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CARBON FOOTPPRINTING

Decarbonisation Index (DCI): an LCA-based key performance indicator for the automotive industry

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Abstract

Purpose Road vehicles cause considerable amounts of CO_2e emissions over their life cycle. Original equipment manufacturers (OEMs) report CO_2e emissions of past years on corporate level according to the Greenhouse Gas (GHG) Protocol and produce vehicle LCAs to identify GHG hotspots on the product-level. However, no approach to combine this past and future orientation of emissions modelling on fleet and product level yet exists. We demonstrate that this research gap is closed by using the "Decarbonisation Index" (DCI).

Methods We identify the missing elements of OEMs' absolute emissions reporting and vehicle LCAs to develop a resource-efficient, dynamic and modular key performance indicator (KPI) addressing both past and future scope 1–3 GHG emissions of OEMs. We assess in how far other existing approaches such as the Organisational LCA (O-LCA), the Organisation Environmental Footprint (OEF) and modular LCA can be used to develop these missing elements in a holistic modelling approach. After the derivation of the DCI, we provide a list of modelling options and data sources showing that the DCI can serve different means of an OEM, from a rough estimate of emissions to a basis for a detailed decarbonisation steering model involving several brands and departments.

Results and discussion In the case study, we compute a 2015 and 2035 DCI (in t CO_2e per vehicle) by using the basic DCI calculation model and publicly available data of the Volkswagen Group as well as data derived from publicly available scenarios. We demonstrate that even with this simplistic approach, the DCI delivers meaningful results indicating the core measures for an OEM's decarbonisation programme: an electrified fleet with renewable energy sources being used throughout the supply chain and use phase. A Monte Carlo simulation of the 2015 results demonstrate the DCI's robustness regarding the identification of core measures but also its dependency on changing (external or internal) methodological requirements.

Conclusions The DCI can be used by OEMs regardless of their company structure, powertrain portfolio or market coverage to monitor past emissions and model future emissions. The DCI combines the product-level of the vehicle LCA with the fleet-level necessary to develop a decarbonisation strategy. Its modular approach facilitates the use of generic LCA data or supplier-specific data on component level. Incrementally incorporating supplier-specific data is crucial to calculate the effect of real-world reduction measures in relation to generic databases used so far. An adaptation of the methodology to newly available data and regulations is thus possible and necessary. By adjusting past-reported DCI values to a new methodological set, an OEM's decarbonisation progress can be analysed albeit the constantly developing methodology.

Keywords Decarbonisation · Key performance indicator · LCA · Automotive OEMs · Supply chain · Carbon management · GHG Protocol

1 Introduction

Light-duty vehicles (LDV) and vans contributed 8% of global direct emissions in 2021 (IEA 2022). Automotive original equipment manufacturers (OEMs) have incorporated climate change in their strategies, aiming at contributing to slow down anthropogenic carbon emissions caused over the life cycle of their products and services. Ford Motor Company, Mercedes-Benz AG, Volkswagen AG, BMW Group, General Motors, Groupe Renault, and Toyota Motor Corporation (i.a.) have committed themselves to meeting verified science-based carbon reduction targets (SBTi 2022). When looking into the future, this commitment

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is especially crucial as the demand for, e.g. urban passenger transport in LDVs in Asia is estimated to increase by 73% between 2015 and 2035 (OECD 2022). The automotive industry thus needs to find sufficient measures to cut carbon emissions while their production output is increasing.

Life cycle assessment (LCA) studies have been applied in the automotive sector for nearly three decades to compare different technical solutions regarding their potential environmental burden (see, e.g. Gradin et al. 2020, Bushi et al. 2019; Lombardi et al. 2017; Muñoz et al. 2006; Saur et al. 1996). Furthermore, LCA studies of vehicles are a powerful tool for OEMs to identify carbon hotspots and consequently reduction measures on the product level. The studies published by OEMs are externally verified to be in line with the ISO 14040/14044 requirements and are usually published for the market launch of a new model. LCA studies describe, however, only a snap-shot of the emissions caused by one vehicle model in a certain point of time and a specific geographic region. Furthermore, mostly generic data sourced from LCA databases is used to model the product carbon footprint and the studies are rarely updated. Due to the immense effort of generating a high-quality LCA for a product as complex as a vehicle, LCAs are so far only publicly available for a certain share of vehicle models in an OEM's portfolio. Though not a product but a fleet perspective on life-cycle carbon emissions is necessary to develop decarbonisation strategies on an organisational scale. The interplay of shares of different vehicle powertrains, vehicle sizes, etc. in different markets matters in order to develop the most CO_2e efficient reduction measures. These encounter adjustments of the vehicle portfolio or realising measures along the product life-cycle from supply chain through production to use as well as recycling.

From a carbon point of view, the scope 1–3 emissions according to the GHG Protocol (WBCSD and WRI 2004) take on an "LCA+" perspective as additional indirect emission sources such as employee commuting and business travel are included (Fig. 1). In contrast to vehicle LCA studies, more specific, up-to-date and regionalized data is used to produce the scope 1–3 emissions inventory. Where possible, the absolute emissions reporting to the Carbon Disclosure Project (CDP) reporting relies on measured primary data for the full fleet of vehicles sold in the respective reporting year. Due to legal regulations, this is the case especially for scope 1 and 2 emissions and for tank-to-wheel emissions of the vehicles according to defined test cycles. For the remaining life cycle phases (supply chain, well-to-tank, recycling), the CDP reporting depends on input from LCA studies and life cycle inventory (LCI) databases (see, e.g. Agyei Boakye et al. 2023). Emissions of the other scope 3 categories are mainly calculated based on generic data sources and have—despite single exceptions (logistics)—merely indirect linkage to the physical vehicle life cycle (Neef 2020).

The yearly updated inventory can also be externally verified, e.g. on limited or reasonable assurance level (see, e.g. (BMW 2020; Toyota 2020; VW 2022). This corporate carbon accounting is the prerequisite for a targeted reduction in emissions: knowledge of sources and amount of past emissions on an organisational scale (Damert et al. 2017). However, long-term strategic decisions cannot solely be based

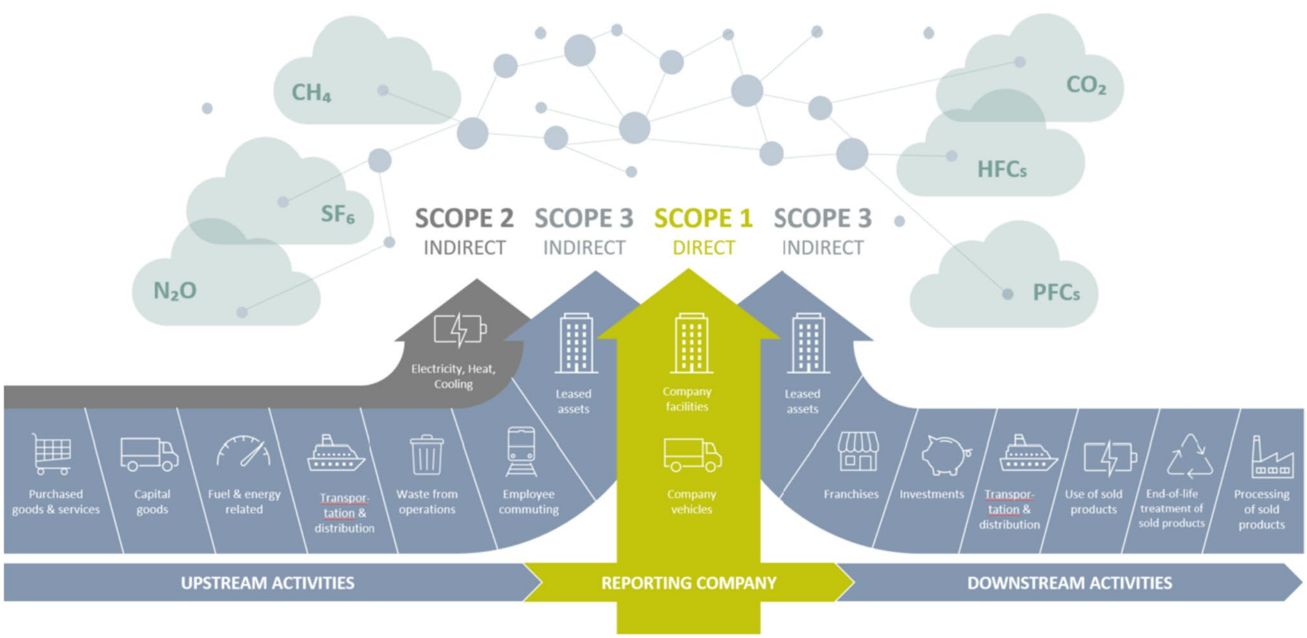

Fig. 1 Scope 1–3 emission categories and included GHGs according to the GHG Protocol (WBCSD and WRI, 2004)

on past carbon performance but need additional modelling of future carbon emissions to evaluate the effect of potential reduction measures (Schaltegger and Csutora 2012).

