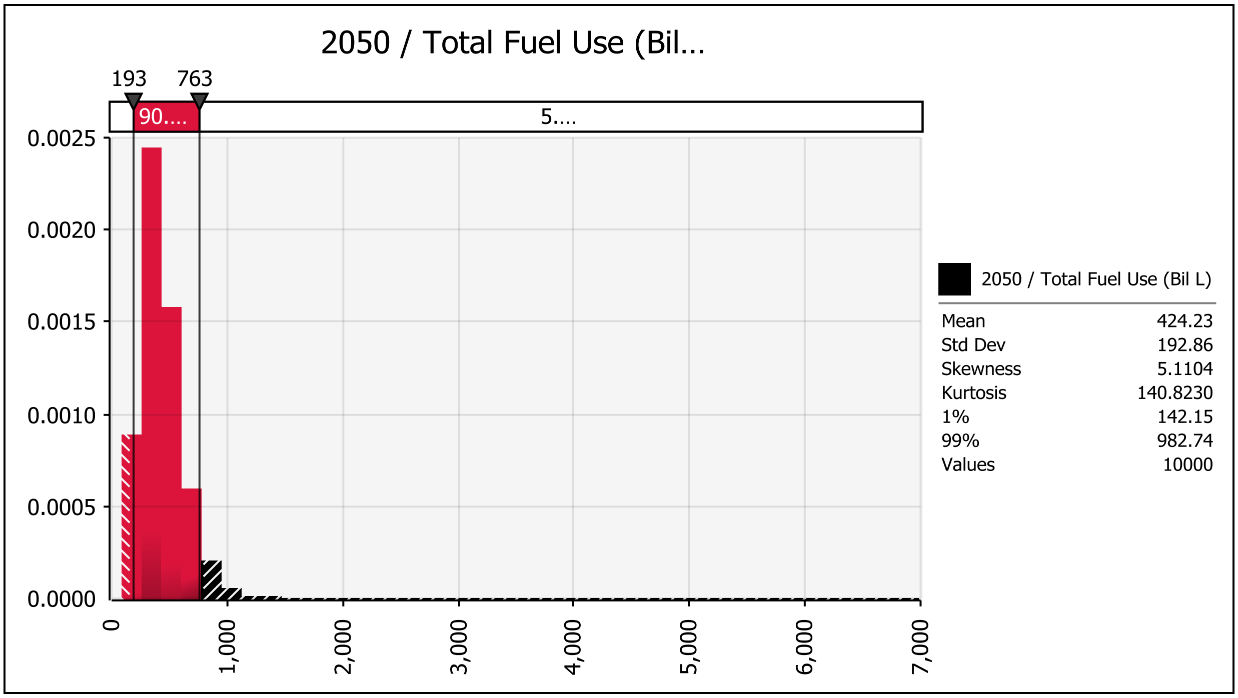

Figure 10-2050 U.S. Fleet fuel use [Bil L gasoline eqv/year]: Illustrative Example C Results

