Using non-parametric statistical methods to identify suitable fuels for the future of road transport

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Abstract

In 2007, global road transport was responsible for 21% of greenhouse gas emissions. To mitigate their growth from this sector, a number of countries have implemented emissions regulations for vehicles during their operation. Such end-of-pipe legislation may result in a push towards using novel fuels. However, such alternatives have larger ecological impacts in their supply than in their use. Moreover, the breadth of estimates representing a single well-to-tank supply chain have not been distilled into a defensible, representative estimate for policy making. This work addresses the latter omission in the first instance. Further, it quantifies: the degree to which fuel supply pathways and vehicle operation efficiency must increase in the future to meet legislative targets; and the proportion of fuels in a mix which minimizes total ecological impact, respects resource limits and meets the need for energy in transport in the future. Specifically, the best estimate fuel supply emissions impacts must be reduced by a median factor 82% and the process improved to become net negative greenhouse as emitting, while the energy conversion technology must become more efficient by a median 6% when using best in class, state of the art fuel supply pathways. These technological improvements are achievable currently.

Key words: Passenger vehicles, Well-to-wheel, Non-parametric statistics, Emissions policies

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1 Introduction

In 2007, global transport required 96.2 EJ [1], or 28% of the total final consumption of energy [1]. The result was 6.1 Gt greenhouse gases (GHG) emitted, or 21% of all global emissions in that year [2]. Of that, light duty road transport accounted for 40% of global energy use at 38 EJ [3] and 2.6 Gt GHG being emitted[2] [4]. Growth in energy used in road transport is forecast to come from the switch to motorized transport from non-motorized modes in the developing world and the increasing size, mass and power of motorized vehicles in the developed world. The latter development is significant as it has negated the advances made in vehicle fuel efficiency to date [5], [6]. The consequence is a projected 91% increase in road transport energy use from the year 2007 level to 72.7 EJ by mid century [3], with a commensurate increase in GHG emissions to 5.1 Gt over the same period [4]. The energy input to and emissions from a vehicle are functions of the fuel used, its associated supply chain (well-to-tank, WTT), the vehicle design and the operation thereof (tank-to-wheel, TTW). When combined, the WTT and TTW components describe the well-to-wheel (WTW) impacts. The significance of the WTT component of WTW analyses is not generally incorporated into most emissions reductions policies, such as legislation from the European Union [7], the United States [8] and the United Kingdom vehicle excise duty (VED) [3] [9].

In order to reduce WTW energy use and the emissions therefrom, alternative fuels which are used in novel vehicle topologies have been proposed and developed. There have been five main contributions to global WTW analyses, in the works by Concawe [10], General Motors (North America, [11] and Europe [12]), MIT, via [13] and the Greenhouse Gases, Regulated Emissions and Energy Use in Transportation (GREET) model of the US Argonne National Laboratory [14] (Appendix C). These contributions do not represent the sum of work in that area, but constitute the largest and most influential of them and their data and findings have been used extensively in subsequent WTW analyses. Each of these reports comprises a WTT and TTW study. Whereas the studies use different WTT estimates for the impacts of the fuels they consider, the ability to compare study findings with each other is lost on the inclusion of the TTW analysis. Specifically, each study uses a different representative vehicle on which to perform the analysis, a different drive cycle and vehicle performance requirements (Table C.1) and in two cases, vehicle

1 EJ = exaJoules, 10^{18} J.

2 The 2007 value was determined by a linear regression on the 2000-2050 dataset of energy and emissions, yielding correlation coefficients of R^2=0.99 and R^2=0.99, respectively.

3 For updated VED rates, see http://www.vcacarfueldata.org.uk/search/vedSearch.asp.

life cycle impacts [13], [14]. Notwithstanding the TTW discrepancies, these works attribute the majority of impacts of vehicles using novel fuels to the particular WTT supply pathway, moreso than during their TTW operation. Therefore, reducing the energy used in and emissions from vehicles requires an analysis of such fuel pathways. But whereas there is an ever-growing body of research quantifying WTT impacts for a particular fuel, the estimates are often not directly comparable due to the difference in system boundaries used in the analyses. Consequently, results vary considerably. Moreover, the global trade means that fuel which originates from natural resources and is produced in one part of the world may be consumed somewhere else. Therefore, accurate WTT estimates must account for the manner in which the initial resource is extracted, converted to the fuel, where it is consumed and the intermediate transport methods.

WTT estimates usually report fuel impacts in MJ/MJ fuel delivered and g GHG/MJ delivered. However, impacts such as the use of material, land and fresh water are largely unreported or unaddressed when focusing on road transport fuels, as observed in the aforementioned WTW works previously referred to and the majority of works surveyed hereafter. Omitting wider biosphere impacts may lead to problem shifting, where the goal of low carbon transport is pursued at the expense of large-scale fresh water use or land area disturbance, for example. Including such factors requires a broadening of WTT analysis boundaries and the inclusion of new functional units of kg material/MJ, m^2 land area/MJ and m^3 water/MJ fuel delivered. Such an approach will yield a more holistic understanding of the advantages and disadvantages of fuels.

For the purposes of policy development or technical assessment, the broad range of WTT estimates must be distilled to a representative and defensible best estimate. To that end, the scope of WTT estimates of different final fuels may be represented by probability density function estimates of their underlying, true distributions. In statistical methods, data which is assumed to follow a known distribution permits the use of parametric analysis tools for its analysis. However, the underlying distribution of the WTT estimates is unknown, requiring the use of non-parametric statistical tools which utilize the actual data. The histogram is the original density estimator which can asymptotically approximate any distribution as the number of (independent) observations tends to infinity [15]. The shape of any histogram (and the ensuing density function) is linked to the number of bins, m, and their respective width, h. h is chosen to balance bias and variance globally [16]. Specifically, as h increases, m shrinks, the bias is large and the variance small, resulting in an oversmoothed distribution. Conversely, small h leads to a large m, small bias, large variance and undersmoothed distribution [17], [18].

First generation methods to determine optimum h include those advanced by Sturges, Scott, Freedman and Diaconis and Silverman which assume an underlying unimodal Gaussian distribution [17], [18], [19]. Although h is generally chosen such that it minimizes the mean integrated square error (MISE), MISE has been shown to be sub-optimal for multimodal densities [20]. This is on account of the global h being inappropriate for distributions with many features [18]. Moreover, the error mimization techniques of MISE and asymptotic MISE require prior knowledge of the distribution function (which is being sought) and its derivative. Cross-validation (CV) methods are independent of the function and derivative, where the optimal bin count is the minimum CV value over the range of bin count possibilities, from 1 to m [20]. While these methods are the most studied [17] and used [21], [22], they can suffer from too much sample variability [23], [24] on account of large bias [19]. A survey of more sophisticated, second generation bandwidth estimation methods yields the plug-in and bootstrap methods as superior alternatives. These offer a more sensible tradeoff between bias and variability, complete with rates of convergence of $n^{-5/14}$, asymptotic to $n^{-1/2}$. Thus, they surpass the first generation rules-of-thumb and CV approaches which have rates of $n^{-1/10}$ [18], [24]. Of the second generation methods, the Sheather and Jones plug-in method (SJPI) [25] has been shown to achieve the asymptotic best convergence rate and is more computationally efficient than the first generation methods and the second generation bootstrap approach [26], [27]. On account of its practical performance and theoretical properties, SJPI is held as the state of the art [27]. However, plug-in methods use pilot estimates for h which are based on a number of prior assumptions about the true h and density. Consequently, if the assumptions fail, the estimate is expected to be poor [27], [28].

True probability density estimates must be differentiable across their entire range. Therefore, the use of continuous functions to divide the data has been proposed by way of kernel density estimators, where the continuous properties of the kernels extend to the overall, emergent probability distribution. Kernel density estimators outperform histograms in both their ability to converge to a distribution faster and use fewer data points [17], may be symmetric or asymmetric and assume a host of functionswith common distributions including uniform, triangle, Epanechnikov, Gaussian and Gamma [18]. They are generally centred on each data point, with the overall density estimate taken as the superposition of kernel heights.

