Integrated CO_2e assessment and decision support model for supplier selections

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”It is worth fighting for each tenth of a degree.”

(Schellnhuber, 2012, p. 59)

Abstract

The fast growing stakeholder interest in sustainability leads to an increased attention both on the ecological and social perspective of industrial companies and its products. While in the past the focus predominantly laid on the environmental impact of the product use phase, it recently shifted towards the manufacturing phase. Hence, both, focal companies and supply chain members are obliged to create and apply new strategies to reduce greenhouse gas emissions (GHG). From a purchasing perspective, the selection of more environmentally efficient suppliers is a possibility to significantly reduce CO_2e emissions. Therefore, transparency is required in form of site-specific and comparable data on suppliers' environmental performance. This data is lacking and the detailed environmental performance criteria has not been integrated in supplier selection decisions yet.

In this dissertation a model is developed and applied to close the transparency gap and to integrate CO_2e as an additional supplier selection criteria in decision-making. For this purpose, a multi-criteria decision analysis approach is developed to derivate criteria weights and a supplier ranking based on expert opinion and quantitative supplier performance data. As decision making based on expert consultation is associated with a certain level of subjectivity, a sensitivity analysis is performed to evaluate the robustness of the model and the results. By means of 'what-if' scenario simulations, the dynamic behavior of the model is further investigated to examine how decisions may change when CO_2e is formulated and considered as a new criteria.

In addition, a systematic and modular life cycle assessment (LCA) based approach is developed to enable an efficient evaluation and comparability of the sustainability performance of raw material suppliers on a production site level, based on publically available data. The model combines a bottom-up calculation of technical process flows with top-down reported site-specific

CO_2 emissions, and explicitly considers technical restrictions and trading of intermediate products.

The developed site-specific performance model is applied in two case studies for primary steel production sites in Europe and primary aluminum sites in Germany. The results, which were validated with industry experts, differ by 58% for the comparison between the most and least efficient production site for steel and by 9% for the examined aluminum production sites and show an opportunity to reduce GHG emissions by selecting more environmentally efficient suppliers.

The combined, integrated CO_2e assessment and decision support model is subsequently applied on an automotive case study for the selection of the most adequate supplier for a powertrain part from an environmental and economic efficiency perspective. The results show that in some cases the integration of the CO_2e performance can have a significant impact on the ranking of the most preferable supplier, despite an initially investigated low importance of the new CO_2e decision criteria.

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Munich, March 2021 *Andreas Schiessl*

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Abbreviations

AHP	Analytical Hierarchy Process
BEV	Battery electric vehicles
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
EIA	Environmental impact assessment
EAF	Electric arc furnace
GHG	Greenhouse gas
ICEV	Internal combustion engine vehicles
LCA	Life cycle assessment
LCI	Life cycle inventory analysis
LCIA	Life cycle impact assessment
SCM	Supply chain management
SSCM	Sustainable supply chain management
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

Symbols of the sub-model B (steel production)

$ps_{x,i,l}, x \in \{1; 6\}$	number of process steps, respectively intermediate products for steel production (1: coke oven, coal; 2: sintering plant, sinter; 3: blast furnace, pig iron; 4: basic oxygen furnace, crude steel; 5: rolling plant, rolled steel; 6: power plant, electricity)
$i \in \{1; 4\}$	number of facilities per process step
$l \in \{1; 22\}$	number of locations
$PV_{ps_x,i,l}$	production volume (in t/a)
$CAP_{ps_x,i,l}$	capacity per process step (in t)
mcr_{ps_x,ps_x}	average material conversion rates (in t/t)
$BOGR_l \in \{1; 0\}$	basic oxygen furnace gas recovery (available/not available)
ipg_{COG}	average input of coke oven gas (in MJ/t)
$ipg_{BF\ Gas}$	average input of blast furnace gas (in MJ/t)
$ipg_{BOF\ Gas}$	average input of basic oxygen furnace gas (in MJ/t)
$ipg_{ps_x,i,l}$	input gas per process step (in MJ/t)
sff	average factor for additional secondary fuels from German steel plants per t crude steel (in GJ natural gas/t pig iron)
$aepg$	average factor for electricity production per t crude steel in Germany (in GJ electricity/t pig iron)
$power_{ps_6,i,l}$	plant specific electricity production per t crude steel (in GJ/a)
$ppo_{ps_6,i,l}$	site specific power plant output (in MW/a)
$ipg_{NG,l}$	input of natural gas as secondary fuel for the power plant (in MJ/t pig iron)
$elect_{ps_6,i,l}$	plant specific electricity production (in GJ/a)
ee_{ps_6}	average electrical efficiency (in %)
$elect_{ps_3,l}^{local}$	local electricity factor (in GJ/t pig iron)
$elect_{ps_3}^{Ø}$	average electricity factor (in GJ/t pig iron)

cc_{COG}	carbon content of coke oven gas (in kg C/MJ)
$cc_{BF\ Gas}$	carbon content of blast furnace gas (in kg C/MJ)
$cc_{BOF\ Gas}$	carbon content of basic oxygen furnace gas (in kg C/MJ)
cc_{NG}	carbon content of natural gas (in kg C/MJ)
cc_{CO_2}	carbon content of carbon dioxide (in kg C/kg CO_2)
$emiss_{ps_x,i,l}^{reported}$	reported CO_2 emissions (in t CO_2/a)
$emiss_{ps_x,i,l}^{theor}$	theoretical emissions (in t CO_2/a)
$emiss_{ps_x,i,l}^{pv}$	allocated emissions according to production volumes (in t CO_2/a)
$\tilde{x}$	auxiliary variable and corresponds to x
$PV_{ps_x,i,l}^{theor}$	theoretical production volume (in t/a)
$APV_{ps_x,i,l}$	additional production volumes (in t/a)
$emiss_{ps_x,i,l}^{apv}$	emission of additional production volumes (t CO_2/a)
$efact_{ps_x}$	industry average emission factors for process steps (in t CO_2/t)
$efact_{ps_6}^{electmix}$	average country specific emission factor for electricity mix for power plant (in t CO_2/GJ)
$efact_{ps_6}^{cc}$	average emission factor derived from 22 plants under study for power plant (in t CO_2/GJ)
$efact_{ps_6,l}^{reported}$	plant specific emission factors for power plant (in t CO_2/GJ)
$emiss_{ps_x,i,l}^{adjusted}$	adjusted emissions (in t CO_2/t)
$emiss_{ps_x,i,l}^{urmsc}$	average emissions for upstream raw material supply chain input (in kg CO_2/a)
$efact_{ps_x}^{urmsc}$	average industry emission factor for upstream raw material supply chain input (in kg CO_2/t)
$efact_{ps_6}^{urmsc,NG}$	average industry emission factor for natural gas (in kg CO_2/t)
$emiss_{ps_6,l}^{urmsc,NG}$	emissions for the externally purchased natural gas for the power plant (in kg CO_2/a)

Symbols of the sub-model B (aluminum production)

$ps_{x,l}, x \in \{1;4\}$	number of process steps, respectively intermediate products for aluminum production (1: anode factory, carbon anode; 2: electrolysis, liquid aluminum; 3: casting plant, raw aluminum; 4: rolling plant, aluminum product)
$l \in \{1;4\}$	number of locations
$PV_{ps_x,l}$	production volume (in t/a)
$CAP_{ps_x,l}$	capacity per process step (in t)
mcr_{ps_x,ps_x}	average material conversion rates (in t/t)
$emiss_l^{reported}$	reported CO_2 emissions (in t CO_2/a)
$emiss_{ps_x,l}^{pv}$	allocated emissions according to production volumes (in t CO_2/a)
$efact_{ps_x,l}^{local}$	local, process step related emission factors
$efact_{ps_x}$	industry average emission factors for process steps (in t CO_2/t)
$emiss_{ps_x,l}^{theor}$	theoretical emissions (in t CO_2/a)
$PV_{ps_3,l}^{theor}$	theoretical production volume (in t/a)
$APV_{ps_x,l}$	additional production volumes (in t/a)
$emiss_{ps_x,l}^{apv}$	emission of additional production volumes (t CO_2/a)
$emiss_{ps_x,l}^{adjusted}$	adjusted emissions (in t CO_2/t)
$ip_{ps_x,l}^{elect}$	average input factors for the electricity amount per process (in GJ/t)
$elect_{ps_x,l}^{pv}$	amount of electricity according to production volumes (in GJ/a)
$efact^{electmix}$	average country specific emission factor for electricity production (in t CO_2/GJ)
$emiss_{ps_x,l}^{elect^{pv}}$	emissions from electricity according to production volumes (in t CO_2/a)
$emiss_{ps_1,l}^{elect^{apv}}$	emissions from electricity according to additional production volumes (in t CO_2/a)

$efact^{EU,CN}$	mean value of the European and Chinese emission factor for electricity production (in t CO_2/GJ)
$emiss_{ps_x,l}^{elect^{adjusted}}$	adjusted emissions from electricity (in t CO_2/a)
$emiss_l^{reported^{pfc}}$	reported PFC emissions (in t/a)
$efact_{Ø}^{pfc}$	industry average emission factors for PFC emissions (in t CO_2/t)
$emiss_l^{pfc}$	PFC emission (in t CO_2/a)
$emiss_l^{urmsc}$	average emissions for upstream raw material supply chain input (in kg CO_2/a)
$emiss_l^{total}$	total emissions per production site (in kg CO_2e/t raw aluminum)
$\tilde{x}$	auxiliary variable and corresponds to x

1 Introduction

1.1 Problem description[1]

For various stakeholders around the globe the topic of CO_2 emissions is constantly growing in significance. The main triggers are the global governmental goals to reduce greenhouse gas emissions (expressed in units of carbon dioxide equivalents - CO_2e) and to consequently limit global warming to 2 respectively 1.5 degrees Celsius (Jaeger and Jaeger, 2010).

