

THE USE OF LIFE CYCLE ASSESSMENT (LCA) TO ESTIMATE GREENHOUSE GAS EMISSIONS FROM THE AUSTRALIAN ROAD TRANSPORT SECTOR

Robin Smit¹

¹ Transport Energy/Emission Research (TER), Launceston, Australia

Abstract

This paper provides an overview and minor update of probabilistic life-cycle assessment (pLCA) studies into the greenhouse gas (GHG) emissions performance of Australian passenger vehicles and trucks. The life-cycle GHG emissions performance strongly depends on the vehicle class, powertrain and year of assessment. Life-cycle emission factor distributions vary substantially in their magnitude, range and shape. Battery electric vehicles provide the most robust and deepest reductions in greenhouse gas emissions as time progresses and the effects of decarbonised electricity generation, improved battery performance, etc. take hold. Hydrogen trucks exhibit the largest uncertainty in emissions performance, which reflects the uncertainty and general lack of information for this technology. Operational emissions (on-road driving and vehicle maintenance combined) dominate life-cycle emissions for all vehicle classes. Sensitivity analysis is a useful tool to explore the main factors affecting lifecycle greenhouse gas emissions performance.

Keywords: LCA, emission, electric, road.

1. Introduction

Road transport is a large and growing source of carbon dioxide (CO₂) emissions around the world, currently contributing about 25% of the European Union's (EU), 23% of the United States' (US) and 16% of Australia's total CO₂ emissions (TER/ICCT 2024). Although heavy-duty vehicles have a small share of total road travel, they are typically responsible for about 25% of total road transport emissions, and their relative contribution is growing (Smit *et al.* 2024).

It is increasingly accepted that life-cycle assessment (LCA) is required for a fair assessment of the greenhouse gas (GHG) emissions performance of different technologies used for road transport, which is currently shifting from fossil fuelled to electric and hydrogen-powered transport. LCA includes all important aspects of GHG emissions throughout the vehicle's life cycle and fuel cycle, including: (1) production of the vehicle, battery and fuel-cell systems, (2) production and distribution of fossil fuels, hydrogen and electricity (extraction, transport and fuel refining, including losses and leakage), (3) on-road operation of the vehicle including maintenance, and (4) disposal and recycling of the vehicle at the end of its life.

A probabilistic life-cycle assessment (pLCA) was conducted for Australian road transport, investigating the greenhouse gas (GHG) emissions performance of passenger vehicles (Smit and Kennedy 2022) and trucks (Smit *et al.* 2024) for a recent past and a future (largely decarbonised) situation in Australia assuming 90% renewables.

For passenger vehicles, the pLCA results suggested that battery electric vehicles will reduce GHG emission rates in all Australian jurisdictions. On average the reduction is 29% to 41% using the 2018 Australian electricity mix, which was still largely fossil fuels based. Large reductions between 74% and 80% were estimated for a 90% renewables scenario.

There are significant differences between states and territories in the extent emissions will be reduced.

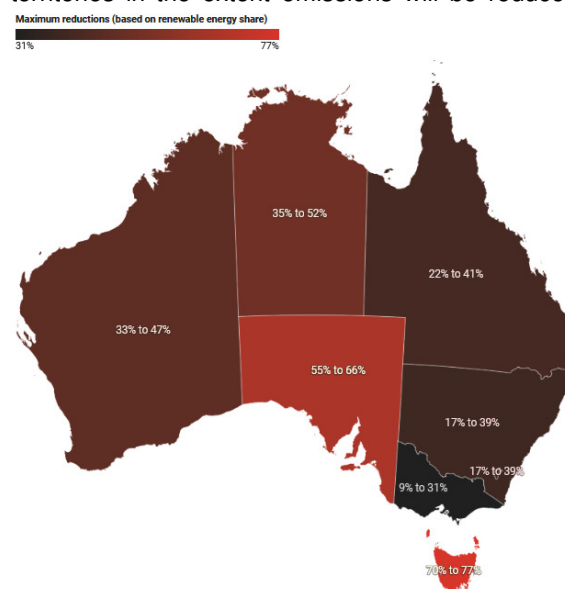


Figure 1. Plausible range of life-cycle greenhouse emissions reductions per kilometre in 2018 when comparing typical electric with fossil-fueled passenger vehicles, by state and territory.