Whereas the underlying message hitherto is that the choice of h is more important than that of kernel [17], [18], [19], the closeness of the estimated distribution to the true is ultimately more important than the estimated h to its true value [28]. Fixed (first and second generation) bandwidth approaches fails to account for the changes in data density [29]. Given that the detail of the underlying distribution emerges as a result of h (and associated data points within a bin), variable bandwidth or adaptive kernel estimators have been proposed. One example is the k^{th} nearest neighbour estimator, some-times called the balloon estimator. However, such balloons only perform well at greater than four dimensions [16] and can have discontinuous derivatives, rendering the method inappropriate for continuous density estimation [30]. Instead, sample point estimation is used, where the kernel is individual in size and orientation based on the observed data and is shown to model more complex, multimodal densities better [16]. Adaptive density estimation refers to the local smoothing to yield an improved, global estimate [31]. Kernel density estimators can be biased near to the boundary or end point rather than the interior. This is known as the boundary bias or edge effect [19],[21] which fixed, symmetric kernels with boundary supports suffer from. Thus, kernels which do not assign weight outside of the support are proposed. In particular, the Gamma kernel is free of boundary bias, always non-negative, obtains optimal convergence rate of the MISE and accommodates sparse areas in the distribution well [21]. Another approach to reducing boundary effects is by data sharpening, where data is moved from areas where it is sparse to those where the density is higher [19].

In summary, delivering 1 MJ of fuel via a pathway to the vehicle tank influences the overall emissions of the vehicle through its use. However, many policies fail to account for this aspect of the WTW performance, focusing instead on the TTW emissions only. This omission is significant as the novel fuels being proposed to address the GHG emissions from road transport have WTT impacts which overshadow those which occur in the TTW phase. The broad range of WTT impact estimates of delivering 1 MJ of fuel across various pathways and functional units, encompassing the range of resource countries of origin and transport distance and methods are consolidated. However, as the underlying distribution of estimates is unknown, non-parametric density estimation based on Gaussian sample point kernel density estimators is used. The results of this novel and transparent approach are representative WTT estimates based on the highest probability and best-in-class measures for both the entire estimate and each pathway. The best-in-class estimate represents the current state of the art by the lowest GHG emissions. Therefore, this work addresses the aforementioned policy omission and the corresponding gap in the knowledge by combining TTW performance with a defensible and representative WTT value for the corresponding fuel and pathway. Such global summary estimates are expected to complement existing TTW policy measures with a view to assessing the extent that novel fuels may mitigate GHG from global road transportation.

2 Method

A scatter plot of independent WTT estimates across the novel fuelsbiodiesel, biogas, diesel, dimethyl ether (DME), electricity, hydrogen, liquefied natural gas (LNG), liquefied petroleum gas (LPG), methanol, naphtha, natural gas, petrol and synthetic dieselillustrates the range values, demarked by ellipses [32] (Figure 1). The set of data used to construct Figure 1 does not represent every study available as many of them refer to the works already included here. The fuels chosen for analysis mirror those presented in Concawe [10] as it is both the most recent of the large WTW works and set in Europe. To that end, there are WTT estimates which are not included in this work, but to which the method hereafter described may be easily applied.

Fig. 1. Scatter of MJ and emitted g GHG when delivering 1 MJ fuel, across all studies and pathways ([10],[11],[12],[13],[14],[33],[34],[35],[36],[37],[38],[39],[40],[41],[42],[43],[44],[45]). Key: Crosses: dark blue, biodiesel; red, diesel; light blue, DME; purple, electricity; yellow, ethanol; and dark grey, hydrogen. Plus signs: dark green, LPG; red, methanol; light blue, naphtha; purple, natural gas; yellow, petrol; and dark grey, synthetic diesel.

Notably, the spread of possible alternative fuel WTT estimates varies greatly, relative to the incumbent petrol and diesel (Figure 2), cementing support of the need for defensible estimates.

To that end, a non-parametric approach to obtaining the density estimate of

Concawe is due to release updated fuel estimates, however they were not available to the public up to the time of submitting this work.

Fig. 2. Scatter of MJ and emitted g GHG when delivering 1 MJ fuel, across all studies and pathways ([10],[11],[12],[13],[14],[33],[34],[35],[36],[37],[38],[39],[40],[41],[42],[43],[44],[45]). Key: Crosses: red, diesel. Plus signs: yellow, petrol; with all other estimates given in dark grey.

the underlying distribution is used. The method proceeds by:

- testing for independence between the estimates, as a prerequisite for probability density estimation using the x^2 test with a threshold of $p > 0, 5$;
- formulating bandwidth estimates using first generation methods of oversmoothing and least squares CV, the second generation SJPI and the adaptive kernel density estimator;
- applying a Gaussian to each MJ/MJ estimate of fuel, j, delivered across all pathways, i using the various h estimates; and
- repeating the above steps for each pathway, i.

h was determined individually for each dimension in the n x 2 data vector of g GHG/MJ and MJ/MJ estimates and later combined to yield the two dimensional density estimate. The algorithms were implemented in Matlab.

(1) For the oversmoothed estimator, h_{o5} is given by:

$$h_{o5} = 1.144 * data\ iqr * n^{-1/5} \tag{1}$$

where data iqr is the interquartile range of the data and n is the number of data points.

(2) The SJPI method was given in [46] [5] to yield h_{sjpi}.

(3) The adaptive kernel estimator followed the procedure given in [29] to:

(a) Split the data into a large number of evenly spaced bins, m bins (100 was chosen here), noting the frequency and bin position,

(b) Determine the number of bins with nonzero frequencies. That is, disregard empty bins to yield a new upper bin count, m unique < m bins:

(c) Perform leave-on-out least squares CV by iterating through the number of bins from 1 to m unique=m. h_{binned} is chosen corresponding to the minimum value of the CV. The least squares CV is calculated in three parts, given as f1, f2 and f3:

$$f1(i) = \frac{1}{n^2} \sum_{i=1}^{m} \sum_{j=1}^{n} freq1(i)^2.[G(t(i), h(i), c) * G(t(i), h(i), c)] \quad (2)$$

where:

- n is the number of estimates in the data vector;
- freq1 (i) is the frequency count of estimates in bin i;
- c= [min x-2*max h, max x+2*max h], incremented by (max x+ 2* max h − min x −2 * max h)/vec length where vec length = 10;
- max $\underline{x}$, min $\underline{x}$, max $\underline{h}$, min $\underline{h}$ are the maximum values of data and h, where h(i) = data range/i and data range = max x − min x;
- * represents a two dimensional convolution;
- t(i) is the mid-point of the bin i; and
- G is a univariate Gaussian function with μ=0, σ = h.

$$f2(i) = \frac{1}{n^2} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{m} n_i.n_k.[G(t(i), h(i), c) * G(t(k), h(k), c)] \quad (3)$$

where $n_i.n_k = freq1(i).freq1(k) \; \forall i \neq k$, 0 otherwise.

$$f3(i) = \frac{-2}{n(n-1)} \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{m} n_{ik}.G(t(i), h(i), c); \quad (4)$$

where $n_{ik} = freq1(i) \; \forall i \neq k$, $n_{ik} = freq1(i) - 1$ otherwise.

(d) Determine the least squares CV value, lsqcv by summing f1, f2 and f3:

$$lsqcv(i) = f1(i) + f2(i) + f3(i); \quad (5)$$

[5] An m-file implementation of this method is available at http://www.mathworks.com/matlabcentral/fileexchange/22999.

(e) Choose optimum bin = m(min(lsqcv)) and corresponding bandwidths for bins 1 to optimum bin.

(f) Apply this vector of h_{adap} of length 1 to optimum bin to the data by matching smallest $h_{adap}(i)$ to bin with highest frequency, in decreasing order and apply $h_{adap}(i)$ to all estimates in the same bin, i.

(g) Calculate density estimate

$$f_{adap}(i) = \sum_{i=1}^{\text{optimum bin}} \sum_{j=1}^{\text{freq}(i)} G(t(i), h(i), c); \quad (6)$$

(4) The least squares CV used the routine given in Equations 2-5.

(5) The bandwidths from each estimation method for each dimension of the data were used in a bivariate Gaussian[5] function to determine the probability distribution.

(6) The values in each dimension corresponding to the indices of the highest probability were chosen as the best estimate values.