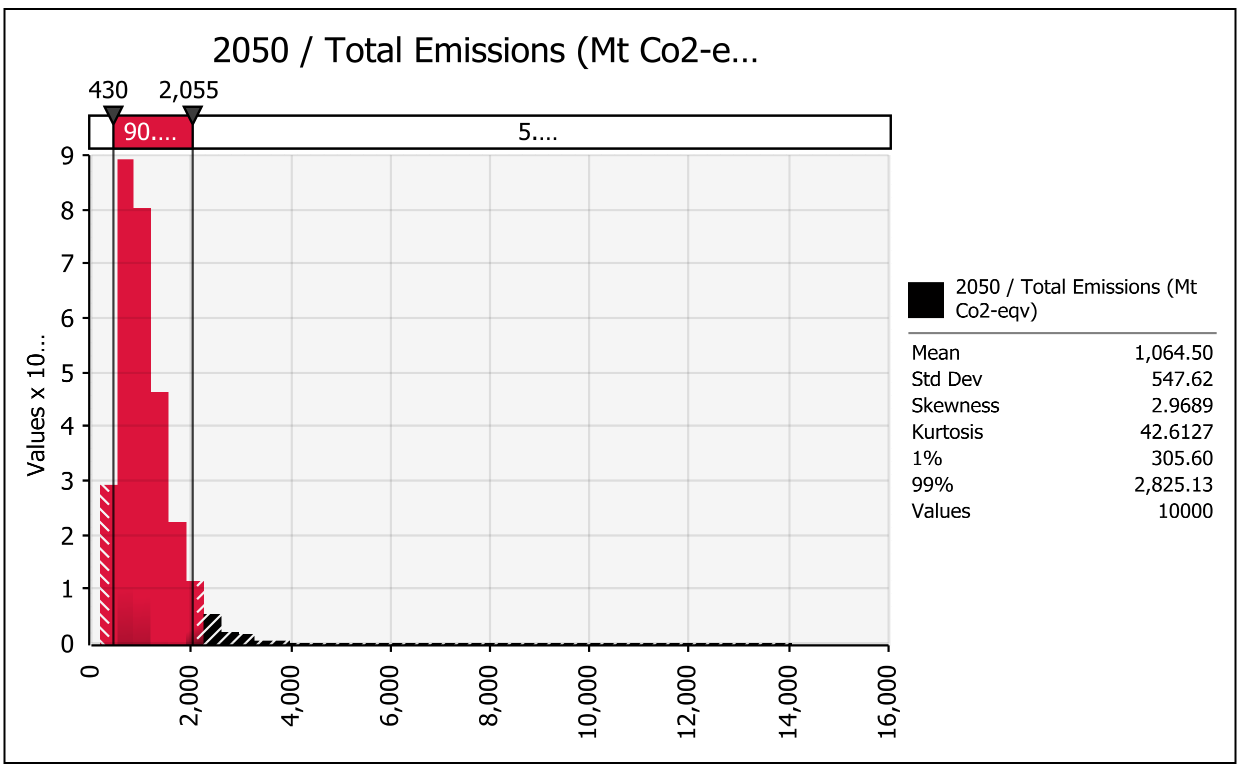

Figure 11-2050 U.S. Fleet GHG emissions [Mt CO_2 eqv/year]:: Illustrative Example C Results

3.4.4 Major Contributing Factors

The following tornado graphs show the major contributors to the fleet fuel use in example A for 2030 and 2050, and ranks them based on their relative importance under uncertainty. 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/yr) the total fuel consumption would increase with a one standard deviation increase in the input shown on the y-axis. Refer to Table1 for a complete list of inputs and statistics (including input standard deviation values).

In year 2030, for instance, if the scrappage rate is increased by one standard deviation (i.e. 8%), the total transport fuel use decreases by about 49 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 inFigure 12, 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 about 20 billion litres. Further the direction in which the outputs are impacted by the inputs is shown by the direction of the bars. For example, as shown in Figure 12, , and Figure 13 below, an increase in scrappage rate decreases the fuel consumption due to faster fleet turn over and thus faster penetration of improved vehicles and retirement of older vehicles. Further, these figures show that an increase in VKT growth increases fuel consumption, due to increase in travelling. Moreover, 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 Figure 12 and Figure 13, 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 Figure 12 and Figure 13, the scrappage rate is the most influential parameter in determining total fuel use in the mid term, and one of the major contributors in the long term. This is attributed to the fact that scrappage rate directly controls the size of the fleet and thus the technology turn over. The VKT annual growth in the short and mid terms is also an important contributor as it captures the actual on the road use of the 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. As shown in the following graphs therefore the relative importance and the impact of major contributing variables change over time.