The situation in 2018 is shown in Figure 1, although it is acknowledged that the situation is now rapidly changing (improving) in various jurisdictions due to decarbonisation efforts in electricity production. The largest emissions reductions occurred in Tasmania, as its electricity largely comes from renewable sources: more than 80% comes from hydroelectricity and about 10% comes from wind. This shows that we don't have to wait for a remote future situation to achieve deep reductions in emissions through electrification of road transport. For states like Tasmania, that situation is already here. For trucks, it was found that the relative and absolute life-cycle GHG emissions performance strongly depended on the vehicle class, powertrain and year of assessment.

Life-cycle emission factor distributions varied substantially in their magnitude, range and shape. This paper briefly presents the results for Australian trucks in the next section, building on a recent and detailed LCA study (Smit *et al.* 2024), but with an update for upstream emissions for diesel trucks.

2. LCA Update

This section provides a brief update of the main results, after including an adjustment for one aspect of the lifecycle assessment (i.e. upstream emissions for diesel trucks). For the background, method, assumptions and detailed discussions, the reader is referred to the previous study (Smit *et al.* 2024). The updated simulation results are visualised as probability density functions (PDFs) in Figure 2 for 2019 and 2050.

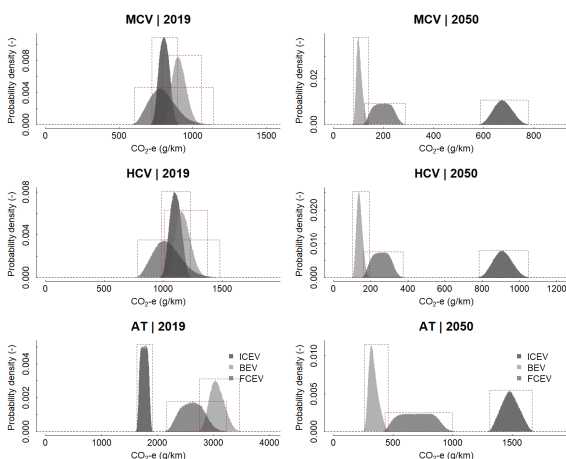


Figure 2. PDFs of lifecycle GHG emission factors by vehicle class and powertrain category. The boxes with dotted lines define the 99.7% confidence intervals (x-axis) and the maximum probability density (y-axis) for each distribution.

A PDF is a curve that quantifies the probability that the variable of interest falls within a particular range

of values. The PDF is non-negative and the area under the curve equals one. The position and shape of the distributions provide information regarding the typical values (e.g. mean, median) and the variability and uncertainty in these values. A wide distribution suggests a higher level of uncertainty, whereas a narrow distribution suggests relatively robust emissions performance.

Table 1 presents the updated summary statistics for these distributions, i.e. the average life-cycle emission factors and the plausible range in these mean values (99.7% confidence interval - CI), which reflects the variability and uncertainty in the mean values.

Table 1. Life-cycle GHG emission factor (g CO₂-e/km) statistics.

Vehicle class	Powertrain technology	Year of assessment	Mean	Median	Lower 99.7% Confidence limit (mean)	Upper 99.7% Confidence limit (mean)
MCV	ICEV	2019	806	806	723	896
MCV	BEV	2019	909	907	792	1058
MCV	FCEV	2019	798	790	602	1139
HCV	ICEV	2019	1105	1104	986	1231
HCV	BEV	2019	1170	1166	1011	1379
HCV	FCEV	2019	1041	1030	784	1481
AT	ICEV	2019	1767	1766	1632	1906
AT	BEV	2019	3070	3061	2749	3471
AT	FCEV	2019	2626	2623	2105	3236
MCV	ICEV	2050	676	676	585	777
MCV	BEV	2050	104	102	79	139
MCV	FCEV	2050	198	196	123	288
HCV	ICEV	2050	911	910	784	1050
HCV	BEV	2050	141	140	104	192
HCV	FCEV	2050	258	258	160	375
AT	ICEV	2050	1483	1482	1312	1667
AT	BEV	2050	337	331	257	458
AT	FCEV	2050	697	697	432	1000