The United Nations German Global Compact Network recommends the use of a key performance indicator (KPI) to monitor the progress towards achieving absolute carbon reduction targets (Deutsches Global Compact Netzwerk (DGCN) 2017). Likewise, establishing a KPI to internally monitor the effectiveness of reduction measures and support their implementation is recommended by Busch (2010) and Zvezdov and Schaltegger (2015). KPIs are therefore related to both past-accounted and future-modelled carbon emissions. Such a decarbonisation KPI is not only complex in its calculation but also in the expectations of different stakeholders it is supposed to meet. For example, an OEMs' strategy department expects stability of calculation principles. Though OEMs' decarbonisation practitioners expect an "evolving KPI" that is adaptable to changing methodological requirements and data specificity, external stakeholders like non-governmental organisations expect both a transparent calculation methodology and the exact depiction of real-world emissions right from the start. Can a decarbonisation KPI meet all these demands? In this study, we discuss this issue among others and address the following research question: How can existing carbon accounting and LCA approaches be combined to a life-cycle-based decarbonisation KPI for the automotive industry?

2 Methods

The above described approaches of producing vehicle LCAs on product level and absolute emission inventories on fleet level currently applied by OEMs are both static and past-oriented. The here developed decarbonisation KPI needs to combine this static and past-oriented perspective for monitoring of past emissions with a modular and future-oriented perspective that allows for scenario-building. As such, external transparency of the OEM's decarbonisation progress for stakeholders as well as internal monitoring, planning and steering of fleet compositions and reduction measures would be facilitated.

The KPI's functional unit of "t CO_2e/vehicle" would allow for an operationalisation of decarbonisation targets in harmony with the internal key processes of OEMs which are product-oriented. In line with Burritt et al. (2011), corporate carbon management schemes should be set-up in a *resource-efficient* way. The decarbonisation KPI should therefore, whenever possible, draw on existing data sources and calculation approaches of the past emissions reporting. A *dynamic modularity* of the KPI calculation model for future emission modelling is necessary to compute scenarios with different fleet compositions and reduction measures to decide on the most efficient strategy to meet the decarbonisation target.

Dynamic because today's absolute past-oriented emissions reporting is calculated for each scope and category separately. As such, the relation of the parameters influencing emissions caused during the life-cycle of vehicles on fleet level cannot be shown by changing an input parameter at one point in the model because no holistic model yet exists. Though this is necessary to model the KPI's development depending on the input received from the fleet planning departments which, in turn, depend on the respective fleet emission legislations, for example, an increasing share of battery electric vehicles (BEV) will lead to increasing material supply chain emissions but a lower fleet emission average. These correlations must be depicted in a dynamic model. The calculation model's *modularity* is important because it also matters (to stay with the example) in which market, by which brand and in which year the share of BEVs increases. Here, the crucial input parameter "CO_2e-intensity of the electricity mix" must be connected to the market, time, brand and life-cycle-phase-specific emissions modelling. When looking exemplarily at the VW Group and its diverse brands, an electrified SUV BEV produced and used in China in 2023 potentially causes higher total carbon emissions and thus a higher effect in the overall Group KPI result than a compact BEV in the EU in the same year: (a) because the CO_2e-intensity of the Chinese electricity grid mix is higher than the EU one; (b) because a SUV BEV would be built with a higher battery capacity, higher vehicle weight and higher electricity consumption per kilometre driving distance than the compact BEV; (c) because more vehicles are sold in China than in the EU; and (d) because sales numbers differ. The example illustrates that the *modularity* of the model must encompass even the component level depending on identified carbon hotspots in the supply chain (in this case the battery cell production). As such, supplier-specific data instead of the generic data used in vehicle LCAs can be used to calculate reduction potentials on fleet level. Below, we describe which other existing approaches can help to achieve this resource-efficient dynamic modularity needed for the decarbonisation KPI.

2.1 Which additional approaches can help to bridge this methodological gap?

An in-depth assessment of suitable approaches for the derivation of the DCI regarding methodological and practical requirements was realised by Neef (2020). Here, we provide a summary of her findings. The Organisational LCA (O-LCA) and the Organisation Environmental Footprint (OEF) can be used to produce corporate emissions inventories in line with the GHG Protocol (EC-JRC 2012;

Martínez Blanco et al. 2015a) Martínez-Blanco et al. 2015b, Martínez-Blanco et al. 2020, Cremer et al. 2020, Pelletier et al. 2014). Next to the standard life-cycle phases covered in a product LCA ("manufacturing", "use", "EoL"), O-LCA recommends to include environmental impacts arising from other indirect activities normally excluded in product LCAs. These activities include employee commuting, business travel, franchising and capital equipment which are mainly based on recommendations by GHG Protocol (WBCSD and WRI 2004) and Organisation Environmental Footprint Guide (OEF) (EC-JRC 2012).O-LCA promotes an approach of using reference LCAs representative for the company's product portfolio similar to the approach applied by OEMs to calculate supply chain and recycling emissions on fleet level. Here, representative LCAs (e.g. per vehicle class and powertrain) are weighted, aggregated and emissions extrapolated based on the vehicles sales of a respective year. These reference LCAs are, however, closed off for further analyses: input parameters like, e.g. electricity mixes or new insights into more accurate clipping rates cannot be changed within the holistic model but must be changed in every reference LCA. Hence, scenario analyses of, e.g. future emissions are not easily possible. Still, the advantage of the reference LCA-approach is that no specific LCA study is needed for every product in the portfolio which makes it efficient and handy for estimating corporate emissions.

The OEF provides an additional opportunity for scenario analyses of corporate emissions by regionally modelling use phase emissions which is also already incorporated in OEMs' absolute emission reporting (Neef 2020). Like this, also future electricity mixes can be connected to a planned share of BEVs in an OEM's fleet thus making at least use phase future emissions modelling possible.

Still, a modular approach to model reduction measures especially in the supply chain must be added to facilitate resource-efficient scenario analyses. Interconnected modules within the reference vehicle LCAs could be used to, e.g. interchangeably model the production of carbon hotspot components with different energy sources. According to Buxmann et al. (2009) and Steubing et al. (2016), such a modular LCA approach can generate the same results as a non-modular LCA study and can potentially better support the decision-making process of product managers. For the decarbonisation KPI, this modular approach should be implemented throughout all life cycle phases and additional scope 3 categories covered by the GHG Protocol. As is the case for the reference LCAs, the single calculation modules need to be connected to the corresponding brand and market-specific input parameters on fleet level, i.e. the number of vehicles affected by the reduction measure modelled within certain activated module. The combination of these methodological characteristics is described in the derivation of a basic version of the Decarbonisation Index (DCI) below.

2.2 The Decarbonisation Index (DCI)

As is the case for the absolute emission reporting to CDP, the DCI covers all scopes and categories according to the GHG Protocol (Fig. 2). The DCI encompasses five sections: supply chain (scope 3, cat. 1), in-house production (scopes 1 and 2 representing the OEM's own production sites), well-to-tank (fuel and charging electricity supply, scope 3, cat. 11), tank-to-wheel (tailpipe emissions, scope 3, cat. 11), recycling (scope 3, cat. 12) and other scope 3 categories (non-product-specific scope 3 categories bundled: 3–10, 13–15).

For each of these sections of the DCI, general calculation rules can be defined. Further specifications regarding the level of detail that is being modelled can be developed at any point depending on the data available. Below, we indicate the basic modelling pathway for the DCI. The DCI on OEM-level ($DCI_{OEM,veh}$) is measured in t CO_2e/vehicle and sums up the different life cycle phases' contribution: supply chain ($E\_Prod\_SC_{OEM,veh}$), in-house production ($E\_Prod\_InH_{OEM,veh}$), well-to-tank ($E\_Use_{OEM,veh,wtt}$), tank-to-wheel ($E\_Use_{OEM,veh,ttw}$), recycling ($E\_EoL_{OEM,veh}$) and scope 3 other categories (non-product-specific scope 3 categories bundled: 3–10, 13–15) ($E\_Oth_{OEM,veh}$):

$$\begin{aligned} DCI_{OEM,veh} = {} & E\_Prod\_SC_{OEM,veh} + E\_Prod\_InH_{OEM,veh} \\ & + E\_Use_{OEM,veh,wtt} + E\_Use_{OEM,veh,ttw} \\ & + E\_EoL_{OEM,veh} + E\_Oth_{OEM,veh} \end{aligned} \tag{1.1}$$

The basic calculation principle of the DCI is the weighted average based on vehicle numbers. As such, the calculation below can be disaggregated into brand and market-levels (and even component-level in the supply chain and recycling phases) and consequently re-aggregated based on the level-specific vehicle numbers. Due to this modular approach, OEMs applying the DCI can chose which level of detail suits their goals, company structure and data availability best. A

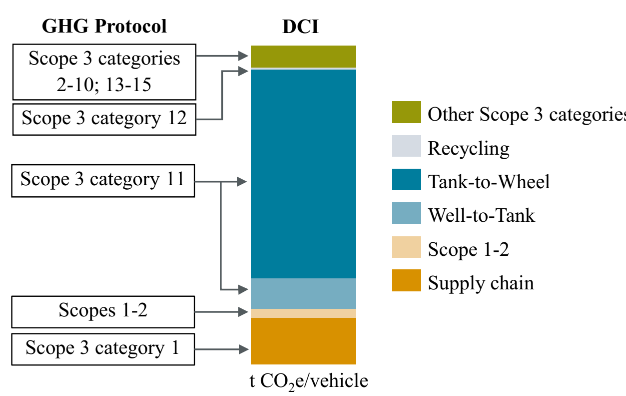

Fig. 2 Allocation of the Greenhouse Gas (GHG) Protocol's emission categories to the Decarbonisation Index (DCI) phases. The DCI is measured in t CO_2e per average vehicle

non-exhaustive overview of modelling options, data specificity and data sources for past emissions is provided in Table 1 and for future emissions in Table 2.