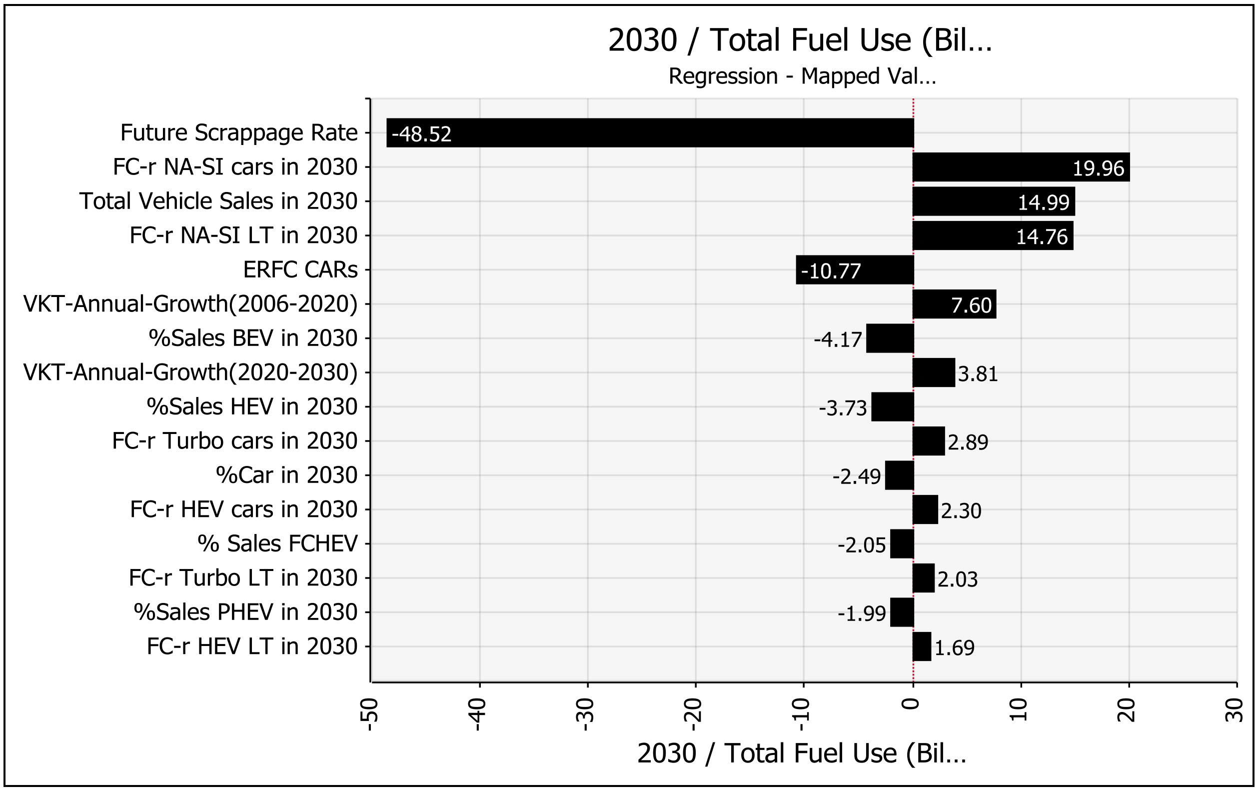

Figure 12-2030 U.S. Fleet fuel use ranked major influences [Bil L gasoline eqv/year]: Illustrative Example B