The full life-cycle simulation shows that the absolute and relative life-cycle GHG emissions performance depends on the vehicle class (MCV/HCV = medium/heavy commercial vehicle, AT = articulated truck), power train (ICEV = internal combustion diesel vehicle, BEV = battery electric vehicle, FCEV = fuel cell hydrogen electric vehicle) and year of assessment. For the current situation (2019), BEV or ICE trucks perform best overall, depending on the truck class.

For the smaller trucks sizes, average life-cycle GHG emission factors for battery electric powertrains are 1% (MCV) and 6% (HCV) lower than diesel trucks. However, for the largest truck size (AT), diesel trucks had the lowest average life-cycle GHG emission factors in 2019, with battery electric powertrains and fuel cell electric powertrains having 74% and 49% higher values, respectively.

For the decarbonised situation (loosely defined as "2050" with 10% fossil fuels remaining in the production of electricity and hydrogen), the picture has changed entirely, where BEV and FCEV technology in combination with the emission intensities of a decarbonised Australian electricity grid and a mostly green hydrogen production pathway provide large to deep reductions. In this case battery electric powertrains provide deep reductions in the average ICEV life-cycle GHG emission factors of 85% (MCV), 85% (HCV) and 77% (AT).

It is important to note this would apply to any current situation where renewable low-carbon energy is used for the different life cycle aspects. Examples are the use of solar panels to charge batteries or the use of grid electricity that is currently generated in Tasmania with almost 95% renewables

Fuel cell electric power-trains also provide substantial reductions, but not as deep as those for battery electric trucks. FCEV reduces the life-cycle GHG emission factors for ICEV by 71% (MCV), 72% (HCV) and 53% (AT), respectively.

Although conventional diesel truck technology exhibit marginal improvements in operational energy efficiency (15-20%), they cannot match the strong improvements in GHG emissions performance of EVs, and BEVs in particular. BEVs show the deepest reductions in overall emissions performance, including a further 45-52% reduction in GHG emissions per kilometre, as compared with FCEV.

In addition, the spread (variability + uncertainty) in the average GHG emissions performance for BEVs is the smallest in 2050. This suggests that, out of the three powertrain options, battery electric trucks will deliver the greatest and most robust emission reductions for all vehicle classes, and therefore carry the lowest risk of not delivering the anticipated life-cycle emissions performance. Fuel-cell electric hydrogen trucks, on the other hand, will also reduce emissions compared with ICE trucks, but these reductions are not as great, and, relevantly, they are the least robust of all the technology options. They therefore carry the highest risk of potentially not achieving the expected reductions.

The simulation results can be examined to assess the relative importance of the different life-cycle aspects on the total GHG emission rates. Table 2 presents summary statistics for these distributions, i.e. the lower and upper confidence limits of the average percentage contribution to the life-cycle GHG emission rates for each life-cycle aspect.

Table 2. Mean and plausible range (99.7 CI, within brackets) of the percentage share of the life-cycle GHG emission factor (g CO₂-e/km) for each life-cycle aspect by vehicle class, powertrain technology and year.