2.2.1 Supply chain

Product-specific supply chain emissions can be extracted from vehicle LCAs which are based on vehicles' bill of materials. The amount and type of material used for manufacturing vehicles determine the brands' supply chain emissions ($E\_Prod\_SC_{abs}$). I.e. heavier vehicles cause higher CO_2e emissions in their supply chains than lighter ones given the same mix of materials. It would be ideal to have an individual LCA per vehicle model, preferably even with regionalized supply chains for each production site. On the other end of the continuum, supply chain emissions of an OEM could be interpolated even from one single vehicle LCA by deriving an emission factor per kilogram of vehicle curb weight. This emission factor can then be used for scaling the impact of other car models based on their individual curb weights. A medium solution would be to use all LCAs available as reference LCAs and to allocate each vehicle model without individual LCA to one of these reference LCAs according to a mapping logic (based on similarity parameters). As an example, differences in brands' product portfolios vehicle curb weights could be used to distinguish vehicle segments "regular" (< 1.7 t) and "large" (> 1.7 t). The powertrain is another factor influencing supply chain CO_2e emissions of a single vehicle and thus also $E\_Prod\_SC_{abs}$. Below, exemplary calculations of emissions caused by internal combustion engine vehicles (ICE), BEVs and plug-in hybrid electric vehicles (PHEV) are described. In this case, only six reference LCAs are utilised: a regular and large example of each included powertrain. $E\_Prod\_SC_{veh}$ for each powertrain and size segment is calculated and set into relation with the respective vehicle curb weight to derive a CO_2e supply chain factor (e.g. kilogram CO_2e per kilogram vehicle curb weight) for every reference vehicle (sc_w). If the data is available, a bottom-up calculation with regionalized material carbon footprints per supplier would be possible at this point. Here, sc_w is used to extrapolate $E\_Prod\_SC_{veh}$ to $E\_Prod\_SC_{abs}$. For this reason, average vehicle curb weights of the defined segments "regular" (w_r) and "large" (w_l) need to be calculated for each brand. Then, average carbon material supply chain emissions per brand, segments and powertrain are calculated per vehicle:

$$E\_Prod\_SC_{veh,r} = sc_{w,r} \times w_r \tag{1.2}$$

$$E\_Prod\_SC_{veh,l} = sc_{w,l} \times w_l \tag{1.3}$$

The share of "regular" (r) and "large" (l) vehicles per brand on the total number of vehicles sold (n_{veh}) is calculated by summing up the number of regular ($n_{veh,r}$) and large ($n_{veh,l}$) vehicles per brand and dividing them by the total number of vehicles:

$$n_{veh} = n_{veh,r} + n_{veh,l} \tag{1.4}$$

$$r = \frac{n_{veh,r}}{n_{veh}} \tag{1.5}$$

$$l = \frac{n_{veh,l}}{n_{veh}} \tag{1.6}$$

To derive $E\_Prod\_SC_{abs}$, n_{veh} needs to be distinguished between the number of vehicles sold per market ($n_{veh,m,i}$):

$$n_{veh} = \sum_{i=1}^{n} n_{veh,m,i} \tag{1.7}$$

Subsequently, for each market, the shares of the three powertrains ($pt_{m,i}$) are needed to calculate supply chain emissions per average brand vehicle ($E\_Prod\_SC_{veh}$):

$$\begin{aligned} E\_Prod\_SC_{veh} = \sum_{i=1}^{3} &(E\_Prod\_SC_{veh,r,pt,i} \times r \\ &+ E\_Prod\_SC_{veh,l,pt,i} \times l) \times pt_{m,i} \end{aligned} \tag{1.8}$$

The average brand vehicle supply chain emissions ($E\_Prod\_SC_{veh}$) are then multiplied with n_{veh} to derive $E\_Prod\_SC_{abs}$:

$$E\_Prod\_SC_{abs} = E\_Prod\_SC_{veh} \times n_{veh} \tag{1.9}$$

Other mapping logics to allocate existing LCAs to the different car models in an OEM's product portfolio are possible as long as they are comprehensible, transparent and well documented.

2.2.2 In-house production

In vehicle LCA studies, both supply chain emissions and scope 1–2 emissions are included based on generic LCI datasets. In order to include brands' scope 1–2 emissions more specifically, not the generic data derived from LCAs but the routinely generated scope 1–2 emissions data from an OEM's environmental management system (EMS) should be used. Scope 1–2 emissions directly controlled by the brand are hereafter called "In-house Production" ($E\_Prod\_InH_{abs}$). $E\_Prod\_InH_{abs}$ is derived from EMS measuring electricity consumption etc. directly on the production sites. $E\_Prod\_InH_{abs}$ thus depends on scope 1–2 emissions caused per vehicle ($E\_Prod\_InH_{veh}$) and the total number of vehicles sold (n_{veh}):

$$E\_Prod\_InH_{abs} = E\_Prod\_InH_{veh} \times n_{veh} \tag{1.10}$$

Table 1 Possible data sources and modelling options for calculating past emissions for each phase of the Decarbonisation Index (DCI) (not exhaustive)

DCI phase	DCI past emissions reporting: Modelling options	Data specificity									Data sources			
		Component	Gearbox	Model	Powertrain	Segment	Market	Brand	Group	Reporting year	Internal	Public	Supplier	Other
Basic input data	A1) Number of vehicles				X	X	X	X		X		X		
Supply chain	B1) Emission factors (kg CO_2e/kg vehicle curb weight) from reference LCA (mapping logic)				X	X						X		
	B2) Emission factors (kg CO_2e/kg vehicle curb weight) from individual vehicle LCAs													
	C1) Vehicle curb weights				X			X				X		
	D1) Reduction measures: specific hotspot calculation													
Scope 1 + 2	E1) Emission factors (t CO_2e/vehicle) from Environmental Information System								X	X		X		
Well-to-tank	F1) Emission factors for fuel production (g CO_2e/km) and electricity production (g CO_2e/kWh)						X			X		X		
	F2) Reduction measure: CO_2e-efficient fuels and charging													
Tank-to-wheel	G1) Fleet emission averages and electricity consumptions per reference LCA				X	X						X		
	G2) Fleet emission averages and electricity consumptions													
Recycling	H1) Emission factor (t CO_2e/vehicle) from reference LCAs (mapping logic)								X			X		
	H2) Emission factors (t CO_2e/kg vehicle) from individual vehicle LCAs													
Other scope 3 categories	I1) Combined average emission factor								X	X		X		
	I2) Emission factor per category													

Data specificity and sources can develop over time depending on new data systems, internal and external reporting requirements. OEMs can use this table to get an overview of their current calculation approach and their potential for improvement. The modelling options, data specificity and sources chosen in this publication's case study are marked with an "X"

Table 2 Possible data sources and modelling options for modelling future emissions for each phase of the Decarbonisation Index (DCI) (not exhaustive)

	DCI future emissions prognosis														
DCI phase	**Modelling options**	**Data specificity**										**Data sources**			
		Component	Gearbox	Model	Powertrain	Segment	Market	Brand	Group	Reporting year	Includes Interpolation	Internal	Public	Supplier	Other
Basic input data	1B) Projection of future vehicle sales						X						X		
	1C) Number of vehicles from group planning rounds														
Supply chain	2A) In case of a decarbonisation target: base year emission factors (t CO_2e/vehicle)														
	2B) Most recent reported emission factors (t CO_2e/vehicle)														
	2C) Re-calculation of emission factors per year based on existing LCAs				X		X	X					X		
	2D) Calculation of emission factors based on ex-ante LCAs														
	3A) Vehicle curb weights of most recent reported year							X					X		
	3C) Projected vehicle curb weights														

Table 2 (continued)

DCI phase	DCI future emissions prognosis: Modelling options	Data specificity: Component	Gearbox	Model	Powertrain	Segment	Market	Brand	Group	Reporting year	Includes Interpolation	Data sources: Internal	Public	Supplier	Other
	4A) Reduction measures: specific hotspot calculation	X			X	X	X				X		X		
Scope 1+2	5A) Most recent reported/past year emission factors								X				X		
	5B) Emission factors including planned reduction measures														
Well-to-tank	6A) Most recent reported/past year emission factors for fuel and electricity production														
	6B) Projected emission factors for fuel and electricity production						X				X		X		
	6C) Reduction measure: CO_2e-efficient fuels and charging						X				X		X		
Tank-to-wheel	7A) Fleet emissions and electricity consumptions per reference LCA				X	X	X						X		

Table 2 (continued)

DCI phase	DCI future emissions prognosis														
	Modelling options	**Data specificity**										**Data sources**			
		Component	Gearbox	Model	Powertrain	Segment	Market	Brand	Group	Reporting year	Includes Interpolation	Internal	Public	Supplier	Other
	7B) Fleet emissions and electricity consumptions per planning round year														
Recycling	8A) Most recent reported emission factors														
	8B) Emission factor (t CO_2e/vehicle) from reference LCAs (mapping logic)								X				X		
Other scope 3 categories	9A) Combined average emission factor of most recent reported year								X				X		
	9B) Emission factor per category														

Data specificity and sources can develop over time depending on new data systems, internal and external reporting requirements. OEMs can use this table to get an overview of their current calculation approach and their potential for improvement. The modelling options, data specificity and sources chosen in this publication's case study are marked with an "X"