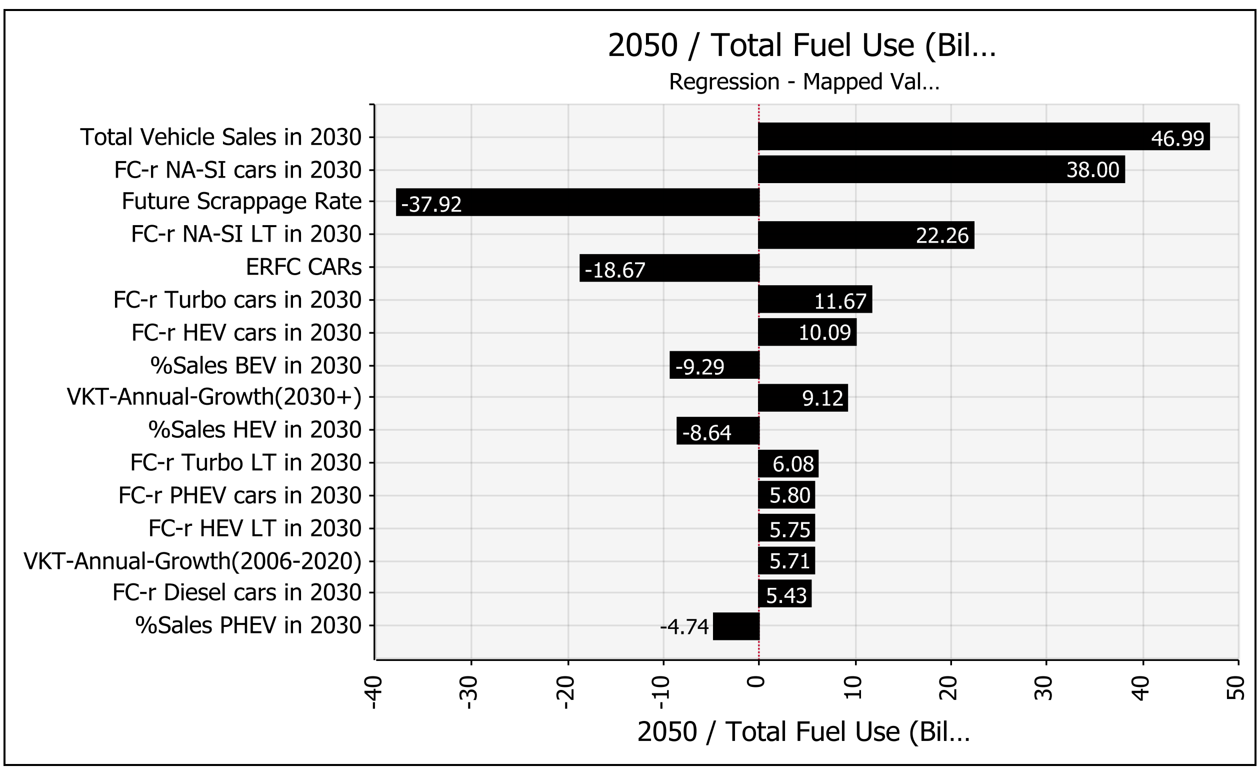

Figure 13- 2050 U.S. Fleet fuel use ranked major influences [Bil L gasoline eqv/year]: Illustrative Example B

Similar tornado graphs can be plotted for GHG emissions, as shown in Figure 14below. In year 2050, for instance, if the scrappage rate is increased by one standard deviation (i.e. 8%), the total transport emissions decreases by about 82 Mt CO_2 equivalent. 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 as shown in Figure 14scrappage rate is not as influential in 2050 compared to the nearer term. This is because scrappage rate directly controls the size of the fleet and thus the technology turn over, and, 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 the long term.

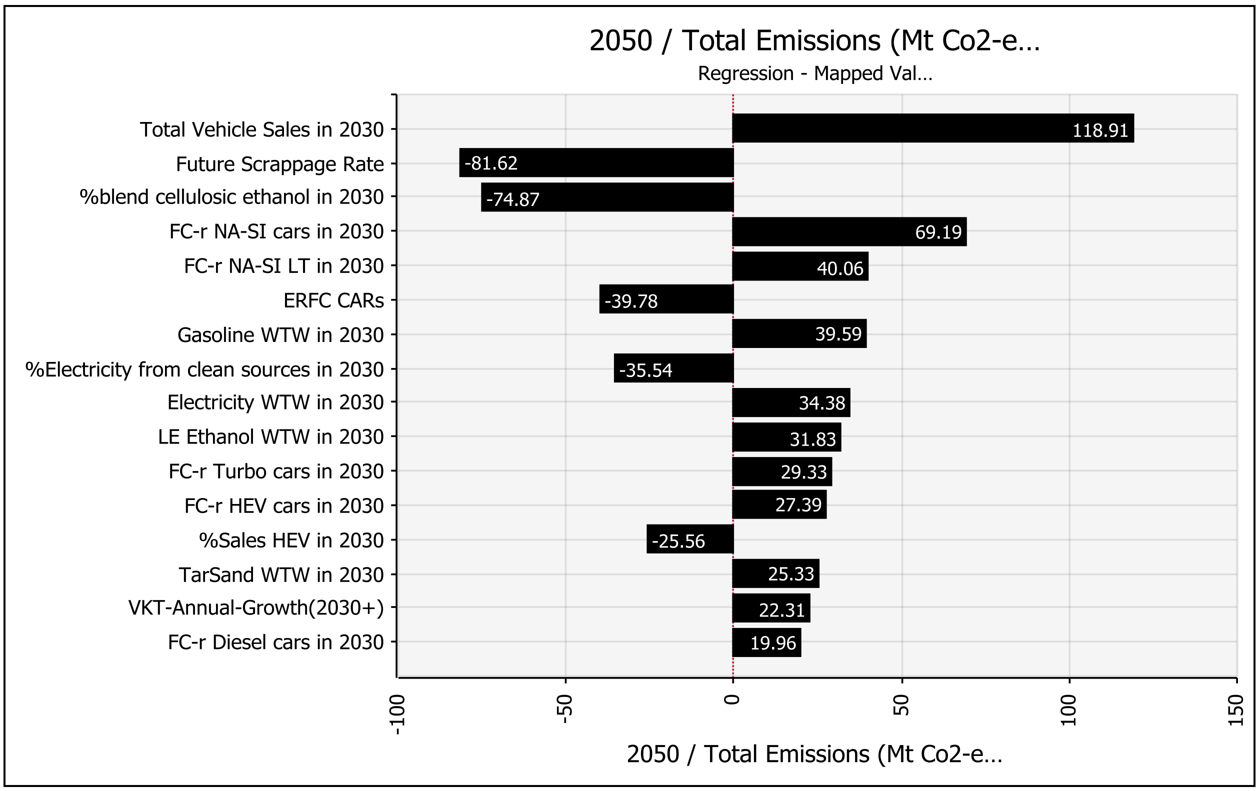

Figure 14- 2050 U.S. GHG Emissions ranked major influences [$MtCO_2$ equivalent)/year]: Illustrative Example B