In Europe, the transport sector accounts for 27% (1.250 Mt CO_2e) of all GHG emissions (4.629 Mt CO_2e, including international aviation and international maritime transport) in 2017 (European Environment Agency, 2019d). It constitutes the second largest emitter of CO_2e among all energy demanding technologies, and thus demands for a further development of CO_2e reduction strategies in order to reach the national climate objectives.

Taking a closer look, with 264 million registered vehicles[2] (European Commission, 2019a) the passenger car sector solely accounted for 32% of the transport sector emissions and represented 9% of the total greenhouse gas emissions in the European Union in 2017 (European Environment Agency, 2019d).

In order to even foster the accomplishment of the two degree Celsius target and to encourage the quick and affordable development of sustainable technologies for implementation, in 2009, a legal framework was introduced to

1 Parts of this research thesis were previously published in Schiessl et al. (2020a) and Schiessl et al. (2020b). Some passages of this publication were exclusively developed and prepared by the author of this thesis and were transferred without citation.

2 Vehicle, car and passenger car are used synonymously in the following.

limit average fleet consumptions for passenger cars. Whereas an initial target/limit of 95 g CO_2/km was set for 2021 (European Commission, 2009), the legal regulation has recently been extended and the goal for 2030 has even been reduced by 37.5% compared to 2021 (European Commission, 2019b).

Consequently, in the automotive industry, the focus regarding CO_2 emissions is laid on the vehicle usage phase. However, an extension of the scope of CO_2e emissions to include the manufacturing process of every component in the upstream supply chain is expected. Moreover, it is necessary to account for the CO_2e emissions of the whole supply chain and to reveal additional potentials for emission reductions (BME, 2014).

Even though currently there are no regulations for CO_2e emissions for the production phase of cars set in place, first activities were initiated. For example, the European Political Strategy Center, which represents the in-house think tank of the European Commission, has identified the embedded emissions for vehicle manufacturing as one future field of activity (EPSC, 2016).

This is especially important, as due to the currently ongoing technology shift from internal combustion engine vehicles (ICEV) towards battery electric vehicles (BEV), the focus will shift from CO_2e emissions within the use phase to the manufacturing phase. According to German Environment Agency (UBA, 2016) the manufacturing phase of an ICEV, in case of a lifetime mileage of 168,000 km, has a proportionally small share of 15% of the overall CO_2e life cycle emissions. In comparison to a BEV100 (battery-electric vehicle with an electric driving range of 100km), calculated with the German energy mix, the manufacturing phase gains more importance with a climate impact of 27% (see section 2.2.2). Newly released initiatives, such as the new Volkswagen ID car project (start of production in 2019), even strive for carbon-neutrality throughout the whole product lifecycle including the manufacturing phase (Volkswagen AG, 2019).

Especially for the purchasing sector in the automotive industry, this change towards carbon emission efficiency and eventually neutrality, may illustrate a major challenge. Up to 75% of the value adding process of a car is outsourced to upstream supply chain partners (Bai and Sarkis, 2011; Hartley and Choi, 1996). As in the past, mostly economic preferences combined with the satisfaction of quality requirements have been pursued by car manufacturers, this development appears particularly challenging. The focus has already been extended and social as well as environmental factors have already gained importance since the early 2000s (Büyüközkan, 2012; Guinée et al., 2011; Roy et al., 2009; Zimmer, 2016; Zimmer et al., 2016). However, all stakeholders in supply chains are on the one hand obligated to develop new comprehensive strategies as well as methods to reduce carbon emissions, and, on the other hand, obligated to foster a quick implementation.

Thus, the selection of more environmentally efficient suppliers for raw material may constitute a promising opportunity from a purchasing perspective to reduce CO_2e emissions within the manufacturing phase of a product, hence this selection can be advantageous for a company or even the industrial sector as a whole. Once specific limits for amounts of CO_2e emitted during production and the corresponding penalties for exceeding these limits are introduced, a change in current supplier selection practices is unavoidable. Thus, a necessity for a more detailed consideration of supplier selection and development, with a focus on site-specific CO_2e performance of suppliers, may arise.

A closer look at the material composition of passenger cars reveals the important role of steel and iron as well as aluminum, and consequently its influence on the pollutant emissions of the manufacturing phase. Taking the example of the Volkswagen Golf as the bestselling car in Europe in 2017, steel and iron products represent 62.9% and aluminum 8.1% of all materials used for the manufacturing (Lieberwirth and Krampitz, 2015; Schmid and Zur-Lage, 2014).

However, in the iron and steel industry, a certain lack of data transparency exists which can be traced back to two main aspects. Particularly in integrated iron and steel mills, a high complexity is revealed due to the material and energy flows as well as the trading of intermediate products with varying levels of process depth among different manufacturer's production sites[3]. Furthermore, access to site-specific primary data is very limited as a result of industrial secret, which is also the case for the aluminum industry.

Hence, a site-specific evaluation, respectively environmental performance assessment, as well as a comparison of production sites, which represents the basis for the formulation and integration of a new decision criteria into supplier selection decisions, is currently not possible.

1.2 Objective and research question

Against this background, it is the objective of this research to develop a proactive approach in advance to a possible introduction of legislative regulations. It shall contribute to improving transparency along the upstream supply chain and enables an efficient evaluation as well as an integration of the sustainability performance of suppliers into supplier selection processes within the framework of sustainable supplier management.

Due to the fact that two consecutive, interdependent goals are pursued, two models are developed and finally coupled. In the following course of this research these models will be addressed as sub-model for decision support, respectively sub-model A, and sub-model for environmental performance assessment, sub-model B.[4]

[3] Site, plant and location are used synonymously in the following.

[4] Parts of this research contribution originate from a research project of the Karlsruhe Institute of Technology (KIT) in cooperation with a German original equipment manufacturer (OEM) and four leading international Tier-1 automotive suppliers.

Despite the subordinate final goal of applying the coupled model in a supplier selection decision-making process, the environmental performance assessment sub-model B is at some stages in the research addressed first, as it constitutes the basis for the integration in the decision support model A.

Thus, the environmental performance assessment sub-model B shall help to create greater transparency on emissions from upstream supply chain activities. This increased transparency shall enable the evaluation of suppliers' performance on the necessary level of detail on which supplier selections are made. In this context, a comparability of the environmental performance results among suppliers' production sites, independent of variances in the level of process depth, constitutes a crucial and compulsory requirement.

By means of the sub-model A for decision support, the evaluation of suppliers, which is currently based on various criteria (among others, cost and quality), shall be extended by the integration of site-specific suppliers environmental performances in order to reduce CO_2e emissions within the manufacturing phase, by the selection of more efficient suppliers. The sub-model A shall allow for what-if simulations to investigate critical points as of which a newly introduced criteria influences current decisions. Hence, future effects on current supplier selection decisions can be derived from an environmental as well as economic perspective. This shall support the formulation of CO_2e as new decision criteria for supplier selection processes and the development of new sustainable, strategic alignments.

In consequence of the problem description and the derived research objective, the following research questions arise:

How can new decision factors, such as CO_2e generated during the production process of vendor parts, be measured and integrated in well-established supplier selection processes, besides existing decision criteria?

These questions trigger additional sub-questions which will be answered in this scientific contribution:

(1) Which economic and ecologic factors are relevant for the evaluation of sustainable supplier performances?

(2) Which decision support method or combination of different methods is suitable to formulate and integrate new criteria?