2.2.3 Well-to-tank

Use phase emissions are the sum of well-to-tank (WTT) ($E\_Use_{abs,wtt}$) and tank-to-wheel (TTW) ($E\_Use_{abs,ttw}$) emissions. $E\_Use_{veh,wtt}$ sums up WTT emissions of vehicles sold in all markets including all powertrains:

$$E\_Use_{veh,wtt} = \sum_{i=1}^{n} E\_Use_{veh,wtt,ICE,m,i} + E\_Use_{veh,wtt,PHEV,m,i} + E\_Use_{veh,wtt,BEV,m,i} \tag{1.11}$$

Both in ICEs' and PHEVs' use phases CO_2e emissions are caused in fossil fuel supply chains. Fossil fuel WTT emissions are calculated based on average WTT emission shares additional to TTW emissions per market ($wtt_{m,i}$) and lk. These shares can, e.g. be sourced from LCA databases taking into account the carbon efficiency of gasoline and diesel refineries per market. The above-described fleet emission average (B_f) includes all powertrains. A pragmatic approach would be to use the reported (and projected) fleet emission average and to apply it to all cars in the fleet for calculation of WTT fuel emissions irrespective of their drivetrain. This would be analogous to the fleet legislation logic. However, in order to calculate WTT emissions powertrain specifically, a powertrain-specific fleet emission average is needed. For this reason, both an ICE and PHEV-specific fleet emission average are calculated ($B_{f,ICE}$ and $B_{f,PHEV}$). $B_{f,ICE}$ is calculated by only referring to the number of ICEs in the fleets ($n_{ICE,r-l,m,i}$):

$$B_{f,\text{ICE}} = \sum_{i=1}^{n} \frac{(LCA_{TTW,ICE,r} \times n_{ICE,r,m,i}) + (LCA_{TTW,ICE,l} \times n_{ICE,l,m,i})}{n_{ICE,m,i}} \tag{1.12}$$

$B_{f,PHEV}$ is calculated by only referring to the number of PHEVs in the fleets ($n_{PHEV,r-l,m,i}$):

$$B_{f,\text{PHEV}} = \sum_{i=1}^{n} \frac{(LCA_{TTW,PHEV,r} \times n_{PHEV,r,m,i}) + (LCA_{TTW,PHEV,l} \times n_{PHEV,l,m,i})}{n_{PHEV,m,i}} \tag{1.13}$$

Average ICE WTT emissions per vehicle ($E\_Use_{veh,wtt,ICE}$) are calculated as follows:

$$E\_Use_{veh,wtt,ICE} = \sum_{i=1}^{n} B_{f,ICE,m,i} \times wtt_{m,i} \times lk \tag{1.14}$$

Average PHEV WTT emissions per vehicle ($E\_Use_{veh,wtt,PHEV}$) consist of both fossil fuel–induced emissions ($E\_Use_{veh,wtt,PHEV,\text{fuel}}$) and energy consumption–induced emissions ($E\_Use_{veh,wtt,PHEV,\text{ec}}$):

$$E\_Use_{veh,wtt,PHEV} = \sum_{i=1}^{n} E\_Use_{veh,wtt,PHEV,fuel,m,i} + E\_Use_{veh,wtt,PHEV,\text{ec},m,i} \tag{1.15}$$

$E\_Use_{veh,wtt,PHEV,\text{fuel}}$ is calculated in the same manner as ICE WTT emissions:

$$B\_Use_{veh,wtt,PHEV,fuel} = \sum_{i=1}^{n} B_{f,PHEV,m,i} \times wtt_{m,i} \times lk \tag{1.16}$$

$E\_Use_{veh,wtt,PHEV,\text{ec}}$ is based on electricity consumption per average PHEV per market ($EC\_PHEV_{wtt,m,i}$) and market-specific CO_2-intensity of energy mixes ($e_{m,i}$) which can, e.g. be obtained from LCA database:

$$E\_Use_{veh,wtt,PHEV,ec} = \sum_{i=1}^{n} EC\_PHEV_{m,i} \times e_{m,i} \times lk \tag{1.17}$$

$EC\_PHEV_{m,i}$ is calculated by using the electricity consumption of PHEV reference vehicles ($LCA_{WTT,PHEV,ec,r-l}$) and the share of PHEVs in brands' market-specific fleet portfolios ($pt_{PHEV,m,i}$):

$$EC\_PHEV_{m,i} = \left(LCA_{WTT,PHEV,ec,r} \times pt_{PHEV,m,i}\right) + \left(LCA_{WTT,PHEV,ec,l} \times pt_{PHEV,m,i}\right) \tag{1.18}$$

BEV WTT emissions ($E\_Use_{veh,wtt,BEV}$) are calculated in the same manner as $E\_Use_{veh,wtt,PHEV,ec}$:

$$E\_Use_{veh,wtt,BEV} = \sum_{i=1}^{n} EC\_BEV_{m,i} \times e_{m,i} \times lk \tag{1.19}$$

$$EC\_BEV_{m,i} = \left(LCA_{WTT,BEV,r} \times pt_{BEV,m,i}\right) + \left(LCA_{WTT,BEV,l} \times pt_{BEV,m,i}\right) \tag{1.20}$$

Equally to the calculation of production phase emissions, first, use phase emissions per average brand vehicle (E_Use_{veh}) are calculated:

$$E\_Use_{veh} = \frac{E\_Use_{abs}}{n_{veh}} \tag{1.21}$$

$$E\_Use_{veh} = E\_Use_{veh,wtt} + E\_Use_{veh,ttw} \tag{1.22}$$

2.2.4 Tank-to-wheel

$E\_Use_{veh,ttw}$ Describes brands' fleet emissions in gram CO_2e per kilometre per average brand vehicle (B_f) multiplied with the vehicle lifetime kilometrage (lk) assumed to be the same for all powertrains:

$$E\_Use_{veh,ttw} = B_f \times lk \tag{1.23}$$

B_f is the product of fleet emissions of average brand vehicles per market ($B_{f,m,i}$) and brand market shares ($b_{m,i}$):

$$B_f = \sum_{i=1}^{n} B_{f,m,i} \times b_{m,i} \tag{1.24}$$

$B_{f,m,i}$ is based on tailpipe emissions of reference ICE ($LCA\_TTW_{ICE,r-l}$) and PHEV ($LCA\_TTW_{PHEV,r-l}$) vehicles of both segments, the number of these types of vehicles per market ($n_{ICE,r-l,m,i}$;$n_{PHEV,r-l,m,i}$) and $n_{veh,m,i}$, i.e. including BEVs which are calculated with zero TTW emissions:

$$B_{f,m,i} = \frac{(LCA\_TTW_{ICE,r} \times n_{ICE,r,m,i}) + (LCA_{TTW\,PHEV,r} \times n_{PHEV,r,m,i}) + (LCA\_TTW_{ICE,l} \times n_{ICE,l,m,i}) + (LCA_{TTW\,PHEV,l} \times n_{PHEV,l,m,i})}{n_{veh,m,i}} \tag{1.25}$$

2.2.5 Recycling

To calculate recycling absolute emissions (E_EoL_{abs}), recycling emissions per vehicle (E_EoL_{veh}) are calculated first:

$$E\_EoL_{veh} = \frac{E\_EoL_{abs}}{n_{veh}} \tag{1.26}$$

E_EoL_{veh} is calculated based on recycling phase carbon emissions per powertrain derived from LCAs ($LCA\_EoL_{pt,r-l}$), the share of "regular" (r) and "large" (l) vehicles per brand and market-specific powertrain shares ($pt_{m,i}$)

$$E\_EoL_{veh} = \sum_{i=1}^{n} (LCA\_EoL_{pt,r} \times pt_{m,i}) + (LCA\_EoL_{pt,r} \times pt_{m,i}) \tag{1.27}$$

2.2.6 Other scope 3 categories

"Other scope 3 categories" ($E\_Oth_{OEM,abs}$) summarises scope 3 categories 2–10 and category 13–15. These emission categories were neither identified as current carbon hotspots nor as main drivers of future emissions (Neef 2020); the single categories do not have to be specifically modelled within the DCI. "Other scope 3 categories" are mostly not directly influenced by choices of powertrains or composition of fleets per brand and market. Therefore, these emission categories do not need to be disaggregated on brand level but could be, if it is necessary and possible for the OEM applying the DCI. "Other scope 3 categories" emissions per vehicle ($E\_Oth_{OEM,veh}$) are calculated as follows:

$$E\_Oth_{OEM,veh} = \frac{E\_Oth_{OEM,abs}}{n_{OEM,veh}} \tag{1.28}$$

Depending on the targeted level of detail by the OEM and depending on the availability of data and IT infrastructure, different modelling options, data specificities and sources can be used to calculate the DCI. The options per DCI phase (without claiming to be exhaustive) are listed in Tables 1 and 2. These options can vary for past and future emissions modelling depending on data availability as well as requirements regarding the assurance level of published GHG inventories. The level of modelling detail of the DCI can also change over time: an OEM might establish a basic data reporting infrastructure and eventually add more in-depth calculations once the data is available. As shown in the case study (see Sect. 3), it is possible to start using the DCI with public data only and establish the basic pillars of a decarbonisation programme. Thereby, the DCI proofs to be a flexible "evolving KPI" that allows for growth and development of the decarbonisation topic within an organisation (the OEM)—from the first attempts to achieve an overview to detailed insights tailored for all involved business units.