3.5 Distributions Comparisons

The first graph in this section shows the dynamic of the output distributions over time: Figure 15compares the fleet fuels distribution from illustrative example B over time from near to long term. As shown on this graph, the mean of the distribution decreases over time while the spread increases noticeably. The reduction in the mean over time is expected given the chosen pathway here, and the increase in the spread is justified by the increase in the uncertainty of knowledge about the future vehicle fleet. A similar dynamic holds for emissions distribution over time.

The coefficient of variance increases from example A to B to C, due to the increase in the uncertainty level in the inputs from A to C. The increase in the coefficient of variance is non-linear. Figure 16 overlays the distribution from illustrative examples A and B for the year 2050. As shown in Figure 16, the mean of example A and B distributions are very close, as expected, due to keeping the input modes the same and the symmetry in the input distributions in these examples. The spread increases from example A to B as the input uncertainties are increased.

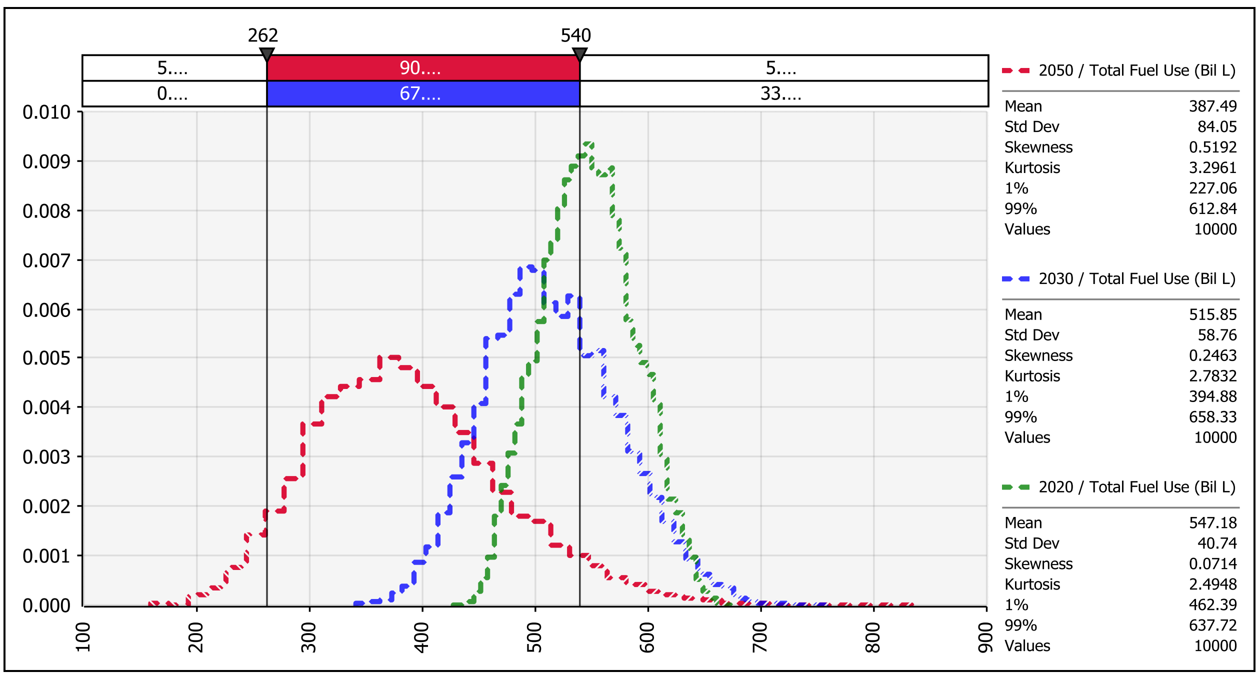

Figure 15- Fleet fuel use distribution [Bil L gasoline eqv/year] over time: Illustrative example B