(3) Which level of transparency, respectively level of data about CO_2-emission regarding upstream supply chain activities, is relevant?

(4) Which method is suitable to estimate material and energy flows of products in order to evaluate and compare the environmental performance of suppliers from a life cycle perspective?

1.3 Research design

To accomplish the research objective and to answer the research questions raised in the previous section 1.2, the structure of the research project is presented as follows (see Figure 1-1).

In section 2, the development and trigger of the sustainability debate is portrayed. This goes along with the introduction of associated definitions and framework information for sustainable supplier management respectively green purchasing, from a general as well as corporate perspective. Additionally, emphasis is laid on environmental sustainability in the course of product life cycle management in the automotive industry, material usage for vehicle manufacturing and on metal production processes for steel and aluminum as key GHG emission contributors.

In section 3, the current state of research in the field of decision making in a multi-criteria environment, with a focus on supplier selection, is critically reviewed. Special emphasis is laid on the selection of adequate decision criteria and the criteria formulation phase. Secondly, approaches for the assessment of environmental performance in the metal industry are analyzed and examined for applicability. The main focus is placed on life cycle assessment (LCA)[5] and respective methods of execution, as well as existing application of these methods in the steel and aluminum industry. At the end of this section, the research gaps are identified.

Section 4 illustrates the structure of the model based on a selection of suitable methods and the description of the model development for the two sub-models. At first, background information and the mathematical principles of the chosen multi-criteria decision analysis methods are described. After the model development, which relies on a chosen case study, a first exemplary application of the basic sub-model is conducted in order to strengthen the necessity for the second sub-model for site-specific environmental performance assessment. In the following, the principles of life cycle analysis as the basis for the new, combined LCA based approach are described. After the description of the framework information and data collection, the calculation approach for the estimation and comparison of site-specific environmental performances is illustrated.

In section 5, an exemplary application of the developed model is illustrated. Initially, the results of the sub-model for environmental performance assessment in the European metal industry are presented, discussed and validated. Moreover, these results are integrated into the developed sub-model for decision support and the two sub-models are coupled. An exemplary automotive case study from Germany is chosen to demonstrate the applicability and the advantages of the proactive model in relation to the research questions.

[5] Life cycle assessment and life cycle analysis are used synonymously in the following.

After testing the robustness of the model by means of sensitivity analysis, two scenario simulation approaches are illustrated to show different ways to support the formulation of CO_2e as additional decision criteria, both from an environmental as well as economic perspective.

Finally, in section 6, a summary and conclusions of the entire research are displayed, a discussion and critical appraisal of the developed model are provided and an outlook on future research is given.

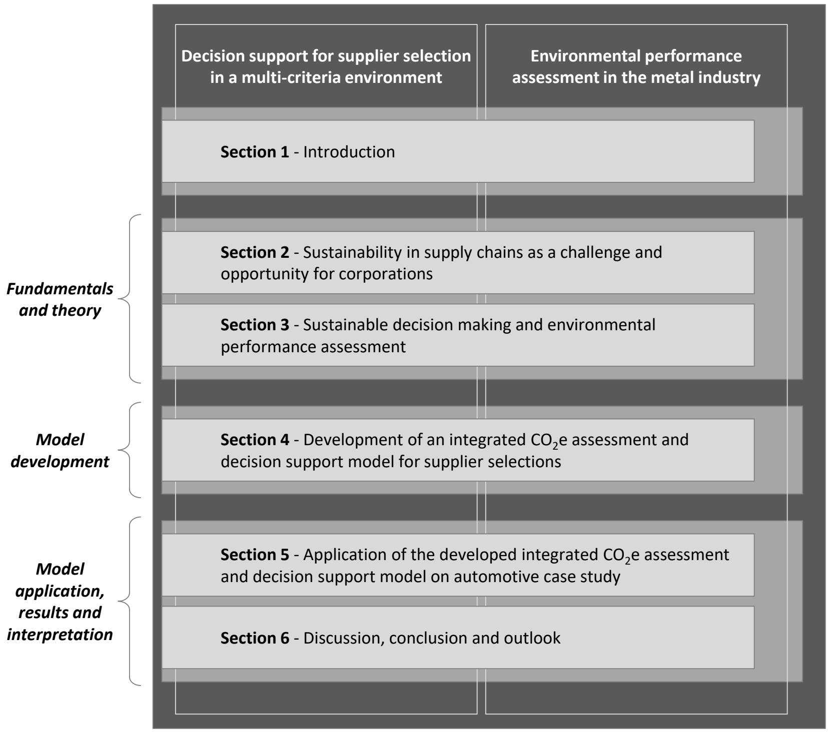


Figure 1-1: Structure of the research project

2 Sustainability in supply chains as a challenge and opportunity for corporations

The following section serves to provide an insight in the area of sustainability within the context of supply chain management and to reveal existing challenges and possibilities. Therefore, the main foundations and key terms regarding the fields of supply chain management and purchasing are illustrated in section 2.1. Subsequently, in section 2.2, the relevant information from the automotive industry with regard to product life cycle considerations are presented. Furthermore, in sections 2.3 and 2.4, general industry as well as technical process information with regard to the steel and aluminum industry are described, which serve as basis for the later examination of production process from an environmental perspective.

2.1 Theoretical foundations of sustainability in supply chain management

Sustainability is gaining importance in corporate business actions and is increasingly adopted in supply chain management structures as well as processes. In the following sections the motivation for the integration of sustainability in supply chain management and specifically purchasing activities, as well as general background information are shown.

2.1.1 Definition of sustainability

"Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987, p. 1).

This definition from the Report of the World Commission on Environment and Development, also cited as Brundtland Report, is often described to be the first definition of sustainability, respectively sustainable development (Pope et al., 2004). The report led to the UN Conference on Environment and Development (UNCED) in Rio de Janeiro in 1992. Since the introduction into international politics, the integration of environmental thinking in social, political and economic aspect has gained a lot of popularity and various definitions of sustainability have arose (Elkington, 1994; Pope et al., 2004; Purvis et al., 2019). The division in economic, social and environmental dimensions by an equitable consideration of all three dimensions can also be traced back to the Report of the World Commission on Environment and Development (WCED, 1987).

In view of the above, Elkington introduced in 1994 the concept of triple bottom line (TBL), which follows the principle of the three dimensions of sustainability in a business context (Elkington, 1994). Since the publication of the book ‘Cannibals With Forks’ (Elkington, 1998), the triple bottom line concept is being considered as one of the most used sustainable accounting methods. It shall enable companies to make long-term sustainable decisions and introduce policies in order to increase performance on economic, social and environmental levels.

Within the three bottom lines approach, a simultaneous achievement of a basic level of all three dimensions of sustainability is required as foundation to reach a desired level of economic, social and environmental sustainability (Elkington, 1998; Slaper and Hall, 2011).

The three performance levels of the triple bottom line include the following characteristics (Alves and Alves, 2015; Elkington, 1998; Goel, 2010):

- Profit: meeting shareholders expectations through value generation or contributing to societies economic benefits,

- People: establishing fair labor conditions as well as practices for people involved in companies/corporate activities, and

- Planet: focusing on securing sustainability as well as efficient energy use and reducing environmental burdens throughout production processes (e.g. greenhouse gas emissions).

Consequently, a sustainable corporation can be defined as “one that creates profit for its shareholders while protecting the environment and improving the lives of those with whom it interacts. It operates so that its business interests and the interests of the environment and society intersect” (Savitz, 2013, p. 2).

2.1.2 Internal drivers and external framework conditions

Sustainability in a corporate environment is driven by various factors (Diabat and Govindan, 2011; Zimmer, 2016). A distinction can be made in internal drivers (sections 2.1.2.1 – 2.1.2.2) and external framework conditions (sections 2.1.2.3 – 2.1.2.7) which motivate respectively urge companies to enhance sustainability and to include sustainable perspectives in corporate activities. At some points, no exact separation is possible as some drivers are internally as well as externally motivated and therefore overlap.

2.1.2.1 Management involvement

Out of several organization-related drivers for sustainability and in reference to green supply chain management, management involvement plays a key role. Walker et al. (2008) state that the personal values and ethical commitment transmitted by a company founder throughout the company are crucial for the establishment of sustainable activities. However, middle management is identified to be most efficient when fostering the development of environmental purchasing (Gopalakrishnan et al., 2012; Walker et al., 2008).

In contrast, Giunipero et al. (2012) point out that top-management is primarily responsible for a company's environmental management system respectively environmentalism, and for the promotion of green supply chain practices.