3 Results: case study

In the following case study, we want to show an exemplary application of the DCI by using publicly available data of the Volkswagen Group as well as scenarios derived from publicly available studies. The data available from the company is suitable for this case study as it covers a variety of brands with different vehicle portfolios and market activities. Like this, the KPI and its use can be shown on different aggregation levels. The DCI's applicability for developing life-cycle-based decarbonisation strategies is shown in an exemplified emission projection for 2035. The modelling options, data specificity and sources pursued in this case study are marked with an "X" in Table 1 (for past emissions/2015) and Table 2 (for future emissions/2035) and are indicated for each data point. The modelling options listed are not exhaustive but are meant to give an idea of the numerous possible options to calculate a DCI depending on the available data and the pursued steering model. The options are grouped along the phases of the DCI plus basic input data that is used throughout all phases. The data specificity options indicated are both on vehicle level (component, gearbox, model, powertrain, segment) and on fleet level (market, brand, group). Additionally, it can be indicated whether the data used is reporting-year specific and, in Table 2 only, whether interpolated data is used to model future emissions. Data sources are distinguished in internal, public, supplier and other. Option A1 in Table 1 can be read as follows: the number of vehicles used for the 2015 DCI calculation is powertrain, segment, market and brand-specific. As the information is sourced from the VW Annual Report 2015, it is reporting year-specific and based on public sources. In turn, option B1 is only indicated to be powertrain and segment-specific because reference vehicle LCAs are used to group all vehicles into their powertrains (ICE/BEV/PHEV) and segment (regular/large). These vehicle LCAs are not reporting year-specific because they have been published in another year. For one example in Table 2, modelling option 4A can be read as follows: the emissions calculation of battery cell manufacturing with renewable energy sources is based on component (i.e. battery cells), segment (i.e. battery capacities of reference vehicle LCAs) and powertrain (i.e. BEV) specific data and includes interpolated data (projected emission factors from an LCA database). In Table 2, two general modelling paths are shown. Either static data from past reported DCIs or dynamic data based on projections and interpolation between data points can be used.

3.1 Data inputs 2015

3.1.1 Portfolio data

The input data is mainly sourced from the VW Group Annual Report 2015 (option A1 in Table 1) and is summarised or modified to fit this exemplary application of the DCI (VW 2016). The total figure of globally sold LDVs in 2015 is 9,374,000. In the case study, the brands VW, AUDI, ŠKODA, SEAT, PORSCHE, VW Commercial Vehicles (VW CV) and the markets EU, USA and China are included. The brands active in China sold vehicles via the Group's Joint Ventures (JV) summarised as "VW China" in the annual report. Therefore, VW China's 3,456,000 vehicles are redistributed to the brands active in China based on their market and Group fleet shares. Based on the brands' Group fleet shares, the 9,374,000 globally sold LDVs are redistributed to the brands (Table 3). Based on VW (2016), the following markets shares per brand are assumed (Table 4). In the 2015 VW Group Annual Report, no indication regarding different powertrains was given. Hence, it is assumed that the global Group portfolio consisted of internal combustion engine vehicles (ICE) only.

Table 4 Assumed 2015 market shares for each Volkswagen Group brand (VW 2016)

Brand	EU share (%)	USA share (%)	China share (%)	Sum (%)
VW	36	13	51	100
AUDI	48	14	38	100
ŠKODA	71	-	29	100
SEAT	94	6	-	100
PORSCHE	38	27	35	100
VW CV	88	4	8	100

3.1.2 Vehicle data

The ICE reference data (Table 5) is correlated with brands' average curb weights for regular and large vehicles (Table 6) (options B1 and C1). For each VW Group model, the highest indicated curb weight provided in the models' technical data sheets is selected. Regular-sized vehicles are defined as weighing up to 1700 kg, large-sized vehicles as weighing more than 1700 kg. The assumed vehicle lifetime kilometrage is 200,000 km. This average was shown as feasible by Weymar and Finkbeiner (2016) and is used within vehicle LCAs and carbon accounting by OEMs alike (see, e.g. AUDI 2016; VW 2020)). The WTT emission factors for the EU, USA and China (option F1) are sourced from the GaBi database (Sphera 2021). For the EU, shares of 45% of diesel and 55% of gasoline-powered vehicles are assumed (ACEA 2019); for the USA and Chinese markets, 100% gasoline-powered vehicles are assumed (Bureau of Transportation Statistics (BTS) 2017; ICCT 2018). The same recycling emission factor is assumed for all vehicles (option H1) (Table 5).

3.1.3 Additional data

In-house production emissions in 2015 for the whole company (option E1) amounted to 1.0 t CO_2e/vehicle (VW 2017a, b).

Table 3 2015 light-duty vehicle sales and respective overall shares for each Volkswagen Group brand excluding Volkswagen China (left) and including VW China (right) (VW 2016)

Brand	VW Group brand w/o VW China		VW China re-allocated
	Sales 2015 (number of vehicles)	Share (%)	Sales 2015 (number of vehicles)
VW	4,424,000	55	5,202,029
AUDI	1,529,000	19	1,797,898
ŠKODA	800,000	10	940,692
SEAT	544,000	7	639,671
PORSCHE	219,000	3	257,515
VW CW	456,000	6	536,195
Sum	7,972,000	100	9,374,000

VW China vehicles were re-allocated to the European brands based on their indicated sales shares in the VW Annual Report to include all 9,347,000 vehicles in the case study

Table 5 Data sourced for small and large reference internal combustion engine vehicles (ICE) used in the case study

Reference model	Supply chain (kg CO_2e/kg vehicle)	Share scope 1–2 on scope 3 cat. 1 (%)	EU curb weight (kg)	TTW emissions (NEDC) (g CO_2e/km)	Recycling (t CO_2e/vehicle)
Golf 8 TSI	6.8 (VW 2021)	14.1 (VW 2017a)	1380 (ADAC 2020)	108 (ADAC 2020)	0.3 (VW 2021)
Audi Q7 3.0 TDI	12 (AUDI 2020)	14.1 (VW 2017a)	2150 (AUDI 2016)	144 (AUDI 2016)	0.3 (assumed)

As the 2015 DCI is modelled, TTW emissions based on the New European Driving Cycle (NEDC) are used instead of the current Woldwide harmonised Light Duty Test Cycle (WLTC)

In 2015, the company only reported emissions for the "other scope 3 emission categories" 2–7, 10, and 13–14. These amounted to 2.6 t CO_2e/vehicle (option I1) (VW 2016).

3.2 Modelling results DCI 2015

The modelled DCI of the VW Group for the base year 2015 covers the markets EU, USA and China (Fig. 3). It amounts to 36.2 t CO_2e per vehicle. Although this figure is not the same as the 2015 DCI value published in the VW Group Sustainability Report (VW 2020), it strongly resembles the shares each DCI phase contributes to the resulting total DCI figure: including rounding errors, the supply chain emissions make up 17%, in-house production emissions 3%, WTT emissions 9%, TTW emissions 63% and recycling and other scope 3 categories 8%. Neef (2020) used a similar data basis to re-model VW Group's 2015 and 2016 absolute emissions reported to CDP and achieved a deviation of the total result of − 14%.

The VW Group DCI value can be disaggregated on brand-level (Fig. 4). The discrepancies of DCI values between the brands as well as the differing shares of DCI-phases for each brand visualise the effect of the brands' different vehicle portfolios. E.g. SKODA's DCI value is low compared to PORSCHE's as the brand offered smaller (lower average curb weight) vehicles which consumed on average less fuel.

Figure 4 indicates which brand causes comparably high or low life-cycle CO_2e emissions per vehicle. Though it does not indicate which brand has the highest impact on VW Group's absolute CO_2e emissions and in which market these are caused, this absolute perspective can be achieved by weighing the relative DCI average emissions with the respective number of vehicles (Figs. 5 and 6). Like this, the question which brand and market has the highest relevance regarding realisation of reduction measures to most effectively reduce the VW Group's carbon footprint can be answered. In 2015, the brand VW and the market EU are the OEM's main emission drivers in this case study.

3.3 Data inputs DCI 2035

The future-orientation of the DCI is achieved by adjusting the relevant input parameters. In this case study, we assume the following exemplary developments for the year 2035.