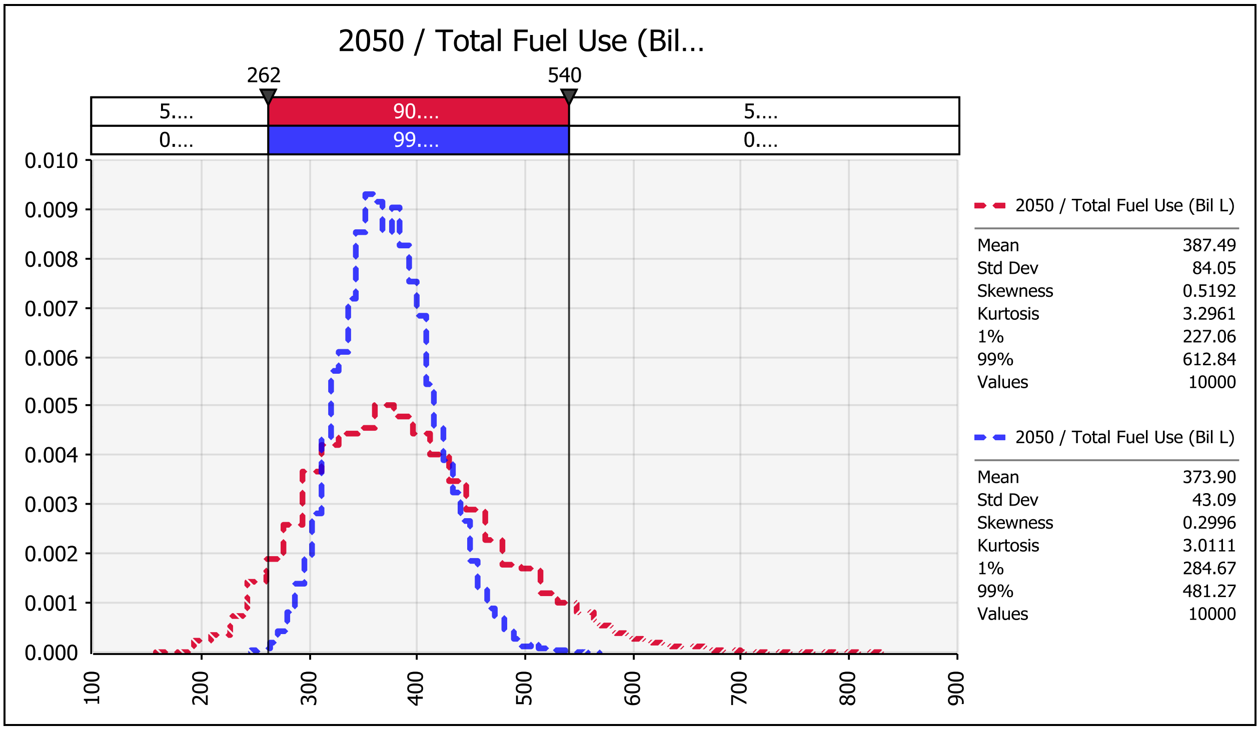

Figure 16-Distribution comparison for 2050 fleet fuel use [Bil L gasoline eqv/year]: Red: Illustrative example B , Blue: Illustrative Example A

4 Discussion and Concluding Remarks

This paper has introduced a stochastic fleet assessment model which quantifies the impact of uncertainties on the U.S. light-duty vehicle fleet fuel use and GHG emissions out to year 2050. The model further identifies and ranks the major influences on future fuel use and emissions under uncertainty and over time. The results show that the impact of uncertainty on future emissions and fuel use is significant and thus needs to be quantified and taken into account when analyzing the future of light-duty vehicle fleet.

The results show that the mere summing of individual inputs uncertainties does not predict the uncertainties in the results, and aggregate quantification of uncertainties accounting for interaction among inputs should be performed using stochastic fleet assessment models such as the one developed in this paper. Moreover, the results show that the symmetry in the output is not solely determined by individual inputs' uncertainty symmetry, as inputs with completely symmetric uncertainty bounds can produce significantly non-symmetric outputs due to the interactions among variables.

The probability distributions provided in this paper further quantify the range of possible outcomes, using measures such as: the expected value, standard deviation, different confidence intervals, skewness and kurtosis, and the coefficient of variance 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 and the confidence level with which future emissions and fuel use can be estimated. Further, the tornado diagrams developed from the model can be used to identify which variables and uncertainties are most important in determining the fleet fuel use and GHG emissions and how they change over time to inform policy prioritization under uncertainty.

Quantification of uncertainties in the emissions and fuel consumption out to year 2050 has been made possible using the methodology described in this paper. This methodology deciphers real-world uncertainties into a set of probabilistic density functions that can be readily interpreted and compared to inform transport research priorities and policy making. This model can be further used by policy makers to explore different views about what the uncertainties may be: to understand the consequences and associated risks based on their informed view on the uncertain states of the world, and identify pathways that lead to the highest reduction of fuel use and emissions with a high probability using numerical evidence. The results from this research can therefore be used to inform policy makers of the possible consequences of their decisions, and help them choose amongst alternatives by providing them with a more complete picture than traditional deterministic models.