Vehicle class	Powertrain technology	Year of assessment	Vehicle manufacturing	Upstream infrastructure fuel and energy	Upstream fuel and energy	Operational (on-road + maintenance)	Disposal and recycling
MCV	ICEV	2019	2.2 (1.4 - 3.1)	0.4 (0.1 - 0.8)	16.7 (11.8 - 21.2)	80.8 (76.0 - 85.7)	0.1 (0.0 - 0.2)
MCV	BEV	2019	7.4 (3.1 - 15.6)	2.3 (0.5 - 4.4)	0.5 (0.9 - 10.4)	81.8 (74.0 - 86.7)	0.1 (0.0 - 0.2)
MCV	FCEV	2019	20.5 (6.1 - 44.3)	2.7 (0.5 - 5.6)	8.1 (4.4 - 13.0)	68.6 (47.6 - 83.2)	0.1 (0.0 - 0.3)
HCV	ICEV	2019	4.7 (3.2 - 6.5)	0.4 (0.1 - 0.8)	16.3 (11.5 - 20.9)	78.4 (73.6 - 83.7)	0.2 (0.0 - 0.4)
HCV	BEV	2019	11.4 (5.7 - 21.1)	2.2 (0.4 - 4.2)	0.2 (0.5 - 10.1)	78.0 (69.1 - 84)	0.3 (0.0 - 0.5)
HCV	FCEV	2019	24.3 (9.5 - 46.9)	2.5 (0.5 - 5.3)	7.8 (4.1 - 12.4)	65.2 (45.3 - 79.9)	0.2 (0.0 - 0.7)
AT	ICEV	2019	2 (1.4 - 2.6)	0.4 (0.1 - 0.8)	16.8 (11.9 - 21.3)	80.9 (76.1 - 85.8)	0.1 (0.0 - 0.2)
AT	BEV	2019	4.7 (1.8 - 9.5)	2.4 (0.5 - 4.5)	0.8 (7.3 - 10.7)	84 (79.1 - 88.1)	0.1 (0.0 - 0.1)
AT	FCEV	2019	8.9 (0.8 - 22)	2.8 (0.6 - 5.7)	9.5 (5.6 - 14.2)	79.1 (66.4 - 87.7)	0.1 (0.0 - 0.3)
MCV	ICEV	2050	0.8 (0.2 - 1.8)	0.4 (0.1 - 0.8)	16.9 (12.0 - 21.5)	81.0 (76.9 - 87.2)	0.0 (0.0 - 0.1)
MCV	BEV	2050	13.1 (5.1 - 23.7)	21.3 (8.4 - 39.4)	6.9 (1.1 - 15.6)	58.4 (43.6 - 73.4)	0.3 (0.0 - 0.9)
MCV	FCEV	2050	10.9 (3.0 - 38.3)	11.9 (3.6 - 21.6)	3.5 (0.7 - 6.9)	74 (52.6 - 87.6)	0.1 (0.0 - 0.5)
HCV	ICEV	2050	1.8 (0.4 - 3.9)	0.4 (0.1 - 0.8)	16.8 (11.9 - 21.5)	81 (75.5 - 86.8)	0.1 (0.0 - 0.2)
HCV	BEV	2050	20.8 (8.1 - 35.4)	19.6 (7.5 - 37.6)	6.4 (1.0 - 14.6)	52.6 (38.6 - 68.7)	0.6 (0.0 - 2.1)
HCV	FCEV	2050	14.9 (4.3 - 34.8)	11.1 (3.5 - 26.5)	3.4 (0.7 - 6.3)	70.4 (48.9 - 85.7)	0.4 (0.0 - 1.3)
AT	ICEV	2050	0.7 (0.2 - 1.5)	0.4 (0.1 - 0.8)	17.0 (12.1 - 21.6)	81.0 (77.0 - 87.1)	0.0 (0.0 - 0.1)
AT	BEV	2050	6.3 (2.4 - 17.7)	23.5 (9.5 - 42.4)	7.7 (1.2 - 17.2)	60.4 (44.4 - 76.1)	0.2 (0.0 - 0.5)
AT	FCEV	2050	4.6 (1.2 - 13.1)	11.9 (3.7 - 28.5)	3.9 (1.9 - 7.4)	79.6 (61.1 - 89.5)	0.1 (0.0 - 0.3)

It is clear from Table 2 and Figures 3 and 4 that operational emissions (on-road driving and vehicle

maintenance) dominate life-cycle emissions for all vehicle classes, powertrain categories and years, with average contributions varying from 53% (HCV BEV 2050) to 84% (AT BEV 2019).