3.3.1 Portfolio data

In line with the EU only allowing zero emission vehicles from 2035 onwards (European Commission 2023a), we assume a 100% BEV fleet in the EU but also in the USA and China in the 2035 DCI scenario. Modelling a future DCI value also requires information on the planned brand-specific market activities of the OEM. Basing on the OECD's urban passenger model (recover scenario), the vehicle kilometres between 2015 and 2035 will develop as follows: + 8% in the European Economic Area + Turkey (used for EU market), + 12% in Canada and the USA

Table 6 Average curb weights per brand for regular (> 1700 kg curb weight) and large (< 1700 kg curb weight) vehicles in 2015

Brand	Average curb weight regular-sized vehicle (share in brand's fleet)	Average curb weight large-sized vehicle (share in brand's fleet)	Number of overall models
VW	1303 kg (97%)	2036 kg (3%)	23
AUDI	1354 kg (40%)	1882 kg (60%)	13
SEAT	1161 kg (93%)	1805 kg (7%)	5
SKODA	1275 kg (100%)	-	7
PORSCHE	1445 kg (23%)	2017 kg (77%)	6
VW commercial vehicles	1576 kg (37%)	2060 kg (63%)	5

This calculation is based on the VW Group Annual Report 2015 (VW 2016) and publicly available data sheets for each model. In the case study, this data is used to calculate supply chain emissions in correlation with the LCA data of the reference vehicles (Tables 5 and 7)

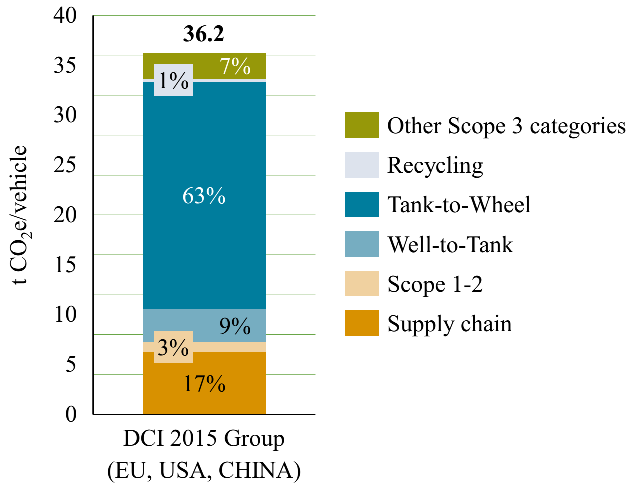

Fig. 3 Case study result of the modelled 2015 Decarbonisation Index (DCI) based on publicly available data of the Volkswagen Group including the markets EU, USA and China

(used for US market), + 73% in Asia (used for Chinese market) (OECD 2022). We use these numbers for the market-specific vehicle sales forecasts which apply for all brands (option 1B in Table 2).

3.3.2 Vehicle data

The BEV reference vehicles and the respective LCA and technical data for regular and large-sized vehicles are shown in Table 7 (options 2C). Supply chain emissions for the 2035 scenario are calculated twofold: the brand- and size-specific curb weights excluding the battery cell production and the in-house production (option 5A) are again calculated based on the average curb weights gathered for 2015 (option 3A), and the battery production emissions are calculated separately (option 4A). This allows for modelling the battery cell production with different energy mixes to distinguish between different markets, points in time and to subsequently estimate the leverage of using renewable energy sources instead of fossil energy (option 4A). In this scenario, we assume that the battery cells are manufactured in the market the vehicle is sold. Based on Dai et al. (2019), we assume an NMC111 battery cell technology which requires 30 MJ electricity and 140 MJ steam per produced kWh battery cell. Battery cell chemistries and the needed amount of production energy are very likely different in 2035 than assumed in this study. The publication of Dai et al. (2019) is used because of its transparency and public availability. The battery cell calculation module is connected to the respective emission factors for market and time-specific emission factors as well as to the reference vehicle technical data. For a basic prognosis scenario, we use the respective market-specific electricity grid mixes which we sourced from the GaBi database CUP 2022.2 for 2030 and 2040 and linearly interpolated for 2035 emission factors (Sphera Solutions 2022). For thermal energy, we used the 2022 market-specific emission factors for thermal energy from natural gas. In order to model the leverage of using renewable energy sources for battery cell production, we applied the 2022 market-specific emission factors for electricity from wind power and thermal energy for biogas (for China, we used the EU-28 biogas factor as no Chinese factor was available).

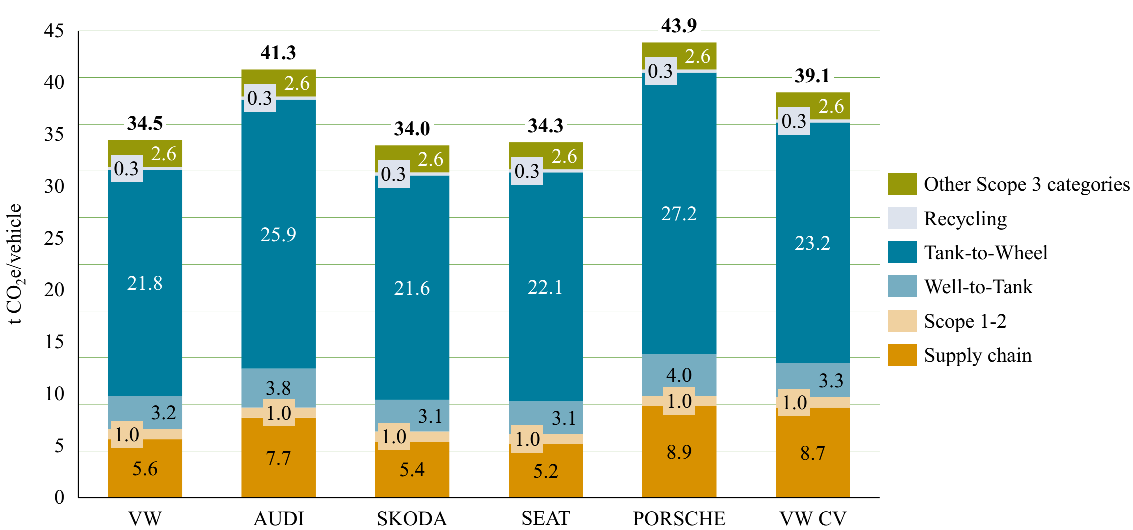

Fig. 4 Case study modelling results of the 2015 Decarbonisation Index (DCI) for the markets EU, USA and China disaggregated on brand level and based on publicly available data of the Volkswagen Group. The respective differing shares of the DCI-phases and the overall DCI values illustrate the impact of the brands' differing product portfolios. E.g. brands with heavier vehicles like PORSCHE and AUDI show higher supply chain emission values than brands producing on average lighter vehicles like SKODA or SEAT

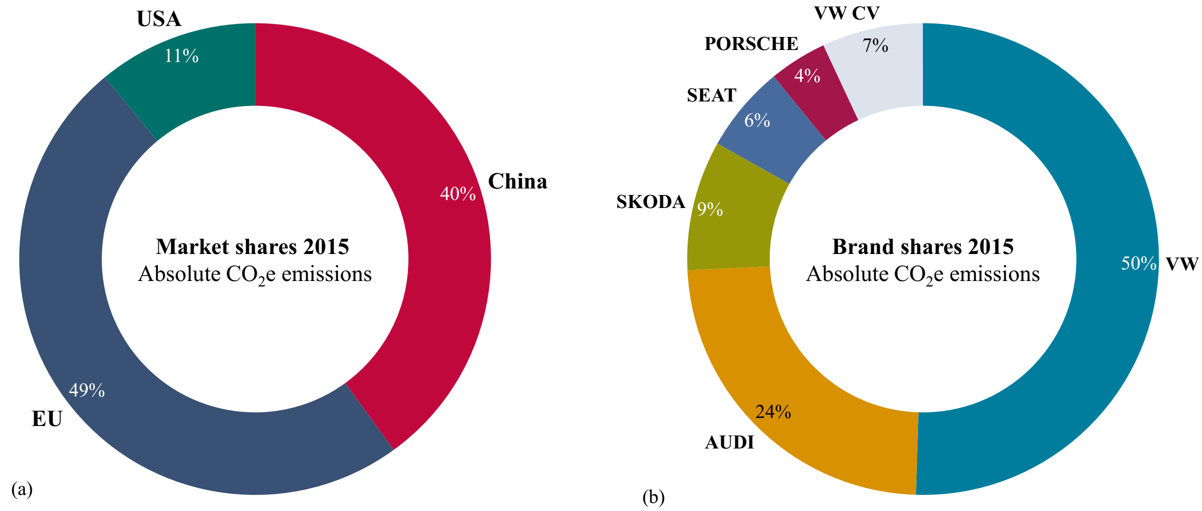

Fig. 5 **a** Modelled exemplary Decarbonisation Index (DCI) shares of the markets EU, USA and China on the Group's absolute CO_2e emissions in 2015. **b** Modelled brand shares on absolute CO_2e emissions in 2015 (EU, USA, China). VW and AUDI were the highest selling brands in 2015 thus contributing most to VW Group's absolute emissions

2035 TTW emissions are calculated based on the reference vehicle data of the base year (option 7A) coupled with the assumed powertrain mix for 2035. As we assume a 100% BEV fleet, TTW emissions are zero. The respective WTT emissions are modelled by using interpolated market-specific emission factors for fuel (if we had ICEs in this scenario) and charging electricity (option 6B). In order to model the leverage of using renewable energy sources for BEV charging, we again applied the 2022 market-specific emission factors for electricity from wind power (option 6C). The electricity consumptions and recycling emissions for each reference vehicle are indicated in Table 7 (option 8B).

3.3.3 Additional data

For both "scope 1–2" and "other scope 3 categories", the base year emission factors were assumed (options 5A, 9A).

3.4 Modelling results 2035

In this example, the modelled complete electrification of the fleet and the growing vehicles sales in China shift the market dominating absolute emissions from the EU to China (Figs. 5 and 6). The Group DCI covering all three markets is reduced by 12.2 t CO_2e/vehicle from 2015 to 2035, i.e. 34%. The electrification of the fleet causes a burden shift from TTW to WTT and supply chain emissions in 2035 compared to 2015 (Fig. 7). 2015 TTW emissions were modelled as 22.8 t CO_2e/vehicle whereas 2035 TTW emissions equal zero. In contrast, WTT emissions show a rise of 7.6 t CO_2e/vehicle from 2015 to 2035 and supply chain emissions of 3.3 t CO_2e/vehicle. For 2035, modelled WTT emissions are highest in China as the CO_2e intensity of the electricity mix is highest there. In the "Renewable energy scenario" on Group-level, a reduction of 0.5 t CO_2e/vehicle in the supply chain (i.e. the battery cell production) and 10.6 t CO_2e/vehicle for WTT emissions can be achieved by applying electricity from wind power and thermal energy from biogas instead of the grid mixes in the regular 2035 DCI. Together, this lowers the 2035 DCI from 24.0 to 12.9 t CO_2e/vehicle.