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Glossary

BEV	Battery electric vehicle
BOF	Steelmaking technique using a basic oxygen furnace.
CAFE	Corporate Average Fuel Economy
CAR	Sedans and Wagons
ERFC	Emphasis on Reducing Fuel Consumption
EPA/USEPA	U.S. 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/100km), which is the inverse of the more commonly 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
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 8,500 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	U.S. National Highway Traffic Safety Administration
NRC	U.S. 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

Appendix: Equations

A.1 Vehicle Stock and Market Share

Parameter	**Symbol**
Total LDV Sales	TLS
Future Scrrapage rate	FSR
Vehicle Stock	VS
Vehicle-in-use	VIU
Model-year	MY
Vehicle-Removed	VR
Non-Survived-Vehicles	NSV

Vehicle Segment	**SEG**
Cars	SEG1
SUVs	SEG2
Other light Trucks (OLT)	SEG3

%Sales Powertrain	**S**
Gasoline-Turbo	S1
Diesel	S2
HEV	S3
PHEV	S4
BEV	S5
FCHEV	S6

%Cars	PCAR
%SUV	PSUV

TLS (i)= TLS (2009) * exp [(ln(TSL(2030)/TSL(2009))/(21))*(i – 2009)]; i=2010-2050 [mil] Eqn (1)

SEG_k (i)= SEG_k (2009) * exp [(ln(SEG_k (2030)/ SEG_k (2009))/(21))*(i – 2009)];

i=2010-2050; K=1,2,3 [ ] Eqn (2)

PACR (i)= PACR (2009) * exp [(ln(PACR (2030)/ PACR (2009))/(21))*(i – 2009)];

i=2010-2050 [ ] Eqn (3)

TLS-SEG1(i)=PCAR(i) * TLS (i) [mil] Eqn (4)

TLS-SEG2(i)=PSUV(i) * TLS (i) [mil] Eqn (5)

TLS-SEG3(i)=(1-PCAR(i)-PSUV(i))*TLS(i) [mil] Eqn (6)

NSV(i, SEG_k)= TLS(i, SEG_k)*FSR; i=2010-2050; K=1-3 [mil] Eqn (7)

VIU(i, SEG_k)= TLS(i, SEG_k)- NSV(i, SEG_k) ; i=2010-2050; K=1-3 [mil] Eqn (8)

VR(i, SEG_k)= NSV(i, SEG_k)-NSV(i-1, SEG_k) ; i=2010-2050; K=1-3 [mil] Eqn (9)

VS(i)= $\sum_{MY}$ [VS(i-1, SEG_k)]$_{MY}$ + TLS (i, SEG_k) – VR (i, SEG_k) ;

i=2010-2050; MY=1990-2050; K=1-3 [mil] Eqn (10)

S_j (i)= S_j (2009) * exp [(ln(S_j (2030)/ S_j (2009))/(21))*(i – 2009); i=2010-2050; j=1-6 [%] Eqn (11)

A.2 Travelling Pattern

VKT Growth	**VKT-G**
VKT-Annual-Growth(2006-2020)	VKT-G1
VKT-Annual-Growth(2020-2030)	VKT-G2

VKT-Annual-Growth(2030+)	VKT-G3
Model Year Decay	MYDC
Vehicle Age	VA
PHEV utility factor	PHEV-UF
PHEV Gasoline VKT	PHEV-G-VKT

$VKT(i, MY_{h,} VA) = VKT(i, MY_h, VA\text{-}1) * \exp(MYDC*VA)$; [km]

VA=1-60, i=2006-2050; h=1960=2050 Eqn (12)

$VKT(i, MY_h) = (1+VKT\text{-}G_r) * VKT(i\text{-}1, MY_h)$; r=1-3; i=2006-2050; h=1960=2050 [km] Eqn (13)

$PHEV\text{-}G\text{-}VKT(i) = (1\text{-}PHEV\text{-}UF) * VKT(i, MY_h)$; i=2006-2050; h=1960=2050 [km] Eqn (14)