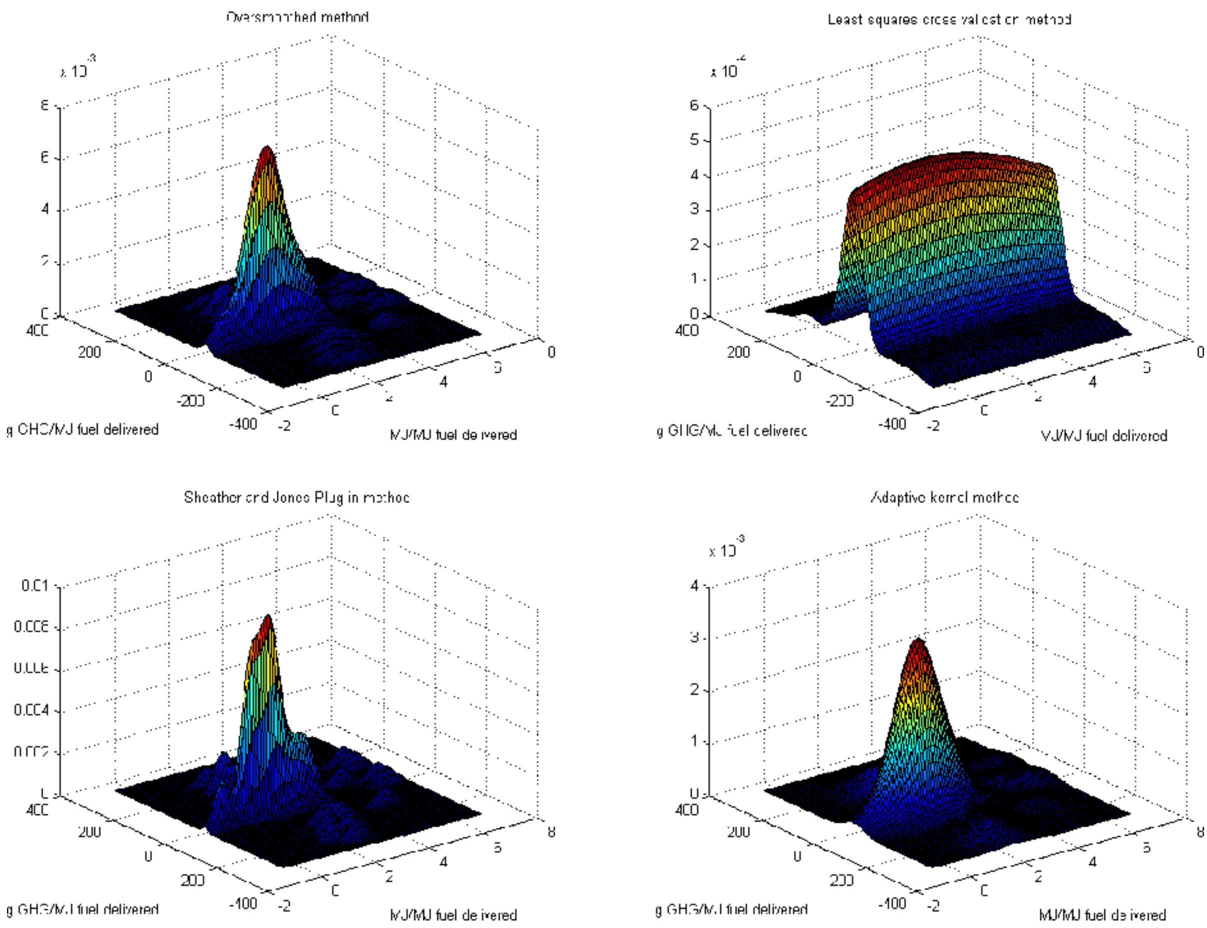
(7) The best in class g GHG/MJ estimate was chosen as the data vector entry with the smallest g GHG/MJ impact and corresponding MJ/MJ value.

3 Results

The work focused on near term European emissions legislation, to be imposed in the UK. Where multiple pathways were available to deliver a fuel, the analysis was performed both on all estimates (designated “All”) and by pathway. The best-in-class GHG estimate was chosen to represent the state of the art across all estimates and by pathway, with its associated MJ/MJ energy penalty. Estimates for the biofuel/fossil-fuel blends were calculated by combining the WTT impact of each individual neat fuels with the proportion of each neat fuel in the mix by volume (Tables 1 and 2).

Estimates using the oversmoothed, least squares CV and SJPI methods are available in Appendix A (Tables A.1 and A.2). Using median values, the errors between the adaptive method, as the central value and the other approaches were 8%, 0% and 14%, respectively (Tables A.3 and A.4). However, in some cases, there was up to a factor 7 difference between the central estimate and the ones determined by the other methods.

Fig. 3. Density estimation of electricity generated via biomass pathways using a)



oversmoothed; b) least squares CV; c) the SJPI approach and d) adaptive kernels.

4 Discussion

In order to achieve the legislative targets on a WTW basis, the WTT emissions in the fuel supply chains must be sufficiently low that, when combined with TTW operations emissions, the upper policy limit is respected. In cases where carbon dioxide (CO_2) is reported, it is upgraded to GHG in the analysis. In Europe, manufacturer-fleet average CO_2 emissions has decreased from 166 g CO_2/km in 2002 [47] to 154 g CO_2/km in 2008 [48]. When combined with the aforementioned 2020 target of 95 g/km [7], an emissions trajectory for new car emissions in Europe can be constructed (Figure 4).

Compared with the European 2020 target, in 2008 the UK independently committed itself to reducing its emissions by 80%, relative to 1990 levels, by 2050 [49]. Linear extrapolations of UK passenger car fleet and vehicle kilometres

Table 1

Best WTT estimates based on adaptive kernel sample point density estimator and best in class GHG estimate with associated energy penalty (Table 1 of 2).

Fuel	Pathway	Best	estimate	Probability	Best	in class
		MJ/MJ	g GHG/MJ		g GHG/MJ	Associated MJ
Petrol	Crude	0.42	15.80	0.021	8.70	0.13
Diesel	Crude	0.62	12.60	0.016	5.43	0.15
Naphtha	Crude	0.28	15.22	0.0052	-60.29	-0.88
Natural gas	Crude	0.25	15.06	0.011	7.56	0.064
LPG	Crude	0.14	8.36	0.023	2.53	0.070
Ethanol	All	1.30	33.73	0.00070	-76.36	1.09
	Wheat	1.31	45.18	0.011	5.39	1.86
	Sugar cane	1.06	21.33	0.0019	9.80	0.00
	Sugar beet	1.28	13.80	0.0018	-70.30	3.59
	Wood	1.85	20.69	0.010	-13.46	1.43
	Maize	0.80	37.62	0.0030	-7.18	0.69
Biodiesel	All	1.09	36.73	0.011	-67.40	0.94
	Rape seed	0.82	42.04	0.0055	-65.20	0.77
	Sunflower seed	0.95	32.04	0.0056	11.40	0.58
	Soy bean	0.92	29.94	0.0017	13.57	0.72
	Wood	1.21	14.20	0.0026	-67.40	0.94
	Biomass	1.08	4.74	0.037	2.40	0.91
	Palm oil	1.31	47.91	0.0075	19.20	1.30
Synthetic diesel	All	0.79	27.58	0.0016	-60.45	-0.88
	CtL	0.84	28.31	0.0062	19.30	0.57
	GtL	0.72	27.06	0.015	-60.45	-0.88
DME	All	0.74	16.96	0.0018	-58.51	1.00
	Biomass	0.88	5.06	0.014	-58.51	1.00
	Fossil	0.58	26.38	0.0019	-54.57	-0.87

travelled in 1990-2007 to 2050[6] [50] yield a forecast passenger vehicle fleet

6 Passenger vehicle fleet and vehicle kilometres travelled in 1990 were 20 million vehicles and 336 billion km, respectively. Applying linear regression to both datasets yielded correlation coefficients of 0.99 each and an annual percentage increase over

Table 2

Best WTT estimates based on adaptive kernel sample point density estimator and best in class GHG estimate with associated energy penalty (Table 2 of 2).

Fuel	Pathway	Best MJ/MJ	estimate g GHG/MJ	Probability	Best g GHG/MJ	in class Associated MJ
Methanol	All	0.63	19.25	0.0057	-159.76	-0.67
	Biomass	0.74	2.74	0.00080	-100.01	2.28
	Fossil	0.63	28.18	0.016	-56.19	-0.87
Hydrogen	All	1.41	115.25	0.00020	0.00	0.66
	Gasification	1.23	30.76	0.00030	6.60	1.37
	Electrolysis	2.76	210.17	0.0014	0.00	0.66
	Steam reforming	1.00	121.83	0.0013	33.10	0.69
Electricity	All	1.36	17.58	0.00050	-243.70	2.74
	Fossil	1.36	135.30	0.0012	30.10	1.55
	Combustible renewables	1.98	15.93	0.0033	-243.70	2.74
	Nuclear	2.34	8.85	0.0032	2.23	2.05
	Mix	1.58	137.75	0.000047	62.03	0.56
	Non-combustible renewables	1.17	20.95	0.0046	0.00	0.030
Petrol/ Ethanol 95/5	Crude + All	0.46	16.70	-	4.45	0.18
	Wheat	0.46	17.27	-	8.53	0.22
	Sugar cane	0.45	16.08	-	8.76	0.13
	Sugar beet	0.46	15.70	-	4.75	0.30
	Wood	0.49	16.05	-	7.59	0.20
	Maize	0.44	16.89	-	7.91	0.16
Diesel/ Biodiesel 95/5	Crude + All	0.64	13.81	-	1.79	0.19
	Rape seed	0.63	14.07	-	1.90	0.18
	Sunflower seed	0.63	13.57	-	5.73	0.17
	Soy bean	0.63	13.47	-	5.84	0.18
	Wood	0.65	12.68	-	1.79	0.19
	Biomass	0.64	12.21	-	5.28	0.19
	Palm oil	0.65	14.37	-	6.12	0.20