In contrast, disposal and recycling make a negligible to small contribution varying on average from 0.03% (MCV ICEV 2050) to 0.63% (HCV BEV 2050). Vehicle manufacturing makes a relatively small contribution to life-cycle emissions from ICEV, on average between approximately 1% to 5%. For BEV and FCEV this is significantly higher in the order of typically 5% to 20%, and 5% to 25%, respectively.

The contribution of infrastructure related emissions to life-cycle emissions is typically small for ICEV with less than 1%, and slightly higher for BEV and FCEV in 2019 (typically 2-3%).

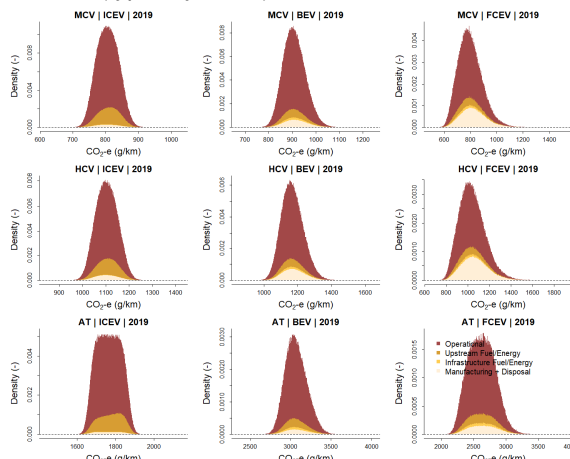


Figure 3. Cumulative life-cycle emission factor distributions including shares of main life-cycle aspects and presented by vehicle class and powertrain category for 2019.

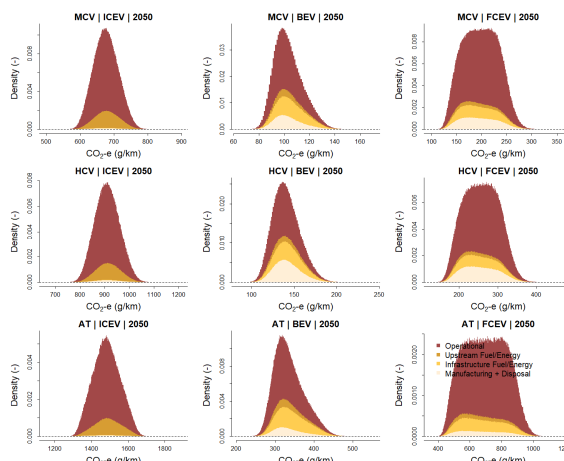


Figure 4. Cumulative life-cycle emission factor distributions including shares of main life-cycle aspects and presented by vehicle class and powertrain category for 2050.

The contribution of infrastructure related emissions for BEV and FCEV increases significantly in 2050 (10-25%), but this shift is mainly caused by a large drop in life-cycle emission rates for these technologies.

Finally, upstream emissions due to the production of fuels and energy make up typically 17% of life-cycle emissions for ICE trucks. For battery electric trucks this is lower with typical contributions of 6 – 9%, and more variable for fuel cell electric hydrogen trucks with typical contributions of 3 – 10%.

3. Sensitivity analysis

Sensitivity analysis (SA) examines how the variation in the output of a model can be apportioned to different sources of variation, and how the given model depends on the information fed into it (Saltelli, Chan and Scott, 2000). The purpose of a sensitivity analysis is to quantify the relative importance and significance of each input variable used in the pLCA simulation. A better understanding of the key inputs provides direction for future research, as well as insight in the most impactful opportunities to improve greenhouse gas emissions performance for different technologies.

There are different ways to conduct a sensitivity analysis, such as graphical, mathematical or statistical methods (Frey and Patil, 2001). A statistical method is used here, which involves running simulations in which inputs are assigned probability distributions and assessing the effect of variance in inputs on the output distribution. Sensitivity of the model results to individual inputs can be evaluated by a variety of techniques and multiple linear regression was used to fit the prediction models.

A variety of techniques were used to ensure a satisfactory fit, including standardisation of input variables, removal of linearly dependent variables, detection and removal of multicollinearity (Variance Inflation Factor - VIF, Hierarchical Cluster Analysis), residual analysis, and the use of performance statistics. The multiple linear regression (MLR) models were then used to assess the impacts of each variable on life-cycle greenhouse gas emissions performance (g CO₂-e/km).