4 Sensitivity analysis

The modelling results presented in the above case study mainly rely on LCA-sourced data and assumptions. Environmental impact data from LCA databases represents sector

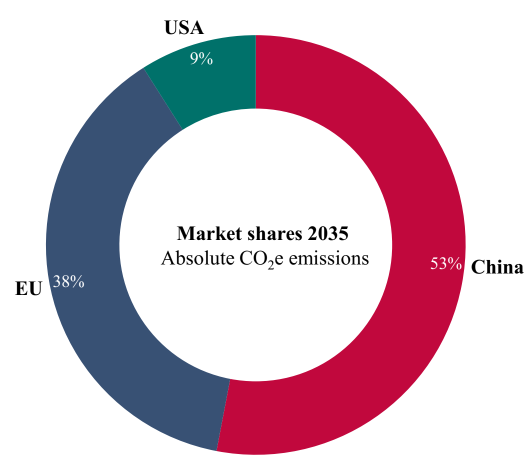

Fig. 6 Modelled market shares of Volkswagen Group's absolute CO_2e emissions in 2035 based on the Group's 2015 vehicle sales and the OECD's 2035 urban passenger model (OECD 2022)

Table 7 Data sourced for small and large reference battery electric vehicles (BEV) used in the case study

Reference model	Production including battery (t CO_2e/vehicle)	Share scope 1–2 on scope 3 cat. 1 (%)	EU curb weight (kg)	Battery capacity (kWh)	Battery cell production	Electricity consumptions NEDC (kWh/100km)	Recycling (t CO_2e/vehicle)
ID.3	13.7 (VW 2021)	14.1 (VW 2017a)	1813 (ADAC 2022)	62 (VW 2021)	30 MJ electricity/kWh battery cell, 140 MJ steam/kWh battery cell (Dai et al. 2019)	12.9 (ADAC 2022)	0.3 (VW 2021)
Audi e-tron 55 quattro	19.0 (AUDI 2020)	14.1 (VW 2017a)	2565 (ADAC 2019)	95 (ADAC 2019)		24.3 (AUDI 2020)	0.3 (assumed)

average or most likely figures. As no measurement is completely certain, such data needs to be considered including its uncertainty ranges, i.e. the parameter uncertainty (Bamber et al. 2020; Bałdowska-Witos et al. 2020). Additionally, the model (in this case, the DCI methodology) resp. its results need to be tested for model uncertainty. Below, we conduct a global sensitivity analysis of selected input parameters regarding their effect on the modelled DCI 2015 figure (Fig. 3) by means of the Monte Carlo (MC) simulation and the software Crystal Ball (10,000 repetitions). Like this, we can identify the parameters which contribute most to the uncertainty of modelled results. Across industry sectors, scientific disciplines and LCA research, the MC simulation for conducting stochastic uncertainty or sensitivity analysis is most commonly used (Bałdowska-Witos et al. 2020).

Chosen input parameters to be tested for their combined effect on the DCI results were assumed to have triangular distributions. The reference New European Driving Cycle (NEDC) use phase emission averages are estimated to have an uncertainty range of a generically set − 10% and a specific + 21%. The + 21% are based on the average deviation of the NEDC and the Worldwide harmonised Light Duty Test Cycle (WLTC) emission values in the EU (Dornhoff et al. 2020). The assumed uncertainty of the modelled lifetime kilometrage of 200,000 km is assumed to be + / − 15% based on Weymar and Finkbeiner (2016). A generic + / − 10% uncertainty range for the vehicle curb weights and the share of scope 1–2 emissions on overall production emissions was assumed due to lack of published specific data. The used supply chain and recycling emission factors are derived from vehicle LCA studies. These studies are based on ca. 40,000 processes modelled within the LCA software GaBi which are connected to specific emission factors within an LCI database. Each factor has its own uncertainty. Unfortunately, the authors of the vehicle LCAs used in this case study did not indicate an overall uncertainty of their published LCIA results. Therefore, the supply chain and recycling emissions factors are also assumed to have a generic + / − 10% uncertainty range.

Figure 8 shows the results of the MC simulation taking into account the described uncertainty ranges for the chosen parameters. The modelled arithmetic mean value of the MC simulation is 38.85 t CO_2e/vehicle and is thus 2.6 t CO_2e/vehicle higher than the benchmark value (36.2 t CO_2e/vehicle, see Fig. 3). The calculated standard deviation is 2.88 t CO_2e/vehicle. The 95% confidence interval is indicated with 33.87 t CO_2e/vehicle at the lower end and 44.87 t CO_2e/vehicle at the upper end. The main drivers for the DCI's model uncertainty are the parameters with the highest rank correlation coefficients: the NEDC tailpipe emissions value of the small ICE reference vehicle (0.51), the lifetime kilometrage (0.33), the NEDC tailpipe emissions value of the large ICE reference vehicle (0.06) and the vehicle curb weights (0.01).

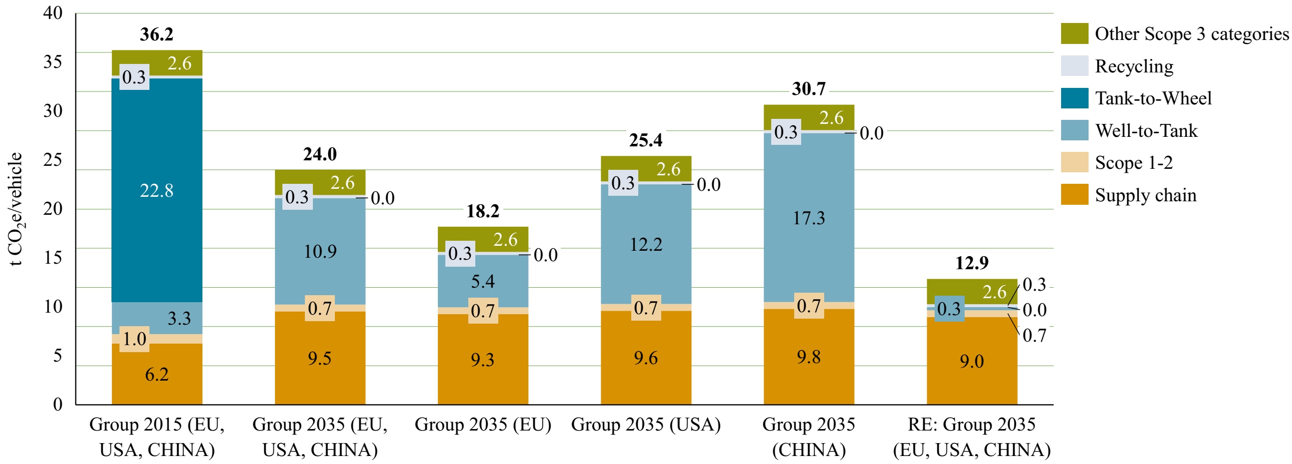

Fig. 7 Volkswagen Group Decarbonisation Index (DCI) values for 2015 and 2035 (EU, USA, China) and market-specific Group DCI values for 2035. The 2035 DCI values are based on the Group's 2015 vehicle sales and the OECD's 2035 urban passenger model (OECD 2022). For the 2035 modelling points, fleets with 100% BEVs are assumed. The assumed 2035 Chinese electricity mix has a higher CO_2e-intensity than the EU and US mixes. The modelled well-to-tank emissions are therefore highest in China. In the "Renewable energy scenario" (RE) for 2035, it is assumed that the electrified vehicles in the included markets are charged with electricity from wind energy and that the battery cells are manufactured by using biogas and wind energy

As shown in the above analysis, the fleet emission averages are crucially defining OEM's reported GHG emissions over the life cycle of their products if ICEs dominate the fleet. A change of legislation regarding driving cycles (like in the EU in 2017 (Dornhoff et al. 2020)) is therefore an external requirement that affects OEMs' reported GHG emissions majorly. Re-calculating past reported emissions becomes necessary when the methodology changes between reporting years. Otherwise, the development of emissions cannot be interpreted correctly.

In order to address the robustness of parameters that are (not yet) legislated, OEMs could, e.g. include market-specific measured vehicle lifetime kilometrages instead of the generic 200,000 km. In this exemplary DCI calculation, only publicly available data was used as input to the model. When applying the DCI method internally, OEMs will have access to more accurate and specific data regarding the fleet emission averages and curb weights per, e.g. brand-powertrain-gearbox combination thus addressing these parameters with higher certainty.

Although the model's sensitivity to the chosen parameters is comprehensible, the complexity of the tested model and the variety of input parameters with further non-included uncertainties should be kept in mind when interpreting the DCI modelling results. This holds especially true for projected future DCI figures when more input parameters (like, e.g. electricity mixes for charging electrified vehicles or battery technologies) are based on forecasting models with further assumptions.