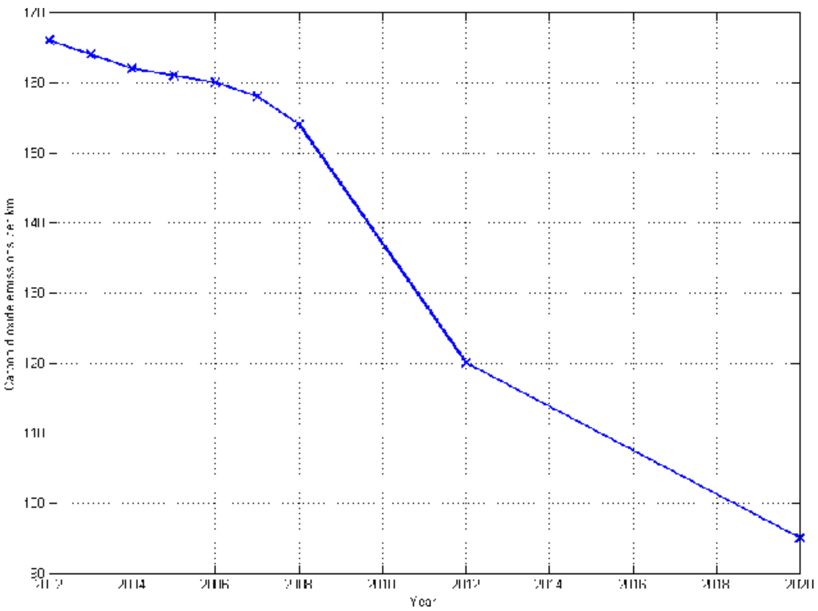


Fig. 4. Composite emissions trajectory (g CO_2/km) for new car emissions in Europe based on historical manufacturer-fleet average [47],[48] and new regulations [7].

and vehicle kilometres travelled of 47 million vehicles and 608 billion km, respectively. In 1990, 73 Mt GHG were emitted from passenger vehicles in the UK [51]. Combining forecast total distance travelled with the assumption that each economic sector must engage in its fair share of the 80% reduction target, the passenger vehicle fleet emissions cap will be 15 Mt GHG, normalized to 24 g GHG/km in 2050, or a factor 7 reduction of emissions relative to 2003 levels[7] [52]. For emphasis, 24 g GHG/km represents the overall WTW emissions as the upper GHG limit imposed by the legislation is assumed to be independent of source (supply pathway or operation).

A review of the best and best in class estimates of WTT fuels and pathways yielded insights into the components of a future fuel mix, notwithstanding any improvements in the ability of vehicles to convert fuel consumed into distance travelled. In particular, not only did the number of final fuels increase, but also the number of sources which fed the fuels' respective pathways. The sources were diversified from the fossil-fuel dominated to include natural gas, farmed biomass and wind-, nuclear- and coal-powered electricity generation. The main difference between the best and best in class estimates was that the latter used waste and byproducts, such as residual straw or flare gas, instead of the primary process output (Table 3). To this end, whereas the GHG penalties were greatly reduced, the resource potential of the byproducts

1990 levels by 0.14% and 0.08% respectively.

7 In 2003, the average emissions per car in the UK was 172.6 g CO_2/km [52].

was lower (Tables B.1, B.2 and B.3 compared with Tables B.4, B.5 and B.6).

Combining the near term EU emissions targets (upgraded from 120 g CO_2/km to 120 g GHG/km), the 2010 advanced vehicle topology performance simulations advanced by Concawe [10] – representing the current and near future state of the artand the best and best in class estimates from the preceding method yielded a short list of suitable pathway/fuel/conversion options (Tables 4-6). Specifically, it was assumed that all Concawe 2010 technologies were available in 2012 at the reported performance levels and fuels used possessed the reported carbon content. The TTW MJ/100 km performance was combined with the carbon content in the fuel in g CO_2/MJ (upgraded to g GHG/MJ) over 100 km. The WTT g GHG/km target became the difference between the TTW emissions per kilometre and the EU 2012 limit of 120 g GHG/km. The WTT target of g GHG/MJ fuel delivered was obtained from the WTT g GHG/km target and the aforementioned efficiency of TTW fuel use in MJ/100 km.

Notably, of the 89 unique fuel/pathway combinations assessed, the best in class estimates provided 51 options which meet the emissions requirement, or 57% of the total. Conversely, the best estimates yielded only 25 viable pathways, representing 28% of the total considered. In general, the European fleet average emissions target was met by using hybridized direct injection compression ignition (DICI), port injected spark ignition (PISI) engines and fuel cells (FC), conventional and hybridized. Of the conventional fuels, diesel remained a viable option, either neat or blended, only when paired with a hybridized powertrain, while petrol was eliminated from the mix. Bioethanol is only viable along two pathways when the state of the art WTT estimates are used: sugar beet and wood. Similarly, whereas biodiesel is only feasible if the best in class WTT estimates are used, there are more pathway options from which to derive the fuel – rape seed, sunflower seed, soy bean, wood and biomass. Best in class estimates of providing synthetic diesel, DME, methanol and hydrogen allow all pathways to be utilized. However, the best estimates of these fuels are more restrictive, excluding synthetic diesel and only permitting the use of biomass for the methanol resource and gasification of woody biomass and steam reforming of natural gas for hydrogen.

By decomposing the WTW chain into WTT and TTW performance, the gap between the target WTW emissions and simulated fuel/pathway/vehicle performance may be analyzed. Whereas there was a constant value for each WTT fuel/pathway, when it was combined with the actual conversion technology, the discrepancy between WTW target and the WTT value became variable. Therefore, to keep the complete set of conversion technologies in the mix, there was a range of performances for the WTT estimates to meet (Table 7). The improvements outlined reflect the worst case such that if the WTT impacts could be reduced by the factors outlined, they could be used in all conver-

Table 3

Comparison of fuel sources and use of primary and byproducts in fuel production for best and best in class estimates.

Source	Fuel	Best estimate	Best in class
Crude oil	Petrol Diesel Naphtha LPG	Product Product Product Product	Product Product Product
Natural gas	Naphtha Natural gas Synthetic diesel Methanol DME Hydrogen Electricity	Product Product Product Product Product Product	Flare gas Product Flare gas Landfill gas Flare gas Biogas Product
Coal	Synthetic diesel Hydrogen Electricity	Product Product Product	Product
Biomass Nuclear Wind Solar thermal Mix	Ethanol Biodiesel DME Methanol Hydrogen Electricity Electricity Electricity Hydrogen Electricity Electricity	Product Sugar beet product Sugar cane Wood Corn Rape seed Sunflower Soy bean Wood product Palm oil Wood Residual Wood Wood product Product Product Product	Residual wheat straw Sugar beet byproduct product product product product seed product product Residual, waste wood product product wood product Liquid manure Product Product Product Product

Table 4
Shortlist (Table 1 of 3) of fuel pathways and energy conversion technologies which meet the EU 2012 new car emissions targets [7] using 2010 performance forecast by Concawe [10]. DICI = direct injection compression ignition; FC = fuel cell; PISI = port injection spark ignition; and DISI = direct injection spark ignition.

Fuel	Pathway	Conversion	WTT target	Best estimate	Best in class
Diesel	Crude	DICI, 1,9 l hybrid	11.80	-	5.43
	Crude	DICI, 1,6 l hybrid	19.77	12.60	5.43
Naphtha	Crude	Reformer + FC, hybrid	2.67	-	-60.29
Natural gas	Crude	PISI, Hybrid	29.84	15.06	7.56
Ethanol	Sugar beet	DISI	-7.52	-	-70.30
	Wood	DISI	-7.52	-	-13.46
Biodiesel	Rape seed	DICI	-3.81	-	-65.20
	Wood	DICI	-3.81	-	-67.40
	Rape seed	DICI, hybrid	14.00	-	-65.20
	Sunflower seed	DICI, hybrid	14.00	-	11.40
	Soy bean	DICI, hybrid	14.00	-	13.57
	Wood	DICI, hybrid	14.00	-	-67.40
	Biomass	DICI, hybrid	14.00	4.74	2.40
Synthetic diesel	GtL	DICI	1.62	-	-60.45
	CtL	DICI, hybrid	19.43	-	19.30
	GtL	DICI, hybrid	19.43	-	-60.45
DME	Biomass	DICI	7.13	5.06	-58.51
	Fossil	DICI	7.13	-	-54.57
	Biomass	DICI, hybrid	25.66	5.06	-58.51
	Fossil	DICI, hybrid	25.66	24.05	-54.57

sion technologies to meet the WTW target. In some cases, the target WTT g GHG/MJ was negative, indicating that the fuel needed both to reduce its absolute value and its production process had to change to yield net negative GHG emissions.