2.1.2.2 Employee involvement

Moreover, the personal involvement and commitment of staff is crucial to drive green supplier chain management and to achieve sustainable results (Gopalakrishnan et al., 2012; Walker et al., 2008). Especially the existence of skillful and motivated policy entrepreneurs in staff positions successfully expedite sustainable practices in supply chain management (Walker et al., 2008). Intrinsic motivation and reward, as well as career advancement can be named as motivation drivers (Walker et al., 2008). Even though the existence of policy entrepreneurs is required to start an internal change process, according to Handfield et al. (1997) it is not sufficient to initiate a wide-scale change of sustainable practices.

2.1.2.3 Society, media and non-governmental organizations (NGO)

Public awareness for environmental pollution and counteracting respectively preventive solutions have constantly increased in recent decades (Giunipero et al., 2012; Gopalakrishnan et al., 2012; Walker et al., 2008). This development is reinforced by an increasing media presence. It intends to make the topic of global warming more transparent, to issue a warning and to promote green initiatives (Hetterich et al., 2012).

Moreover, the public demand for environmentally friendly produced products is rising strongly. The companies´ reputation in terms of sustainable as well as transparent upstream supply chain activities became a decisive buying criterion (Walker et al., 2008). Stakeholder interest for sustainability can be found in a bundled form by the socially aware, non-governmental organizations and green pressure groups (Giunipero et al., 2012; Gopalakrishnan et al., 2012; Walker et al., 2008).

2.1.2.4 Governmental regulations

As described in section 2.1.1, the topic of sustainability has already found its way into global politics. The ever more frequently appearing effects of climate change and global warming have driven international governments to implement new laws with the aim to control and reduce social and environmental impacts of corporations (Gopalakrishnan et al., 2012; Sathiendrakumar, 2003). The introduction of penalties and legal cost have emphasized the relevance for companies to comply with legal requirements (Cordano, 1993). It presents the main motivation for corporate sustainability activities besides cost and quality factors (Preuss, 2001). According to Berns et al. (2009), environmental legislation illustrates the main driver for sustainability considerations and has the greatest influence on corporations. The Environmental Liability Directive 2004/35/EC and REACH regulation (EC) No 1907/2006 (Registration, Evaluation, Authorisation and Restriction of Chemicals) are two examples of European legislations, which urge companies to act in a more sustainable matter and to reduce environmental impacts (Gopalakrishnan et al., 2012). In order to promote the introduction of sustainability on an international level, various conferences are held on a yearly basis. These comprise among others the United Nations Climate Conferences, which are connected to the United Nations Framework Convention on Climate Change (UNFCCC), and serve as official meeting of the Conference of the Parties (COP). The goal is on the one hand to trace the realization of the convention and on the other hand to monitor as well as control the implementation of the adopted regulations defined in the Kyoto Protocol (COP 3) and in the successive Paris agreement (COP 21) (UNFCCC, 2020).

2.1.2.5 Customer demand

In connection to society as external driver, customers or consumers have a significant influence on the sustainable performance of companies and their product portfolio (Giunipero et al., 2012; Sroufe, 2003). Starting in the 1990s customer buying behavior has come into the focus.

Since then, also customer demands have changed and ecological consciousness has come into the fore (Roberts, 1996). The belief to solve environmental issues by making conscious purchasing decisions defines individual customer behavior (Giunipero et al., 2012). Even though the influence of customer concerns is found to be more critical outside of Europe and the United States (Berns et al., 2009), global consumer power is constantly increasing in terms of sustainability aspects. The higher the reputation of a company, and depending on the company's size, the higher is the sensitivity on customer pressure. Unwillingness or incapability to enhance environmental performance can negatively influence companies' bottom lines (Gopalakrishnan et al., 2012; Walker et al., 2008).

2.1.2.6 Competitive advantage and financial benefit

As a consequence of changing customer behavior and due to the increased awareness of global society for sustainable activities as well as products, green marketing is very well received among corporations. Moreover, it presents a solution for companies to attain and even increase competitive advantages in a constantly growing competitive, global market (Giunipero et al., 2012; Gopalakrishnan et al., 2012). The integration of sustainable management in production processes can lead for example to a reduction of environmental impact and thus be attributional to the competitive advantage of a company (Porter and van der Linde, 1995). According to Waddock and Graves (1997), sustainable and especially social performance is positively related to the overall profitability of corporations. Moreover, Stone and Wakefield (2000) found out that companies which rely on and follow sustainable principles show a better performance in the marketplace. As a result, the economic bottom line of corporations is positively affected by sustainable activities (Pullman et al., 2009).

Usage of resources: The ever-increasing global consumerism and the growing share of society becoming middle class are to be seen as main accelerators and triggers for global climate change as well as exhaustion of natural resources. There is a conflict between supply chains in order to meet customer demands and, at the same time, to assure a long-term preservation of natural resources for upcoming generations (Gopalakrishnan et al., 2012). A prudent and efficient usage of resources enables a decrease of cost and leads to an increased profitability, which is still the main objective of corporations. Thus, for example reduced energy expenditure, increased recycling of waste, lean practices and high safety standards can be considered as crucial drivers for sustainable corporate behavior (Giunipero et al., 2012). Even though, a longer time horizon is often needed before receiving the financial output of investments in sustainability, the long-term effects for corporations and the global environment as a whole are tremendous (Gopalakrishnan et al., 2012).

2.1.2.7 Environmental standards

The previously described external drivers, such as increased global consumerism especially in emerging markets, resource depletion and legislative regulation make the adaption of environmental standards necessary for supply chains (Gopalakrishnan et al., 2012). Certification standards, such as the ISO 14000 or ISO 14001, introduced by the International Organisation for Standardisation (ISO), lead corporations to focus on the performance of Environmental Management Systems (EMS) and to pay attention on the environmental impact assessment as well as impact reduction of production processes (Giunipero et al., 2012; Gopalakrishnan et al., 2012; Handfield et al., 2002). In the opposite direction, the increased focus on environmental responsibility can also be regarded as consequence of the introduction of environmental certification standards (Handfield et al., 2002). In this context, purchasing, which is responsible for the sourcing of materials and thus for upstream supply chain activities, takes on a crucial role and is addressed as a key process in the ISO 14000 and 14001 standard (Handfield et al., 2002). Hence, measures regarding purchasing decisions, as for example in regards to waste reduction, material packaging as well as logistics, are not only covered but also recommended in the standard. As supplier selections based on sustainable performances become more popular, the implementation of sustainable performances was defined as an obligatory selection criteria in the ISO 14001. It aims at simultaneously improving sustainable performances while fostering respectively increasing efficiency in operations (Curkovic and Sroufe, 2011; Gopalakrishnan et al., 2012).

2.1.3 Sustainable supply chain management

"A company is no more sustainable than its supply chain — that is, a company is no more sustainable than the suppliers that are selected and retained by the company" (Krause et al., 2009, p. 18).

According to Krause et al. (2009), the supply chain plays a key role in sustainable business management. Due to rapid growth of international competition, rising customer demands, accelerating technological transitions and ever shorter product-life cycles (Krause et al., 1998) companies strive for cost efficiency, downsizing of the work force and the concentration on core competencies, such as for example design, marketing and sales (Pounder et al., 2013). Therefore, the outsourcing to external providers of products and services, which are considered as non-core, as for example parts manufacturing (Pounder et al., 2013), is pursued to increase competitive advantages (Krause et al., 1998).

Several definitions of supply chains were created over the years, as for example by Mentzer et al. (2001) who define a supply chain as "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer" (p. 4).

In terms of complexity and scope of collaboration between suppliers and customers, Mentzer et al. (2001) described three degrees, a direct supply chain, an extended supply chain and an ultimate supply chain (see Figure 2-1). The ultimate supply chain, not illustrated in Figure 2-1, can be considered as a further extension of an extended supply chain, incorporating additional supply chain members such as financial providers, market research firms and third party logistics suppliers (Mentzer et al., 2001).

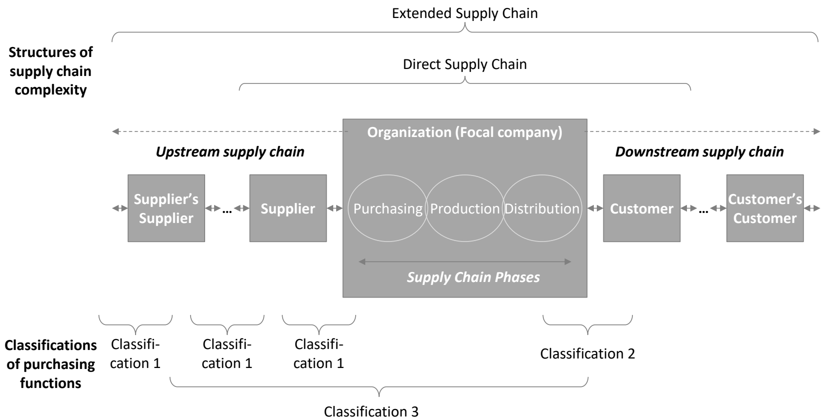


Figure 2-1: Supply chain phases, structures and purchase functions (based on Mentzer et al. (2001); Chen and Paulraj (2004); Igarashi et al. (2013); Omurca (2013))

Thus, the relationship between suppliers and buyers gains increasing importance. Besides the management of performances, a management of the entire supply chain and the activities as well as of its members is crucial for organizations long-term survival (Bai and Sarkis, 2011; Sarkis, 2003).