5 Discussion

The DCI combines the static perspective of past emissions monitoring and reporting with the dynamic perspective of OEMs long-term vehicle sales planning. Existing data sources and approaches from the past emissions reporting (to, e.g. the CDP platform) can be used to calculate the DCI resource efficiently. Likewise, the KPI's modular calculation facilitates scenario-building for future emissions throughout the vehicles' life cycle on a fleet level while taking reduction measures on product and component level into account. As such, the most efficient strategy to achieving a carbon reduction target can be identified and used as a decision basis by the OEM managers. In this study, even with only the basic DCI calculation and data available, the most impactful reduction measures (a) electrification of the fleet, (b) renewable energy sources for charging and (c) the battery cell manufacturing were identified.

The DCI thus meets the methodological requirements developed for its derivation (see Sect. 2). But does it also meet the expectations of the different stakeholders we brought up in the introduction? The DCI cannot be a "stable" KPI in a way that its calculation principles are set in stone. The MC analysis showed, i.a. that the DCI result is susceptible to change depending on the standardised driving cycle taken as a basis for the calculation. The (automotive) decarbonisation field is developing constantly with new standards and regulations on the way. Examples include a required carbon footprint for EV batteries in the

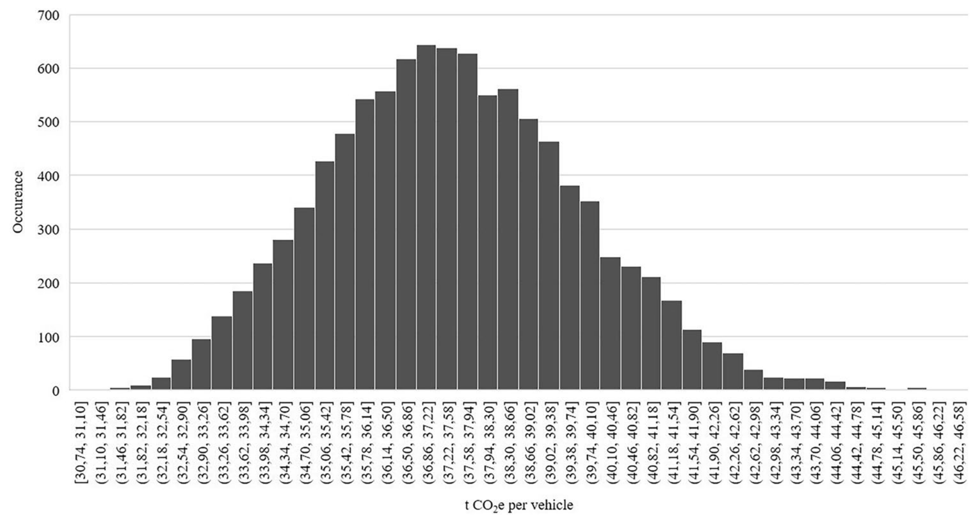

Fig. 8 Result of the Monte Carlo simulation for the modelled 2015 Volkswagen Group Decarbonisation Index (DCI) including EU, USA and China (10,000 repetitions). The modelled arithmetic mean value is 38.85 t CO_2e/vehicle and thus deviates from the benchmark value of 36.25 t CO_2e/vehicle by 2.6 t CO_2e/vehicle. This is mainly due to the assumed high uncertainty (+21%) of the tank-to-wheel NEDC emission value of the small reference ICE vehicle

EU starting 2024 calculated with a specific set of rules (European Parliament 2022; European Commission 2023b) and the currently updated guidance for the transport sector of the Science Based Targets initiative (SBTi) (SBTi 2023). The GHG Protocol confirms that the adoption of standards helps to reduce the uncertainty of inventory data. It also stresses the process of improving the inventory data while providing a data basis suitable for decision-makers inside and outside of the company (WRI; WBCSD 2011). Consequently, change is inherent when setting up and working with a decarbonisation KPI. Nonetheless, the decision-making basis for OEM strategists and external stakeholders must remain stable in a way that the same decision would be made disregarding the "calculation premises" that are applied to calculate the DCI. Here, "calculation premises" refer to the list of calculation methods and data used to calculate the DCI for a specific year. Examples are the driving cycles applied in the use phase, clipping rates for certain components or specific data obtained from suppliers versus generic secondary data. Accordingly, the overall DCI result in t CO_2e per vehicle can differ, but the conclusions remain the same.

This dynamic development regarding regulations and standards is mirrored and fuelled by the development process happening inside the company setting up their DCI. At first, a rough estimate of emissions (like in this study) to deduct the most pressing measures is calculated. Subsequently, the OEM's decarbonisation practitioners will opt for exchanging the generic database with specific data to calculate the reduction potential of further measures. Like this, a higher degree of "transparency" is introduced to the DCI model. But what will the effects be? Will a specific aluminium supplier have a higher or lower carbon footprint than the European aluminium mix data that is currently sourced from the LCA databases? It is hence possible that more data transparency leads to higher DCI values at first. Though OEMs should not be afraid to pursue this higher level of calculation accuracy, only with such a (stepwise) introduction of supplier-specific data can crucial reduction measures in the component production be identified, measured, their effect be reported and a deep decarbonisation of the material supply chains be achieved.

Consequently, more departments outside the decarbonisation and LCA departments will become part of the "DCI team" by providing specific data and using the KPI as a steering instrument themselves. These are, e.g. the fleet planners, the procurement, the logistics and production departments. Vehicle-specific data for the use phase is already standardised based on driving cycles and the established reporting to the authorities (in many markets). Though, especially the material supply chain was shown to be the hotspot phase to realise reduction measures in an electrified fleet (Fig. 7). Gathering specific data from suppliers for every reporting year is a challenge for OEMs and suppliers alike regarding data quality and IT infrastructure. Thus, the need for new cross-industry standards rises. An example for an ongoing supply chain related data initiative is Catena-x (Catena-x 2023).

The described developments inside and outside the company lead to constantly changing sets of "calculation premises" for the DCI. When internal insights in processes and available data evolve and external requirements for reporting change (e.g. the legislative change from NEDC to WLTC in the EU), the DCI calculation premises must be adapted in order to reflect the current methods and data environment. Like this, however, analysing the actual decarbonisation progress happening on the OEM's product is difficult to impossible because the calculation premises differ for each reporting year. Therefore, re-calculating already published DCI results of past reporting years is necessary to be able to assess the OEM's decarbonisation effort. This is especially important when a decarbonisation target (e.g. a Science

Based Target) is set by the OEM. Here, the base year, the current reporting year and the target year must be calculated with the same calculation premises. In order to keep these adjustments to a minimum, a threshold could be used to define the magnitude of change compared to the last set of calculation premises that make re-calculation necessary. Another way to prevent numerous adjustments, to increase transparency for external stakeholders and to facilitate the external verification of the DCI results on, e.g. reasonable assurance-level for publication within the OEM's annual or sustainability report are again standardisation or harmonisation initiatives. Ongoing examples for such vehicle LCA related initiatives are TranSensus LCA (Fraunhofer LBF 2023) and UNECE GRPE IWG LCA (UNECE 2022). Though even when faced with these complex methodological developments, OEMs should not hesitate to implement the DCI starting with basic calculation premises and data sets. It will be a continuous improvement process regarding the accuracy of results, but the deduction of most pressing measures is possible right from the start.

The financial aspect of developing and implementing an OEM's decarbonisation strategy is outside the scope of this study. Still, OEM managers will not base their decisions on fleet compositions and operationalisation of reduction measures only on the carbon reduction leverage indicated by the DCI but also on the costs. Therefore, future research could address how the DCI methodology can be coupled with an internal carbon pricing system. The cooperation with the financial departments is especially important when considering the dependence of the automotive industry's decarbonisation success on developments in other industrial sectors. How should high and long-term investments be handled that are necessary to, e.g. support the retrofitting of steelworks or the provision of renewable electricity? Harpankar (2019) provides an overview of carbon pricing approaches which could be used as a basis to develop an internal carbon pricing system in accordance with the DCI methodology. Likewise, the DCI could be adapted to heavy-duty vehicles and two-wheelers to cover the whole product range of OEMs.

6 Conclusions and outlook

The here developed KPI "Decarbonisation Index" (DCI) is applicable by any OEM regardless of their company structure, powertrain portfolio or market coverage to monitor past emissions and to model future emissions by using the common denominator of t CO_2e/average vehicle. The DCI combines the product-level view of the vehicle LCA with the fleet-level view necessary to develop a life-cycle-based decarbonisation strategy for meeting a GHG reduction target. The DCI's modular approach facilitates the use of both generic LCA data and supplier-specific data on component level depending on the OEM's access to data and overall purpose of using the KPI for internal steering and/or external reporting. The DCI is an "evolving KPI" as its methodological basis is constantly changing due to OEMs' own data requirements and insights or new external standardisation initiatives. Nonetheless, the DCI is also a stable and reliable KPI as past reported emission values can be adjusted by using the current methodological set. As such, both external stakeholders and OEM managers can analyse the decarbonisation progress and deduct the most impactful reduction measures although the absolute DCI values differ between methodological sets. An OEM's DCI result also depends on the decarbonisation efforts in coupled sectors such as the energy sector. A close cooperation between OEMs and energy providers is therefore crucial. Lastly, the standardisation and digital exchange of material and component carbon footprints between OEMs and suppliers is necessary to achieve a deep decarbonisation of the supply chains and is likely to shape the DCI results in the future.

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Declarations

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