Using the best estimates, the g GHG/MJ efficiency of all fuels needed to be improved. The supply of natural gas required the least improvements with a 1.01, while supplying synthetic diesel required a factor 16 improvement in

Table 5
Shortlist (Table 2 of 3) of fuel pathways and energy conversion technologies which meet the EU 2012 new car emissions targets [7] using 2010 performance forecast by Concawe [10]. DICI = direct injection compression ignition; FC = fuel cell; PISI = port injection spark ignition; and DISI = direct injection spark ignition.

Fuel	Pathway	Conversion	WTT target	Best estimate	Best in class
Methanol	Biomass	Reformer + FC, hybrid	11.98	2.74	-100.01
	Fossil	Reformer + FC, hybrid	11.98	-	-56.19
Hydrogen, liquid	Gasification	PISI	71.64	30.76	6.60
	Electrolysis	PISI	71.64	-	0.00
	Steam reforming	PISI	71.64	-	33.10
	Gasification	PISI, hybrid	84.87	30.76	6.60
	Electrolysis	PISI, hybrid	84.87	-	0.00
	Steam reforming	PISI, hybrid	84.87	-	33.10
	Gasification	FC	127.66	30.76	6.60
	Electrolysis	FC	127.66	-	0.00
	Steam reforming	FC	127.66	121.83	33.10
	Gasification	FC, hybrid	143.37	30.76	6.60
	Electrolysis	FC, hybrid	143.37	-	0.00
	Steam reforming	FC, hybrid	143.37	121.83	33.10

the worst case, with a median improvement of factor -82% required across all fuels, indicating an 82% drop in the absolute g GHG/MJ and a shift in the production process to achieve net negative GHG emissions. The fuels which needed to achieve negative WTT performance were petrol, diesel, LPG, ethanol, biodiesel and the petrol and diesel blends with biofuels. The best in class estimates for supplying naphtha, DME, methanol and hydrogen required no improvements to meet the overall WTW target, while the same fuels which had negative factors for the best estimates were negative for the best in class case, albeit with smaller absolute values. Of the estimates which did not meet the WTW target, natural gas required the minimum improvement of 1% and synthetic diesel at factor 11, while the median improvement was -2 times.

An alternative to meeting the WTW target through fuel supply efficiency increases was to fix the WTT performance at the best-in-class values and improve the energy conversion TTW phase. Again, the maximum necessary

Table 6
Shortlist (Table 3 of 3) of fuel pathways and energy conversion technologies which meet the EU 2012 new car emissions targets [7] using 2010 performance forecast by Concawe [10]. DICI = direct injection compression ignition; FC = fuel cell; PISI = port injection spark ignition; and DISI = direct injection spark ignition.

Fuel	Pathway	Conversion	WTT target	Best estimate	Best in class
Hydrogen,	Gasification	PISI	71.64	30.76	6.60
compressed	Electrolysis	PISI	71.64	-	0.00
	Steam reforming	PISI	71.64	-	33.10
	Gasification	PISI, hybrid	80.81	30.76	6.60
	Electrolysis	PISI, hybrid	80.81	-	0.00
	Steam reforming	PISI, hybrid	80.81	-	33.10
	Gasification	FC	127.66	30.76	6.60
	Electrolysis	FC	127.66	-	0.00
	Steam reforming	FC	127.66	121.83	33.10
	Gasification	FC, hybrid	143.37	30.76	6.60
	Electrolysis	FC, hybrid	143.37	-	0.00
	Steam reforming	FC, hybrid	143.37	121.83	33.10
Diesel/	Rape seed	DICI, hybrid	16.84	13.81	1.90
biodiesel 95/5	Sunflower seed	DICI, hybrid	16.84	14.07	5.73
	Soy bean	DICI, hybrid	16.84	13.57	5.84
	Wood	DICI, hybrid	16.84	12.68	1.79
	Biomass	DICI, hybrid	16.84	12.21	5.28
	Palm oil	DICI, hybrid	16.84	14.37	6.12

efficiency was used. FCs already operate at the required efficiency, while the MJ/100 km efficiency of the DISI, hybrid must improve by 6% in the best case and 30% DICI engines in the worst case. The median required improvement was 6% (Table 8).

TTW vehicle performance may be improved by efficiency gains in both the engine/energy conversion system and the characteristics of the vehicle itself, such as aerodynamics and tires. Non-hybridized drivetrains can benefit from engine operation efficiency improvements of 0.5-25%, with variable valve timing as the largest contributor. Non-engine advances can contribute 0.5-13%, dominated by lightweighting [6]. Hybridization adds 15-18% improvements to petrol and diesel engines. Consequently, there is flexibility in existing engine and non-engine technology options to increase TTW efficiency to meet and

Table 7

Maximum factor fuel improvements required from the best estimates and best in class in order to meet the WTT target, holding TTW performance fixed. Negative values indicate fuel needs to reduce by both the absolute factor and have negative net GHG emissions in its supply pathway.

Fuel	Best estimate	Best in class estimate
Petrol	-2.66	-1.91
Diesel	-16.18	-7.54
Naphtha	4.70	-
Natural gas	1.01	0.01
LPG	-4.31	-2.00
Ethanol	-7.01	-2.30
Biodiesel	-13.57	-6.04
Synthetic diesel	16.47	10.91
DME	2.70	-
Methanol	1.35	-
Hydrogen, liquid	1.93	-
Hydrogen, comp	1.93	-
Petrol, Ethanol 95/5	-2.66	-1.84
Diesel, biodiesel 95/5	-15.81	-7.31
Minimum	-16.18	-7.54
Median	-0.82	-2.00
Maximum	16.47	10.91

surpass the WTW target. This suggests that vehicle technology improvements may yield larger gains for smaller effort, relative to improving the WTT fuel impacts in general, and those of the fuels requiring negative factor changes in particular. However, as the emissions regulations become more strict in time, the limits to what engine and non-engine technological improvements can do will be met. As such, neither the scope for WTT improvements nor the challenges with which such improvements can be achieved should be disregarded, as these issues may need to be resolved in future.

The total energy requirement of the UK passenger vehicle fleet in 2012 was assumed bounded by the best and worst energy conversion technologies. In the best case, if all new cars were FC hybrids using compressed hydrogen, 84 MJ would be required to drive 100 km using the Concawe vehicle. Conversely, all cars using ethanol in a direct injection spark ignition (DISI) engine would

Table 8

Minimum, median and maximum percentage improvements required in TTW conversion efficiency with best in class WTT estimates to meet WTW target.

Energy conversion technology	Necessary % improvement
DISI	25.78
DISI 1,6 l hybrid	11.53
DISI, 1,3 l hybrid	5.74
Reformer + FC, hybrid	11.16
DICI	30.18
PISI	7.69
PISI, hybrid	-
FC	-
FC, hybrid	-
Minimum	0.00
Median	5.74
Maximum	30.18

require 188 MJ per 100 km in the worst case. Therefore, at the fleet level, there would be an energy requirement of 4-8 e^{11} MJ or 8-17 Mt motor spirit equivalent [8] to deliver the forecast 433 billion vehicle kilometres to be driven in 2012. Repeating the earlier linear projection analysis ($R^2 = -0.85$) with respect to consumed fuel suggested 21 Mt motor spirit equivalent would be used in 2012.

Recall the assertion that focusing on emissions only may lead to problem shifting. The concepts of material and space input per unit service (MIPS [54] and SIPS [55]) were introduced to account for the use of natural resources (material and water) and land in the provision of each MJ of fuel. The combination of MIPS, SIPS and GHG impacts cover the aggregate categories of the Ecoindicator 99 and recently updated Recipe metrics for assessing life cycle impact [56]. The two MIPS measures are expressed in kg material/MJ and kg water/MJ, while the SIPS indicator assesses m^2/MJ fuel delivered.

DISCUSS MIPS AND SIPS REFERRING TO SCATTER PLOT TO EMPHASIZE IMPORTANCE.