The origin of the concept of supply chain management is a much discussed topic in the scientific field. Whereas various researchers consider supply chain management as new concept, there is a strong resemblance to logistic concepts, developed already in the 1960s (Forrester, 1961; Heskett, 1964).

Considering supply chain management (SCM) either as an evolutionary or as a completely new construct, the origin of the term is often traced back to management consultants Oliver and Webber from 1982 (Oliver and Webber, 1982). However, supply chain management has received a lot of attention since the 1990s and is still widely discussed in scientific literature today (Giunipero et al., 2008; Lambert et al., 1998; Svensson, 2008). In the early years of the 1990s, academics primarily focused on the determination of a definition of SCM.

It centered around topics such as flow of goods, relationship management and an extended concept reaching from suppliers to final customers (Giunipero et al., 2008; Lambert et al., 2005).

Over the years, several more mature definitions were derived. For example Mentzer et al. (2001) defined supply chain management as "the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole" (p. 18).

Within supply chain management, three major phases were established (Boer et al., 2001; Chen and Paulraj, 2004; Felea and Albăstroiu, 2013; Omurca, 2013; Suraraksa and Shin, 2019):

- Purchasing, which ensures the sourcing of materials for the production,
- Production, which further processes the purchased materials and converts them into finished products, and
- Distribution, which focuses on enabling a supply through diverse distribution channels (e.g. warehouses, distributors or retailers) to customers.

In Figure 2-1, an example of the placement of the three phases within the supply chain is given. The phases can find implementation at diverse stages of the supply chain. With regards to the supply chain structures illustrated by Mentzer et al. (2001), the three phases can even present an entire supply chain consisting of supplier, organization and customer.

As described in the previous section 2.1.2, sustainability thinking finds increasing attention and application within the context of corporate activities.

Based on this development, the classical concept of supply chain management has evolved within the past two decades and presents a major field of interest for scientific research (Ahi and Searcy, 2013, 2015; Seuring, 2013; Zimmer et al., 2016). Companies and supply chains are seen as key actors in the discussion on sustainable development (Thun and Müller, 2009). Hence, the three dimensions of sustainability (economic, social and environmental) steadily become more important in the context of supply chain management (Seuring, 2013).

Seuring and Müller (2008) have identified three key topics of sustainable supply chain management (SSCM), which generally describe the distinction from and extension of SCM.

Sustainable supply chain management:

- Has to take a greater range of issues into consideration and thus needs to examine a longer scope of the supply chain,
- Covers a broader spectrum of criteria and performance targets, given the fact of an extended perspective including environmental and social aspects, in line with the triple bottom line principle (Elkington, 1994), and
- Requires an even more close relationship management with all member companies along the entire supply chain.

In the past two decades, several definitions of SSCM were created, which vary in reference of characteristics included from the concepts of SCM and sustainability. A widely used definition in scientific literature is given by Seuring and Müller (2008): “Sustainable SCM is the management of material, information and capital flows as well as cooperation among companies along the supply chain while integrating goals from all three dimensions of sustainable development, i.e., economic, environmental and social, which are derived from customer and stakeholder requirements. In sustainable supply chains, environmental and social criteria need to be fulfilled by the members to remain within the supply chain, while it is expected that competitiveness would be maintained through meeting customer needs and related economic criteria" (p. 1700).

Even though no specific definition was either established or found widespread application, more elaborated definitions in terms of broader scope of characteristics came to the fore: "The creation of coordinated supply chains through the voluntary integration of economic, environmental, and social considerations with key inter-organizational business systems designed to efficiently and effectively manage the material, information, and capital flows associated with the procurement, production, and distribution of products or services in order to meet stakeholder requirements and improve the profitability, competitiveness, and resilience of the organization over the short- and long-term" (Ahi and Searcy, 2013, p. 339).

With regard to the above, over the last years, especially the environmental dimension has gained a lot of attention in the scientific field. Green supply chain management has been established and has found strong appeal. Similar to sustainable supply chain management no single valid definition for GSCM has prevailed (Ahi and Searcy, 2015).

As described in the triple bottom-line concept for sustainability from Elkington (1994), a basic level in all three dimensions needs to be simultaneously and uniformly achieved. Green supply chain management, with a focus on the environmental dimension, can generally be considered as sub-concept or subfield of sustainable supply chain management which follows the principles as well as characteristics described in the previously stated definitions (Ahi and Searcy, 2013, 2015; Seuring and Müller, 2008).

The global importance of the environmental dimension for current and future society is emphasized and clearly illustrated by Gordon Brown during its speech to the United Nations Ambassadors, in New York 2006: "Environmental sustainability is not an option - it is a necessity. For economics to flourish, for global poverty to be banished, for the well-being of the world's people to be enhanced - not just in this generation but in succeeding generations - we have a compelling and ever more urgent duty of stewardship to take care of the natural environment and resources on which our economic activity and social fabric depend" (Brown, 2006).

In the further course of this research, the term green and environmental will be used synonymously in regard to environmental dimension of the triple bottom line concept. The social pillar is not in the primary focus of this research but is regarded as an indispensable, fundamental prerequisite for the considered business activities.

2.1.4 Green purchasing and supplier selection

Referring back to the statement from Krause et al. (2009) and the development of the term green supply chain management described in section 2.1.3, the complexity of managing relationships became apparent.

The focus on core competencies associated with outsourcing of diverse manufacturing and service activities has led to a growing importance of the purchasing function. It is responsible for a share of 50-90% of the total turnover in industrial companies (Boer et al., 2001; Telgen, 1994). Thus, it becomes obvious that the success of a company is dependent on the supplier performance and the components purchased in the supply chain (Lee and Drake, 2010). The boundary spanning purchasing function, dealing with efficient sourcing of material for production from upstream supply chain, plays a central role in supply chain activities and processes (Lima-Junior and Carpinetti, 2016). Along with the evolution of supply chain management, purchasing has been transformed over the years to a strategic activity. It makes a crucial contribution to a company's goal of offering end-products at the highest quality and lowest cost level possible, at fast delivery rates and in a high variety (Burt, 1989).

It is not only held responsible for providing materials, components and services from suitable suppliers but also for managing all transactions among supply chain members in order to ensure on-time delivery. As the concept of sustainability is progressively integrated in the concept of supply chain management, purchasing constitutes a central function, which makes a huge contributing to the efforts of a company in sustainable development (Krause et al., 2009; Schoenherr et al., 2012). In this context, relationships with the suppliers, which are only based on the commodity and price, can be considered as insufficient, if a company is pursuing sustainable goals with a focus on social and environmental aspects (Bai and Sarkis, 2010).

Sustainable purchasing can be defined as “the consideration of environmental, social, ethical and economic issues in the management of the organization’s external resources in such a way that the supply of all goods, services, capabilities and knowledge that are necessary for running, maintaining and managing the organization’s primary and support activities provide value not only to the organization but also to society and the economy” (Miemczyk et al., 2012, p. 489). Sustainable purchasing is interrelated with sustainable supplier management as part of sustainable supply chain management (Suraraksa and Shin, 2019; Zimmer et al., 2016). In line with Bevilacqua and Petroni (2002) and Zimmer et al. (2016), the terms sustainable purchasing and sustainable supplier management are in this research regarded as equal. In terms of the environmental perspective of sustainable purchasing, the term green purchasing is commonly used in scientific literature (Giunipero et al., 2012). It encompasses all aspects of the environmental pillar in combination with traditional purchasing operations.

The sustainable supplier management process respectively sustainable purchasing process, which also counts for green purchasing, can primarily be divided into three major operations: supplier selection, supplier monitoring and supplier development (Bai and Sarkis, 2011; Suraraksa and Shin, 2019; Zimmer et al., 2016).

Furthermore, the process of supplier selection generally consists of several sub steps (see Figure 2-2). It correlates with the general decision-making process illustrated by Simon et al. (1987), consisting of four steps (decision criteria setting, finding of adequate alternatives and the evaluation as well as selection of the most suitable alternative).