The relative sensitivity (θ , %) is computed as the difference between the variable-specific predictions (P) and the base prediction (B), divided by the base prediction, i.e. $\theta = (P-B)/B$. The base prediction assumes that all predictor variables are at their nominal value. Since the predictor variables are scaled and normalised, the nominal values are zero for all predictor variables, which means that the base prediction equals the model intercept value.

Four values are computed for the variable-specific predictions, using the minimum and maximum

values for the predictor variable of interest, as well as the values reflecting $\pm$ one standard deviation (σ). The first shows the maximum plausible range in the sensitivity, whereas the latter is a more robust and stable estimate of the relative sensitivity.

Tornado plots were then used to visualise the results from the sensitivity analysis. Tornado plots have a number of features. The center of the tornado is plotted at the response expected from the mean of each input variable (base prediction). For a given predictor variable, the width of the tornado is determined by the response to a change in each input variable (MIN, -1σ , $+1\sigma$, MAX), while holding all others constant at their mean value (zero).

Variables are ordered vertically with the widest bar at the top (largest sensitivity) and narrowest at the bottom (smallest sensitivity). The Tornado plot also shows the direction of the impact, where a red arrow pointing up means that an increase in the predictor variable, increases the life-cycle greenhouse gas emissions performance. A green arrow pointing down means that an increase in the predictor variable, decreases the life-cycle greenhouse gas emissions performance. To improve the readability of the tornado plots, predictor variables without statistically significant coefficients ($p > 0.05$) or with an (absolute) relative sensitivity (MIN, MAX) of less than 1% were removed from the plot.

As an example Figure 5 shows the results for battery electric articulated trucks in 2019 and 2050.

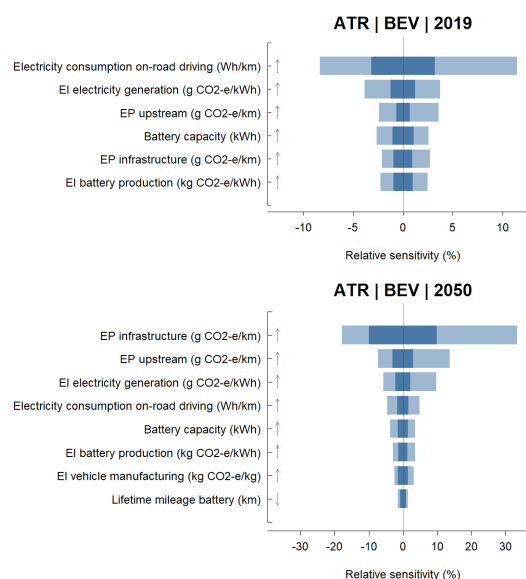


Figure 5. Tornado plots for battery electric trucks in 2019 and 2050.

Fleet average lifecycle greenhouse gas emissions performance of BEVs is sensitive to several variables, showing a complex picture.

In 2019 the largest sensitivity is found for the uncertainty and variability in on-road driving conditions (electricity consumption), but this is no longer the case in 2050 where the life-cycle emissions performance of energy infrastructure shows the largest sensitivity. Energy infrastructure emissions are associated with the construction and retirement of fossil-fuel power plants, facilities involved in fossil fuel processing (such as refineries and fuel storage), hydrogen production and distribution infrastructure, as well as renewable energy sources (including solar plants, wind farms, hydropower facilities, etc.).

In 2019 there are a number of input variables with a sensitivity > 1%, including the emission intensity of electricity generation and associated upstream emissions, battery capacity and the emission intensity of battery and vehicle production, and the life-cycle emissions performance of infrastructure. In 2050, other key inputs are the upstream life-cycle emissions due to electricity generation, the emission intensity of electricity generation, electricity consumption during on-road driving and electric vehicle manufacturing, including battery production and the size (capacity) and durability (lifetime mileage) of the battery systems.

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