Whereas each of the shortlisted fuels at least met the 2012 emissions targets, inspection of their wider MIPS and SIPS impacts introduced a more holistic basis for their differentiation. Moreover, accounting for the suite of new fuels

8 Use 47.1 GJ/t motor spirit [53].

sharing common parent resources raised the awareness of resource potentials. In combination, the tensions represented by GHG penalties, energy use, MIPS, SIPS, upper resource potentials and the desire to satisfy total energy demands suggested the need to optimize the proportion of different fuel types, resources and pathways in the final mix.

In the first instance, the best estimates were used (with resource potentials given in Tables B.1 and B.2) with their corresponding representative pathways. Here, the representative pathway was that with the minimum absolute error between the g GHG/MJ of each data point and that of the best estimate), while the best in class estimates were used to show the fuel mix at the limit of its performance, based on the current state of the art (Tables B.4 and B.5). The optimization set out to:

$$\text{minimize} \sum_{i}^{n} (ghg_i + mj_i + mips_i + water_i + sips_i) * x_i \tag{7}$$

where i represents the i^{th} short listed unique fuel-pathway combination; ghg_i, mj_i, $mips_i$ and $sips_i$ represent the g GHG, MJ, kg material, kg water, m2 required to deliver 1 MJ of the i^{th} fuel to the tank; and x_i is the MJ supplied of each fuel i.

Subject to:

- All fractions sum to 1;

$$\frac{1}{t} \sum_{i}^{n} x_i = 1; \tag{8}$$

  where t is the total energy required by the UK passenger vehicle fleet.

- Each fuel fraction lies between 0 and and its upper resource potential, inclusive

$$0 \leq x_i \leq max\, mj_i \quad \forall i = 1, \ldots, n \tag{9}$$

  where max mj_i is the upper resource energy potential in MJ per year for each fuel, i.

5 Conclusions

Fossil-fuel use in road transport accounted for 21% of global GHG emissions in 2007. To mitigate the emissions from a growing road transport sector, countries have implemented emissions standards for their passenger vehicle fleets which focus on the operational phase only. Thus, they disregard both the WTT energy and emissions impacts and the wider sustainability issues surrounding the use of land, water and natural resources. Simultaneously, there are many studies which advance estimates of WTT impacts of various fuels and delivery pathways, but there is no defensible, representative value that could be used to drive emissions policy in a holistic, WTW manner.

This work has applied advanced, non-parametric statistical methods to the wealth of WTT estimates for the range of fuels proposed in the Concawe report, as the most recent large WTW work set in Europe. Estimates of fuel WTT impacts were chosen based on highest probability when using the adaptive kernel density estimator. The estimate with the lowest g GHG/MJ represented the best in class and state of the art. Analysis of the fuels was based on the conventional function groups of g GHG/MJ and MJ/MJ and the wider holistic MIPS and SIPS metrics of kg material/MJ, kg water/MJ and m^2/MJ, respectively.

The introduction of new fuels led to the consideration of new production pathways, derived from a small set of primary resources. When the TTW operation of 2010 energy conversion technology and European upper legislative limits of 120 g CO_2/km in 2012 were combined, the necessary WTT performance of fuels was quantified and a short list of fit for purpose fuels emerged. Of the 89 unique fuel estimates, only 25 pathways were viable for the best estimates and 51 for the best in class. These centred around the use of diesel, natural gas, biomass and biodiesel and bioethanol fuel crops. Improving WTW performance to allow all fuels into the mix required a median factor 82% improvement in absolute value and a change in process to ensure net negative GHG emissions. Conversely, a median 6% improvement in TTW efficiency was necessary if all state of the art fuels were to be used, which is achievable with current technology. Moreover, vehicle technology improvements may be easier to attain relative to the necessary changes in WTT fuel pathways, though the challenges surrounding the latter should not be disregarded.

The tradeoffs in WTT impacts across the functional groups coupled with a small set of shared primary resources suggests an optimum mix of fuels for the transport sector, which minimizes total ecological impacts, subscribes to the primary resource limits and meets a forecast total transport energy need of $8e^{11}$ MJ in 2012.

Table A.1. Best WTT estimates based on oversmoothed, least squares CV and SJPI methods (Table 1 of 2).

Fuel	Pathway	Oversmoothed		Least squares CV		SJPI	
		MJ/MJ	g GHG/MJ	MJ/MJ	g GHG/MJ	MJ/MJ	g GHG/MJ
Petrol	Crude	0.06	5.43	0.21	15.63	0.21	15.96
Diesel	Crude	1.15	12.13	1.24	16.46	1.14	12.13
Naphtha	Crude	0.24	14.07	0.24	12.93	0.12	9.48
Natural gas	Crude	0.15	12.97	0.18	15.06	0.16	13.24
LPG	Crude	0.12	7.92	0.12	8.14	0.12	7.92
Ethanol	All	1.01	2.32	1.12	2.32	0.96	2.05
	Wheat	1.05	4.00	0.91	40.99	1.15	4.92
	Sugar cane	0.63	1.89	1.01	2.05	0.15	1.73
	Sugar beet	1.25	1.38	1.25	2.36	1.28	2.56
	Wood	1.93	19.44	1.85	20.69	1.93	18.82
	Maize	0.75	28.88	0.77	28.88	0.78	20.14
Biodiesel	All	1.09	39.29	0.96	39.29	1.09	39.29
	Rape seed	0.96	43.90	0.82	42.04	1.07	42.04
	Sunflower seed	0.94	29.43	0.92	29.43	0.93	28.57
	Soy bean	1.50	44.06	1.32	42.12	0.48	33.36
	Wood	0.89	721.67	1.24	16.69	0.70	113.86
	Biomass	1.10	4.537	1.08	4.74	1.14	5.13
	Palm	1.32	49.43	1.32	47.91	1.32	47.91

Table A.2. Best WTT estimates based on oversmoothed, least squares CV and SJPI methods (Table 2 of 2).

Fuel	Pathway	Oversmoothed		Least squares CV		SJPI	
		MJ/MJ	g GHG/MJ	MJ/MJ	g GHG/MJ	MJ/MJ	g GHG/MJ
Synthetic diesel	All	0.70	30.12	0.70	25.05	0.67	25.05
	CtL	0.85	90.98	0.69	100.38	0.74	97.24
	GtL	0.68	27.06	0.68	25.82	0.68	27.06
DME	All	0.61	21.72	0.74	16.96	0.56	21.72
	Biomass	0.95	5.06	0.88	5.06	1.01	5.06
	Fossil	0.58	26.38	0.58	26.37	0.56	24.05
Methanol	All	0.60	22.85	0.54	19.25	0.60	26.45
	Biomass	0.93	5.10	0.44	2.69	0.99	5.10
	Fossil	0.61	25.95	0.63	25.95	0.61	25.95
Hydrogen	All	1.03	96.81	1.16	121.4	0.97	109.11
	Gasification	1.03	14.19	1.23	30.76	1.03	11.43
	Electrolysis	2.76	221.6	2.76	210.17	2.64	210.17
	Steam reforming	0.93	114.44	0.96	117.72	0.86	107.88
Electricity	All	0.45	17.58	1.36	17.58	0.15	10.47
	Fossil	1.26	146.67	1.33	131.51	1.23	139.09
	Combustible renewables	1.91	9.40	2.13	9.40	1.91	9.40
	Nuclear	2.44	6.83	2.34	8.85	2.66	3.48
	Mix	1.72	148.65	1.76	137.75	1.85	144.29
	Non-combustible renewables	0.06	10.21	0.17	20.95	0.04	5.91

Table A.3. % difference in estimates about the adaptive kernel density central value (Table 1 of 2).

Fuel	Pathway	h for g GHG/MJ			h for MJ/MJ		
		OS	CV	SJPI	OS	CV	SJPI
Petrol	Crude	1.98%	1.98%	5.93%	51.62%	3.43%	55.05%
Diesel	Crude	5.23%	0.00%	7.85%	46.81%	0.00%	86.21%
Naphtha	Crude	7.54%	15.09%	37.72%	14.06%	14.06%	56.23%
Natural gas	Crude	12.13%	12.13%	3.47%	37.79%	21.59%	32.40%
LPG	Crude	2.68%	0.00%	2.68%	0.00%	0.00%	3.01%
Ethanol	All	23.45%	31.27%	31.27%	25.31%	5.06%	40.51%
	Wheat	2.40%	2.40%	21.57%	12.58%	2.51%	37.74%
	Sugar cane	11.28%	3.76%	18.81%	40.50%	5.06%	86.08%
	Sugar beet	0.00%	71.27%	85.53%	2.66%	2.66%	0.00%
	Wood	6.03%	0.00%	9.04%	4.28%	0.00%	4.28%
	Maize	23.24%	23.24%	46.47%	6.01%	4.01%	2.01%
Biodiesel	All	6.96%	6.96%	6.96%	0.00%	0.00%	0.00%
	Rape seed	4.42%	0.00%	0.00%	17.59%	0.00%	30.16%
	Sunflower seed	8.14%	8.14%	10.85%	0.91%	2.72%	1.81%
	Soy bean	20.83%	0.00%	3.47%	27.73%	0.00%	27.73%
	Wood	52.65%	17.55%	701.98%	27.09%	2.08%	42.71%
	Biomass	4.20%	0.00%	8.39%	1.50%	0.00%	5.54%
	Palm oil	3.17%	0.00%	0.00%	0.89%	0.89%	0.89%

Table A.4. % difference in estimates about the adaptive kernel density central value (Table 2 of 2).