At the beginning, typically the needs and specifications are identified, before decision criteria are formulated respectively selected, according to company-specific requirements. The information submitted from the suppliers based on the call for tenders will be reviewed in the qualification step and may take several rounds (Igarashi et al., 2013). Finally the most suitable supplier complying with the initial requirements will be selected in the final selection step.

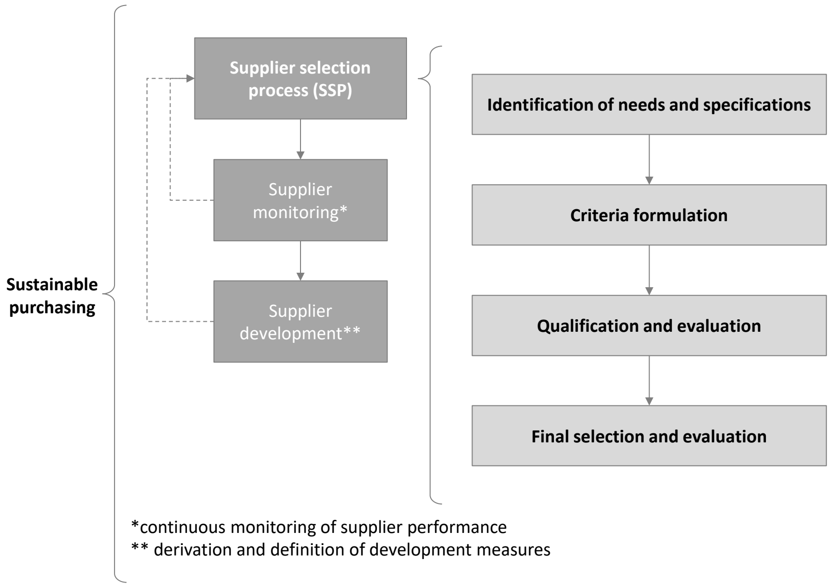


Figure 2-2: Supplier selection process as one of sustainable purchasing's core tasks (based on Boer et al. (2001); Igarashi et al. (2013); Zimmer et al. (2016))

At a later, post-selection stage, the performance of suppliers will be reviewed and once again evaluated. This step, often referred to as supplier monitoring, was defined by Zimmer et al. (2016) as “the continuous analysis and evaluation of supplier and supply chain information with regard to the compliance of defined minimum requirements and the performance improvement taking into account the three dimensions of sustainability” (p. 1414). The results of the re-evaluation can be used to monitor the success on a continuous basis, in order to replace underperforming suppliers if necessary or initiate development programs with the existing suppliers.

Sustainable supplier development is an interrelated process which can not only be applied as consecutive step after the supplier monitoring, but also within the steps of supplier selection. An application in the qualification step, for example by setting up a development program in collaboration with a supplier, enables the achievement or extension of the basic, minimum requirements (Hahn et al., 1990; Zimmer et al., 2016). It can generally be defined as “any set of activities undertaken by a buying firm to identify, measure and improve the sustainable supplier and supply chain performance and facilitate the continuous improvement of the overall value of goods and services supplied to the buying company’s business unit” (Krause et al., 1998, p. 40).

Due to the described interrelation of the independent phases of supplier purchasing, especially the formulation and definition of the selection criteria plays a crucial role. Besides illustrating the basis for the final selection phase in the supplier selection process, it also serves as a basis for performance metrics to later evaluate the suppliers performance in the monitoring phase, and even to derive according improvement measures in the development phase (Suraraksa and Shin, 2019; Zimmer et al., 2016). Due to different stakeholder interests, as illustrated in section 2.1.1, the criteria formulation, selection and application in supplier selection decision however strongly depend on the field of business activity and industry.

The supplier selection process is often considered to be the most important step in the process of purchasing (Hashemi et al., 2015; Hsu et al., 2013;

Seuring and Müller, 2008; Verma and Pullman, 1998; Zimmer et al., 2016). On the one hand, purchasing is responsible for the selection of the best suitable supplier at a certain point in the process, without having an hundred percent assurance that the selected supplier will finally meet the companies targets entirely (Bevilacqua and Petroni, 2002). Whereas the right choice of suppliers can contribute to the reduction of purchasing cost, the contrary may create issues in operations and can lead to financial problems (Omurca, 2013). However, at the final selection stage of a supplier, the purchasing enterprise occupies the best bargaining position. It can thus not only influence the strategic purchasing and the achievement of sustainability targets, but also the overall company's competitiveness (Ghodsypour and O'Brien, 1998).

In the field of supplier selection, often no differentiation between green and sustainable is made (Igarashi et al., 2013). Similar to green supply chain management or purchasing, which are considered as subsystems of the three pillar scope of sustainability, in this research, green supplier selection is considered as one sub-concept of sustainable supplier selection. In line with Igarashi et al. (2013), the focus is considered to be exclusively on the environmental pillar of the triple bottom line concept.

In the framework of sustainable or green supply chain management, which takes all activities of the entire supply chain into consideration, supplier selection takes place at several phases. Igarashi et al. (2013) introduced a structure of three classifications (see Figure 2-1), which illustrates where buyers, who are responsible for purchasing, can be located within a supply chain: The buying firm is according to the classification

(1) an organization respectively focal company (such as end-product manufacturer, construction company or service provider) or an upstream supplier (such as parts manufacturers or sub-system providers),

(2) a downstream customer except personal consumers (such as governmental agencies and customers from the municipal and private sector), and

(3) an entity which is simultaneously involved in upstream and downstream supply chain activities.

In the decision-making process of supplier selection, a distinction is made by selecting one supplier as single source or several suppliers as multiple sources, according to the defined requirements. Not only strategic decisions, such as reducing dependencies from one company, but also existing market conditions, such as capacity restrictions, can lead to a more complex multiple sourcing decisions (Ghodsypour and O'Brien, 1998). Depending on the initial research questions raised in section 1.2, in the context of this research only single source supplier selection decisions will be pursued.

In the general context of managing an entire supply chain, and especially upstream supply chain in a sustainable manner, focal companies play a significant role. In accordance with the success of a company based on the value of its products, burdens occurring in the supply chain might come along. Focal companies, especially brand holding companies, are often considered as key players in supply chains and are therefore, in terms of environmental and social performance, held responsible for upstream supply chain activities (Kovács, 2008; Roberts, 2003; Seuring and Müller, 2008). For example in the case of the automotive industry, original equipment manufacturers (OEMs) are regarded to be responsible for the entire upstream supply chain due the extremely high volume purchased from the market (Zimmer et al., 2017). Nevertheless, due to its central role, focal companies can positively influence the environmental, economic and social performance of the entire upstream supply chain by selecting adequate suppliers.

2.2 Environmental sustainability in the automotive industry

In the automotive industry, the focus is shifting towards environmental sustainability and product life cycle management. Thus, the key information with regard to supply chain structures and product life cycle phases are presented in this section. Moreover, existing governmental regulations for the management of sustainability, as well as framework information on the material usage in car manufacturing are illustrated.

2.2.1 Definition of the lifecycle process and supply chains

In the automotive industry the product life cycle of a vehicle can be roughly structured into five phases (see Figure 2-3): raw material extraction, material production, vehicle production, vehicle usage, and vehicle recycling.

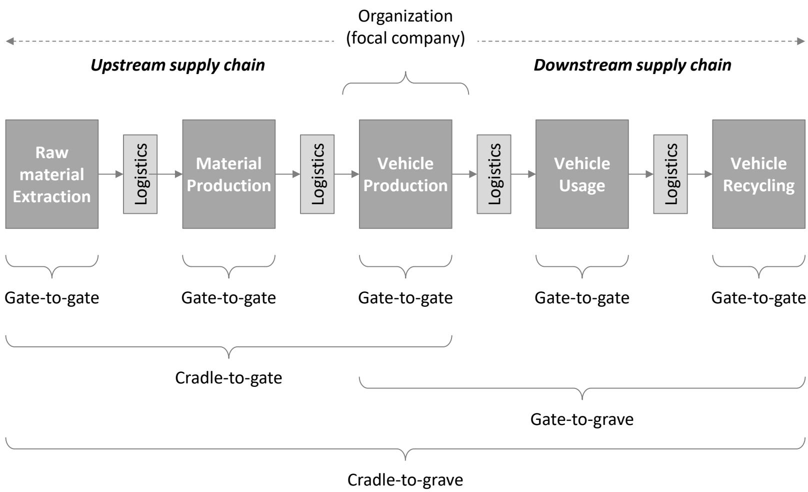


Figure 2-3: Structure of an automotive product life cycle in a supply chain perspective

Recycling however does not only take place at the end-of-life stage, in terms of post-consumer scrap but already during the material and vehicle production phase, in form of pre-consumer scrap (Burchart-Korol, 2011; International Standards Organisation, 2006a). Additionally, the intermediate transport and logistics activities need to be taken into account. All upstream activities before the vehicle production by means of vehicle manufacturers, so called focal companies, can be characterized as upstream supply chain. In contrast, the vehicle usage and recycling are considered as downstream supply chain activities. In terms of system boundaries of a full life cycle consideration, three main phases can be distinguished: cradle-to-gate, gate-to-gate and gate-to-grave. The entire life cycle assessment is called cradle-to-grave and includes all impacts related to the production a product, from the initial raw material extraction (cradle) to the final disposal of waste (grave) (see Figure 2-3).