A.3 Fuel Economy, Fuel use, and Energy Consumption

*Note: fuel consumption is the inverse of fuel economy and has unit of L/100km

ERFC

Cars	ERFC-1
Light Trucks (LT)	ERFC-2

Relative Fuel Consumption	**FC-r**
NA-SI Car	FC-r-1
Gasoline-Turbo Car	FC-r-2
Diesel Car	FC-r-3
HEV Car	FC-r-4
PHEV Car	FC-r-5
BEV Car	FC-r-6

FCHEV Car	FC-r-7
NA-SI Light Truck (LT)	FC-r-8
Gasoline-Turbo LT	FC-r-9
Diesel LT	FC-r-10
HEV LT	FC-r-11
PHEV LT	FC-r-12
BEV LT	FC-r-13
FCHEV LT	FC-r-14
Fuel consumption (L/100km)	FC
Fuel use	**FU**
Gasoline equivalent	FU-1
Diesel equivalent	FU-2
Electricity	FU-3
Hydrogen use	FU-4
Cellulosic Ethanol	FU-5
Corn Ethanol	FU-6
Bio-diesel	FU-7
Tarsand	FU-8
Gasoline	FU-9
Diesel	FU-10
Total liquid based	FU-t
Total Electricity use	FU-E
%Clean Source	**PCS**
Blend Cellulosic Ethanol	PCS-1

Blend Corn Ethanol	PCS-2
Bio-diesel	PCS-3
Tarsand	PCS-4
Renewable Electricity	PCS-5
Fuel Density [MJ/L, MJ/kWh]	FD
Energy Consumption [MJ]	EC

$ERFC_u$ (i)= $ERFC_u$ (2009) * exp [(ln($ERFC_u$ (2030)/ $ERFC_u$ (2009))/(21))*(i – 2009)];		
i=2010-2050; u=1,2	[ ]	Eqn (15)
FC-r_e (i)= FC-r_e (2009) * exp [(ln(FC-r_e (2030)/ FC-r_e (2009))/(21))*(i – 2009)];		
i=2010-2050; e=1-14	[ ]	Eqn (16)
FC-r_e ($ERFC_{u,i}$,i)= f(FC-r_e(100%,i), FC-r_e(0%,i)); u=1,2; e=1-14; i=2009-2050	[ ]	Eqn (17)
FC-SEG_k (i)= FC-r-SEG_k (i)*FC-r-SEG_k (2009); k=1-3; i=2010-2050	[L/100km]	Eqn (18)
FU_m (i)=∑ FC-SEG_k (i)* VKT(i, MY_h)* VS(i); i,h=1960-2050; m=1-4, k=1-3	[Bil L]	Eqn (19)
PCS_o (i)= PCS_o (2009) * exp [(ln(PCS_o (2030)/ PCS_o (2009))/(21))*(i – 2009)];		
i=2010-2050; o=1-5	[%]	Eqn (20)
FU_p (i)= PCS_o (i)*FU_m (i); i=2010-2050; o=1-4; m=5-8	[Bil L]	Eqn (21)
FU_b (i)= FU_m (i)-[∑ FU_p (i) (p|1-4)]; i=1960-2050;b=9,10	[Bil L]	Eqn (22)
FU-t(i) = ∑ FU_m (i); i=1960-2050; m=1,2	[Bil L]	Eqn (23)
EC(i)= ∑[FU_a (i) *FD_a] + FU-E(i)*$FD_{3;}$ i=1960-2050; a=4-10	[MJ]	Eqn (24)

A.4 Life-cycle Emissions

Fuel Well-to-Wheel Emissions	**WTW**
Cellulosic Ethanol WTW	WTW-1

Corn Ethanol WTW	WTW-2
Bio-diesel WTW	WTW-3
Conventional Electricity WTW	WTW-4
Gasoline WTW	WTW-5
Diesel WTW	WTW-6
Hydrogen WTW	WTW-7
Tarsand WTW	WTW-8
Average Electricity Grid WTW	WTW-E
Clean Electricity WTW	WTW-EC
Total WTW	WTW-t

WTW_d (i)= WTW_d (2009) * exp [(ln(WTW_d (2030)/ WTW_d (2009))/(21))*(i – 2009)];

i=2010-2050; d=1-8 [gCO_2eqv/MJ, g/kWh] Eqn (25)

WTW-E (i)= (1-PCS-5(i))* WTW-EC+ PSC-5(i)*WTW-EC; i=2010-2050 [gCO_2eqv/kWh] Eqn(26)

WTW-t (i)= $\sum$ WTW_d (i) * FU_p; i=2008-2050; d=1-6; p=1-8 [Mt CO_2 eqv] Eqn(27)

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