Fuel	Pathway	h for g GHG/MJ			h for MJ/MJ		
		OS	CV	SJPI	OS	CV	SJPI
Synthetic diesel	All	20.23%	0.00%	0.00%	0.00%	0.00%	3.50%
	CtL	221.37%	254.58%	243.51%	1.62%	17.78%	12.12%
	GtL	4.79%	0.00%	4.79%	0.00%	0.00%	0.00%
DME	All	28.03%	0.00%	28.03%	17.15%	0.00%	24.01%
	Biomass	0.00%	0.00%	0.00%	8.84%	0.00%	15.71%
	Fossil	0.00%	0.00%	8.83%	0.00%	0.00%	3.92%
Methanol	All	18.69%	0.00%	37.38%	8.59%	0.00%	0.00%
	Biomass	0.00%	0.00%	104.89%	29.18%	0.00%	93.36%
	Fossil	7.93%	7.93%	7.93%	3.46%	0.00%	3.46%
Hydrogen	All	10.67%	5.33%	0.00%	22.19%	13.32%	31.07%
	Gasification	53.86%	0.00%	62.84%	16.78%	0.00%	16.78%
	Electrolysis	2.72%	0.00%	0.00%	2.17%	0.00%	6.51%
	Steam reforming	7.11%	2.37%	9.47%	6.90%	3.44%	13.80%
Electricity	All	0.00%	0.00%	40.44%	66.85%	0.00%	89.14%
	Fossil	8.41%	2.80%	2.80%	6.87%	2.29%	9.17%
	Combustible renewables	41.00%	41.00%	41.00%	3.73%	7.47%	3.73%
	Nuclear	22.73%	0.00%	60.62%	4.35%	0.00%	13.92%
	Mix	7.91%	0.00%	4.75%	9.12%	11.73%	16.94%
	Non-combustible renewables	41.03%	0.00%	71.79%	6.78%	0.00%	10.17%
Absolute Minimum		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Median		7.91%	0.00%	9.04%	6.90%	0.00%	13.80%
Maximum		221.37%	254.58%	701.98%	66.85%	21.59%	93.36%

A Best estimates using different kernel density estimation methods

B Sources and resource potentials for best and best in class WTT estimates

C Overview of well-to-wheel studies

From the data on best and worst performing vehicles (Table C.2 and C.3), hydrogen FC (pure and hybrids) vehicles using electricity from renewables or internal combustion engines (IC Es) with biogas from liquid manure are capable of attaining near zero emissions per unit distance. However, there is an energy penalty associated with these low carbon pathways. That is, the vehicle with lowest WTW energy input is not the one with lowest GHG emissions, suggesting that an optimum exists to simultaneously reduce carbon and energy.

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Table B.1. Best WTT GHG estimates with pathways, sources and resource limits (Table 1 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit
Petrol	Crude	15.63	Refinery for lead free petrol in Germany in 2020, co-product sulphur (credit) [33]	1.86×10^{14} [57]
Diesel	Crude	15.01	Crude oil [11]	1.86×10^{14} [57]
Naphtha	Crude	22.11	Crude oil [11]	1.86×10^{14} [57]
Natural gas	Crude	16.37	North American NG, compressed [11]	1.16×10^{14} [57]
LPG	Crude	12.5	Crude [14]	1.86×10^{14} [57]
Ethanol	All	2.58	Conventional fermentation of sugar beet, ethanol from refinery; rotational set-aside planted with Egyptian clover [12]	4.87×10^{11} [58], [59]
	Wheat	6.86	Residual straw from agriculture, converted to bioethanol using enzymes in Germany, year 2020 [33]	7.00×10^{13} [58]
	Scane	1.61	Sugar cane from Brazil, credit for bagasse [10]	3.71×10^{12} [58], [59]
	Sbeet	-5.87	Conventional fermentation of sugar beet, pulp as animal feed; rotational set-aside planted with Egyptian clover [12]	4.87×10^{11} [58], [59]
	Wood	21.94	Farmed wood [10]	4.73×10^{18} [59]
	Maize	24.51	Corn feedstock from the US, system boundary expansion co-product credit, cultivation using no-tillage practice, ref 38 [37]	5.96×10^{12} [58], [59]
Biodiesel	All	59.73	Rapeseed to FAME/FAEE, byproducts used [10]	8.49×10^{11} [58], [59]
	Rape	58.75	Rapeseed to FAME, glycerine and meal as animal feed [10]	8.49×10^{11} [58], [59]
	Sunflower	29.43	Sunflower seed to ME, glycerine as chemical, meal as feed [10]	1.41×10^{12} [58], [59]
	Soy	76.18	Imported soy beans to FAME, glycerine to biogas [10]	1.26×10^{12} [58], [59]
	Wood	-10.72	Poplar wood chips from short rotation forestry (SRF) via FT, with electricity and heat co-product credits, year 2030 [33]	4.73×10^{18} [59]

Table B.2. Best WTT GHG estimates with pathways, sources and resource limits (Table 2 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit
Biodiesel	Biomass	6.92	Farmed wood [10]	4.73×10^{18} [59]
	Palm	50.19	Imported palm oil to FAME, glycerine as chemical, CH_4 emissions from waste, no heat credit [10]	2.04×10^{12} [58], [59]
Synthetic diesel	All	25.05	GTL at remote plant, blended with regular diesel [10]	1.16×10^{14} [57]
	CTL	148.94	Coal via FT [14]	1.40×10^{14} [57]
	GTL	41.9	M. East natural gas to liquids via FT in Shell middle distillate synthesis (SMDS) in 2000 MW facility [40]	1.16×10^{14} [57]
DME	All	-59.11	Biomass [14]	5.00×10^{14} [58]
	Biomass	-58.75	Biomass [14]	5.00×10^{14} [58]
	Fossil	42.68	Natural gas, piped 7000 km [10]	1.16×10^{14} [57]
Methanol	All	22.85	Non-North American NG [11]	1.16×10^{14} [57]
	Biomass	5.1	Farmed wood [10]	4.73×10^{18} [59]
	Fossil	25.95	Piped, 4000 km [10]	1.16×10^{14} [57]
Hydrogen	All	139.84	Natural gas at a remote location to H2, liquefied and shipped [10]	1.16×10^{14} [57]
	Gasification	25.24	Gasification of farmed wood or poplar [10]	4.73×10^{18} [59]
	Electrolysis	221.6	Electricity from coal, central electrolysis [10]	1.40×10^{14} [57]
	Steam reforming	107.88	Natural gas from EU, piped 1000 km, reformed onsite at a refuelling station [10]	1.16×10^{14} [57]
Electricity	All	10.47	Poplar wood chips from SRF, gasified and combusted in a small-scale CCGT plant, year 2030 [33]	4.73×10^{18} [59]
	Fossil	267.98	Coal [10]	1.40×10^{14} [57]

Table B.3. Best WTT GHG estimates with pathways, sources and resource limits (Table 3 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit
Electricity	Combustible renewables	9.4	Farmed wood in 10 MW gasifier, CCGT [10]	4.73×10^{18} [59]
	Nuclear	2.14	CANDU reactor in Canada, year 2000 [33]	1.01×10^{13} [60]
	Mix	65.85	Austria mix , year 2000 [33]	6.81×10^{13} [60]
	Non-combustible renewables	3.76	European wind farms [33]	4.68×10^{11} [60]