As mentioned before, in section 1.1, the majority of value adding processes of a vehicle manufacturing process takes place in the upstream supply chain. Upstream supply chains are often structured in a multi-Tier respectively n-Tier architecture (from 1 until n Tiers) and thus involve several supply chain members as well as according activities.

Taking a closer look, focal companies have a contractual agreement with Tier-1 suppliers, which represent direct suppliers. They receive specific purchase orders for a certain component or service. The same accounts for the according upstream suppliers, up to the supplier (Tier-n), which is placed at the beginning of the process (Lee et al., 2012). The example of a metallurgical supply chain (see Figure 2-4) illustrates the complexity of upstream supply chain management activities. Due to various direct and indirect supply chain relationships and vertical production ranges, a supplier, as for example a manufacturer for metal, can appear in different Tier positions. Steel produced in an integrated iron and steel mill can be supplied to a Tier-2 supplier, a Tier-1 supplier or directly to a focal company for the production of a certain component (see Figure 2-4).

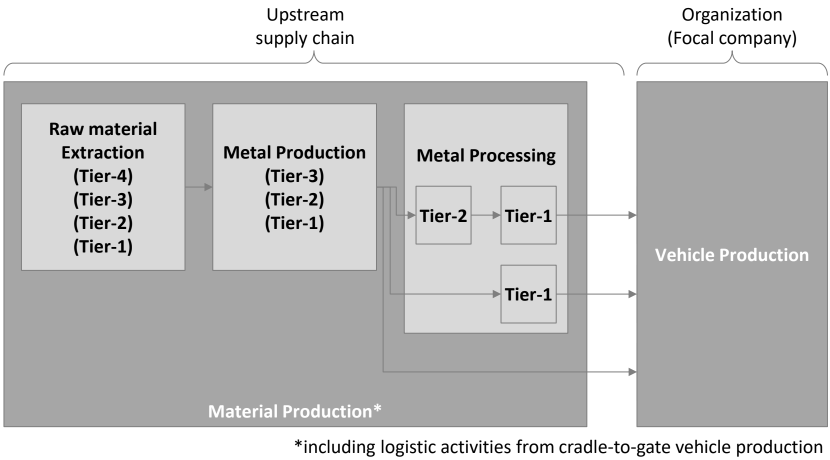


Figure 2-4: Exemplary structure of an upstream metallurgical supply chain for automotive products

2.2.2 Environmental impact of automotive lifecycle phases

The goal to reduce greenhouse gas emissions from vehicle transport has led to the introduction of strong environmental regulations, and has consequently triggered a shift in power train technologies towards electromobility (section 1.1). However, not only the shift from one technology to another, but also a holistic view of the entire product life cycle of vehicles and according emission reduction potentials in all phases is necessary. A more in-depth examination and comparison of the environmental impact of the product life cycle phases of an ICEV and BEV is illustrated in Figure 2-5. According to German Environment Agency (UBA, 2016), the vehicle use-phase for an ICEV, represented by fuel supply, direct exhaust emissions and maintenance, makes for the biggest share of roughly 81% (17% and 64%) of the overall CO_2e emissions per km (lifetime mileage of 168,000 km). The manufacturing phase however has a proportionally small share of 15%, only followed by vehicle disposal and maintenance with a combined share of 4%. In case of a BEV100, calculated with the German energy mix from 2012, the use-phase, representing the energy consumption as well as production, makes for 68% of total life cycle emissions. Vehicle disposal and maintenance accounts for a fairly similar share of 5%. In contrast, the manufacturing phase gains more importance with an increased share of 27% of the total climate impact.

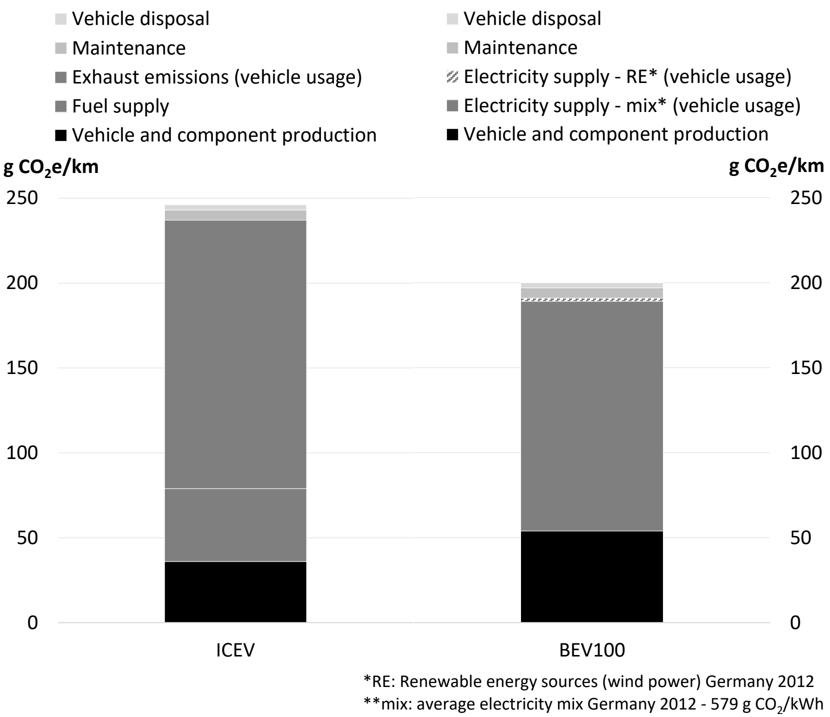


Figure 2-5: Environmental impact of automotive lifecycle phases (based on IFEU (2013); UBA (2016))

On the assumption of making exclusive use of renewable energy to power a battery-electric vehicle with a range of 100km[6], the environmental impact per km shows a reduction potential of 74% compared to an internal combustion engine vehicle. In this case, the manufacturing phase would be almost exclusively responsible for the definition of the entire carbon footprint, representing 83% of the entire emissions per km (IFEU, 2013; UBA, 2016).

2.2.3 Existing regulations in the automotive sector

Governmental regulations, which are considered as key driver for the enhancement of sustainable solutions (see section 2.1.2.4) do also play an essential role in the automotive industry.

The self-commitment of the European Automobile Manufacturers' Association (ACEA) – 'ACEA commitment on CO_2 emission reductions from new passenger cars in the framework of an environmental agreement between the European Commission and ACEA' (European Commission, 1998), which was signed July 27th 1998, is often considered as official kickoff for legal regulations.

As a starting value, an average CO_2 emission for new passenger cars was set at 185 g CO_2/km for the year 1995 (European Commission, 2000a, 2000b). The value used by the ACEA is based on statistical evaluations provided by the Association Auxiliaire de L'Automobile (AAA), which rely on official data from EU-member states (European Commission, 2000b). It is based on a reference vehicle M1, which is defined by the European Commission (2007) as "vehicles designed and constructed for the carriage of passengers and comprising no more than eight seats in addition to the driver's seat" (p. 62) and averaged over all new passenger car registrations in the member states, for petrol and

6 The according environmental impact per km is based on the reference year 2012 and may differ in the course of vehicle lifetime, specifically due to changes in electricity supply (UBA, 2016).

diesel fueled cars (European Commission, 2000b). The 1995 value, which is based on a voluntary self-disclosure, serves as reference value for percentage emission reductions and respectively derived emission targets, considering the average of the entire vehicle fleets of European car manufacturers. Hence, the limits can be rather considered as efficiency targets than specific emission targets, which will be derived from the overall goal to limit global warming to 2 respectively 1.5 degrees Celsius.

Based on the voluntary and so far unbinding reduction targets of the ACEA and its members, in 2009 the EU regulation EC 443/2009 was introduced as mandatory standard in order to ensure compliance of emission reduction targets (European Commission, 2009). Official emission reduction targets were set for 2015 with a target value of 130 g CO_2/km, representing an 11% reduction in comparison to the 2009 reference value of 146 g CO_2/km.