Table B.4. Best in class WTT GHG estimates with pathways, sources and resource limits (Table 1 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit [a] MJ/yr
Petrol	Crude	7.56	Crude, best [34]	1.86×10^{14} [57]
Diesel	Crude	3.85	Crude [41]	1.86×10^{14} [57]
Naphtha	Crude	-60.29	Natural gas, flare gas [14]	1.10×10^{12} [61] [b]
Natural gas	Crude	7.56	Natural gas [14]	1.16×10^{14} [57]
LPG	Crude	2.53	Field, best [34]	1.86×10^{14} [57]
Ethanol	All	-76.36	From cellulosic biomass [11]	5.00×10^{14} [58]
	Wheat	5.39	Residual straw from agriculture, converted to bioethanol using enzymes in Germany, year 2030 [33]	7.00×10^{13} [58]
	Sugar cane	9.80	Sugar cane from Brazil, credit for bagasse [10]	3.71×10^{12} [58], [59]
	Sugar beet	-70.30	Enzymatic hydrolysis of sugar beet pulp [12]	4.87×10^{11} [58], [59]
	Wood	-13.46	Farmed trees [14]	4.73×10^{18} [58], [59] [c]
	Maize	-7.18	From corn [11]	5.96×10^{12} [58], [59]
Biodiesel	All	-67.40	Diesel/naphtha from residual woody biomass via HTU/HDO process [12]	7.00×10^{13} [58]
	Rape seed	-65.20	Bio-ester from rape seed, var 4 b) [12]	8.49×10^{11} [58], [59]
	Sunflower seed	11.40	Sunflower seed to ME, glycerine and cake to biogas [10]	1.41×10^{12} [58], [59] [d]
	Soy bean	19.00	Soy bean feedstock from Italy, ref 59 [37]	1.26×10^{12} [58], [59]
	Wood	-67.40	Diesel/naphtha from residual woody biomass via HTU/HDO process [12]	7.00×10^{13} [58]

[a] The resource limits are due to global production capacity. It is acknowledged that production capacity is different from global potential and increases through time. The upper or sustainable limits are used in the case of fuel production from bio resources. 2008 data is used throughout, except for CO_2 emissions from gas flaring which are from 2007.

[b] Use 20.3 MJ/kg CO_2 emitted for natural gas.

[c] Use 15 000 MJ/t dry wood.

[d] Use 39 490 MJ/t sunflower oil.

Table B.5. Best in class WTT GHG estimates with pathways, sources and resource limits (Table 2 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit
Biodiesel	Biomass	2.40	Black liquor from waste wood [10]	5.00×10^{13} [58]
	Palm oil	19.20	Imported palm oil to FAME, glycerine as chemical, with no CH_4 emissions [10]	2.04×10^{12} [58], [59]
Synthetic diesel	All	-60.45	Natural gas, flare gas via FT [14]	1.10×10^{12} [61]
	CtL	19.30	Coal via FT [14]	1.40×10^{14} [57]
	GtL	-60.45	Natural gas, flare gas via FT [14]	1.10×10^{12} [61]
DME	All	-58.51	Biomass [14]	5.00×10^{14} [58]
	Biomass	-58.51	Biomass [14]	5.00×10^{14} [58]
	Fossil	-54.57	Natural gas, flare gas [14]	1.10×10^{12} [61]
Methanol	All	-159.76	Landfill gas [14]	
	Biomass	-61.80	Gasification of residual woody biomass, BCL [12]	7.00×10^{13} [58]
	Fossil	-56.19	Natural gas, flare gas [14]	1.10×10^{12} [61]
Hydrogen	All	0.00	Wind estimates [10],[12],[11]	
	Gasification	6.60	Farmed wood with large scale gasification, 200 MW, liquefaction [10]	4.73×10^{18} [58], [59]
	Electrolysis	0.00	Wind estimates [10],[12],[11]	4.68×10^{11} [60]
	Steam reforming	33.10	Natural gas from EU, piped 4000 km, reformed centrally with CCS and piped to refuelling station [10]	1.16×10^{14} [57]
Electricity	All	-243.70	Liquid manure, small plant [10]	
	Fossil	30.10	Natural gas, piped 4 000 km, in CCGT with CCS [10]	1.16×10^{14} [57]
	Combustible renewables	-243.70	Liquid manure, small plant [10]	5.50×10^{13} [58]

Table B.6. Best in class WTT GHG estimates with pathways, sources and resource limits (Table 3 of 3).

Fuel	Pathway	g GHG/MJ	Specific pathway	Resource limit
Electricity	Nuclear	2.23	CANDU reactor in Canada, year 2000 [33]	1.01×10^{13} [60]
	Mix	62.03	Austria mix, year 2030 [33]	6.81×10^{13} [60]
	Non-combustible renewables	0.00	Wind estimates [10],[12]	4.68×10^{11} [60]

Table C.1. Test vehicle and performance requirements for each WTW study

Study	Concawe	GM		MIT	GREET
Location	Europe	N. America	Europe	USA	USA
Test Vehicle	VW Golf	Chevrolet Silverado	Opel Zafira	Toyota Camry	
- Type	car, compact	truck, full-size	people carrier	car, mid-size	-
- Engine size, l	1.60	4.30	1.80	2.50	-
- Engine type	Petrol, PISI	Petrol, SI	Petrol	Petrol, SI	Petrol
- Drive cycle	NEDC [a]	55/45 city, highway	EDC [b]	55/45 city, highway	-
- Reference year	2002	2010	2002	1996	2005
- Target year	2010	2016	2010	2020	2010
- Simulation	ADVISOR	GM Proprietary		ADVISOR	PSAT
- Mass, kg	1 181.00	2 056.36	1 445.00 [c]	1 236	-
- Drag coefficient	0.32	-	0.33	0.33	-
- Frontal area, m^2	2.10	-	2.39	2.00	-
- Tyre radius, m	0.31	0.38	0.34	0.34	-
Performance					
- Top speed, kph	180.00	176.99	180.00	-	-
- 0-50 kph, s	4.00	4.00	4.00	-	-
- 0-100 kph, s	13.00	10.36	12.00	-	-
- 80-120 kph in top gear, s	13.00	18.54	15.00	-	-
- Acceleration, m/s^2	4.00	5.00	4.50	-	-
- Range, km	610.00	-	650.00	600.00	-
- All electric range, km	20.00	12.07	20.00	-	-

[a] New European Drive Cycle.
[b] European Drive Cycle, combined over a city and highway sub-cycle.
[c] Specifications for Opel Zafira taken from Carfolio.com, available online at `http://www.carfolio.com/specifications/models/car/?car=92818`

Table C.2. Best and worst WTW performance vehicle configuration, by study (and WTT and TTW decomposition in brackets) (Table 1 of 2).

Study	Concawe	GM		MIT	GREET
Location	Europe	N. America	Europe	USA	USA
Reference vehicle					
MJ/km	2.55 (0.31; 2.24)	4.46	2.84	2.73	4.03
g GHG/km	196 (28, 168)	343.07	217.00	195.43	297.08
Best MJ/km	1.26 (0.43; 0.84)	1.33	1.73	0.51	2.41
Vehicle topology	FC, hybrid	ICE, SI	FC, hybrid	EV	CIDI, hybrid
Fuel	H_2, gas	Ethanol	Naphtha	Electricity	Diesel
Pathway	Wood waste via black liquor	Cellulosic	Crude	Mix with 54 g C/MJ	Crude
g GHG/km	8.00	95.71	111.00	0.00	187.46
Best g GHG/km	-171.00 (-304.00; 132.00)	0.00	0.00	0.00	143.79
Vehicle topology	ICE, SI	FC	1) FC, 2) FC, hybrid	1) EV, 2) FC, hybrid	FC
Fuel	Biogas	H_2, gas	H_2, gas	1) Electricity, 2) H_2	Ethanol
Pathway	Liquid manure	Electricity renewables	Electricity, wind or organic waste	1) Mix with 54 g C/MJ 2) Natural gas	Corn
MJ/km	4.46	2.39	3.52	0.81	5.63

Table C.3. Best and worst WTW performance vehicle configuration, by study (and WTT and TTW decomposition in brackets) (Table 2 of 2).

Study	Concawe	GM		MIT	GREET
Location	Europe	N. America	Europe	USA	USA
Worst MJ/km	10.85 (9.05; 1.80)	14.19	10.74	2.73	10.28
Vehicle topology	ICE, SI	ICE, SI	ICE	ICE, Reference	ICE, flex-fuel
Fuel	H_2, gas	H_2, liquid	H_2, liquid	Petrol	Butanol
Pathway	EU mix, nuclear electrolysis	US electricity average	EU electricity central electrolysis	Crude	Corn
g GHG/km	13.00	1 124.30	244.50	195.43	190.73
Worst g GHG/km	854.00 (854.00; 0)	1 124.00	486.00	195.43	642.58
Vehicle topology	ICE, SI	ICE, SI	ICE	ICE, Reference	PHEV, SI
Fuel	H_2, liquid	H_2, liquid	H_2, liquid	Petrol	H_2, liquid
Pathway	EU mix, coal central electrolysis	US electricity average	EU electricity central electrolysis	Crude	US electricity
MJ/km	8.52	14.19	6.99	2.73	4.96

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