In 2019, the legislative regulation was updated and the scope for future emission targets was extended. The new regulation (EU) 2019/631 (European Commission, 2019b) further tightens the emission limits for M1 vehicles in Europe and sets new targets at 81 g CO_2/km for 2025 and 59 g CO_2/km for 2030. Between the years 2015 and 2018 diverse phase-in requirements, such as super credits and yearly increasing penalties for emission exceedance, were set in place. These shall provide manufacturers with an opportunity to constantly adjust to the emission targets (European Commission, 2009). Since 2019, the excess of emission limits has been severely penalized with 95 €/g CO_2/km and super credits for zero- and low-emission cars below 50 g CO_2/km have been reduced until final suspension in 2023 (European Commission, 2019b).

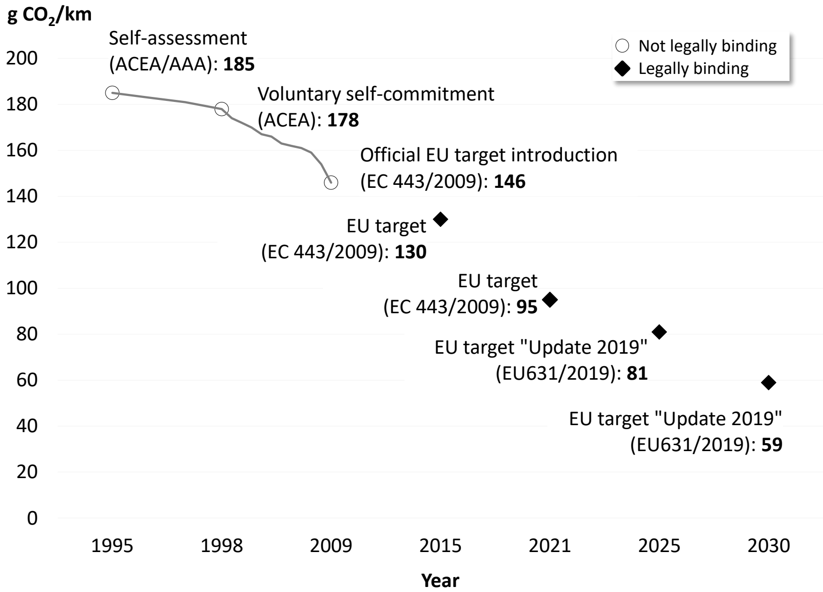


Figure 2-6: History and future development of European CO_2 emission performance targets for vehicle manufacturers (based on European Commission (1998); European Commission (2000b); European Commission (2009); European Commission (2019b); ICCT (2011); ICCT (2018b); ICCT (2019))

2.2.4 Material usage in automotive manufacturing

Due to the growing attention on and importance of sustainability (see section 2.1.1) the automotive industry is forced to constantly adapt and improve designs in order to meet changing stakeholder respectively customer requirements (Balitskii et al., 2016). More specifically, manufacturers are faced with the challenge of constantly increasing fuel efficiency in order to reduce the consumption of energy and air pollution in the vehicle use-phase (Balitskii et al., 2016; Miller et al., 2000).

Besides advanced power train technologies and design improvements, especially weight reduction plays a key role (Miller et al., 2000). While simultaneously fulfilling various requirements for construction materials (see Figure 2-6), vehicle manufacturers are constantly trying to decrease weight by introducing new as well as more light-weight materials. The focus lies on materials which fulfill the necessary requirements of high performance, low density and high strength (Balitskii et al., 2016). The substitution of conventional materials by high-strength steel, aluminum, magnesium and polymers, for example for body and power train as well as engine components, provides certain opportunities to reduce vehicle mass (Palazzo and Geyer, 2019). This is shown for example by the increased usage of aluminum in the production of passenger vehicles in Europe, which has grown by 80% from approximately 32 kg (in 1978) to 160 kg per vehicle (in 2015) (GDA, 2015).

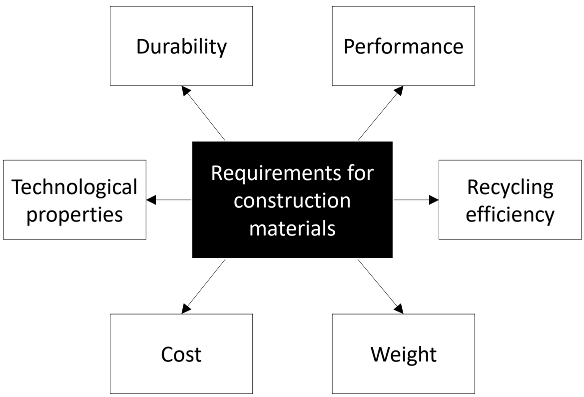


Figure 2-7: Technical and economic criteria for the selection of construction materials (based on Balitskii et al. (2016))

Currently there exist a huge variety of types of passenger cars from large-scale production up to small-batch production in the luxury segment. It ranges from compact cars to sport utility vehicles (SUV). Moreover, the combination of optional extra equipment and diverse powertrain concepts results in a broad spectrum of material compositions. In order to illustrate a representative average material composition of cars, the Volkswagen Golf is chosen, representing the bestselling vehicle in Europe (see Figure 2-7).

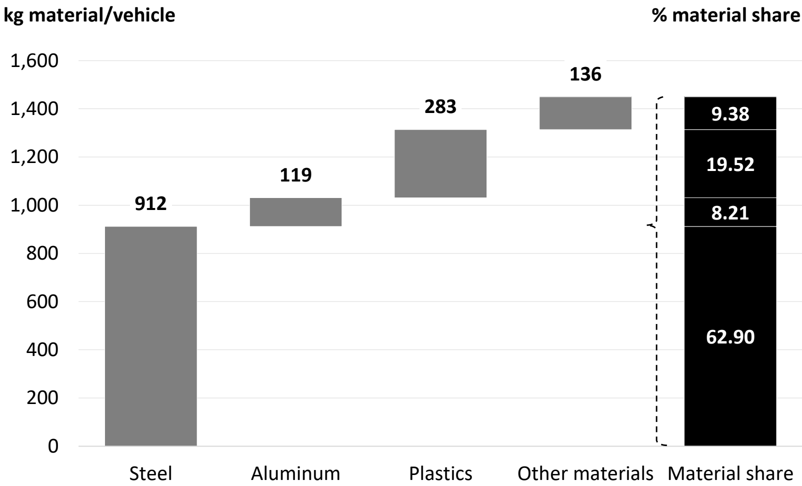


Figure 2-8: Average material composition of the bestselling car in Europe - Volkswagen Golf (based on Lieberwirth and Krampitz (2015); Schmid and Zur-Lage (2014))

Despite the widely discussed light-weight strategies (Palazzo and Geyer, 2019), a closer look at the percentage distribution of materials reveals the continuingly decisive role of steel and iron with a share of 62.9% of the overall car weight, 1,450 kg. This can be traced back to the development of new, highly innovative steel. For example a study of ThyssenKrupp Steel Europe (Seyfried and Sudowe, 2007) reveals that advanced high strength steels can achieve similar weight reductions compared to innovative aluminum constructions, while simultaneously offering huge economic advantages (Seyfried et al., 2015).

Product life cycle management also comprises the phase of upstream material production. Based on the defined scope of this research project and the average material composition of a sample vehicle (see section 2.2.4), the industry background information as well as environmental impact of the selected material production are shown in the following. Furthermore, the production processes, which represent the basis for the calculation of site-specific environmental performances, are described.

2.3 The iron and steel industry[7]

The production of steel represents the most dominate sector in the metal producing industry. The majority of global steel production volume is produced in integrated iron and steel mills by means of the basic oxygen process (approximately 71%). The remaining steel production is conducted in electric arc furnaces (EAF) which relies on recycled steel scrap (approximately 29%) (World Steel Association, 2018c). The overall production volume has constantly been growing over the last decade and reached a new peak in 2019, with an estimated amount of 1,808,400 thousand metric tons of produced crude steel on a global scale (World Steel Association, 2020a).

In Europe, which represents roughly 9.3% of global production, the development of the overall production volume for both, primary steel produced in oxygen furnaces (approximately 58%) and recycled steel from the EAF route (approximately 42%), has remained relatively stable over the last decade (see Figure 2-9). The same accounts for the production volumes in Germany (2.3% share of global steel production), which however show a more explicit ratio of 70/30% for basic oxygen compared to electric steel produced in EAF (World Steel Association, 2018a, 2018b).

[7] Parts of this section were previously published in Schiessl et al. (2020b). Some passages were exclusively developed by the author of this thesis and are used without citation.

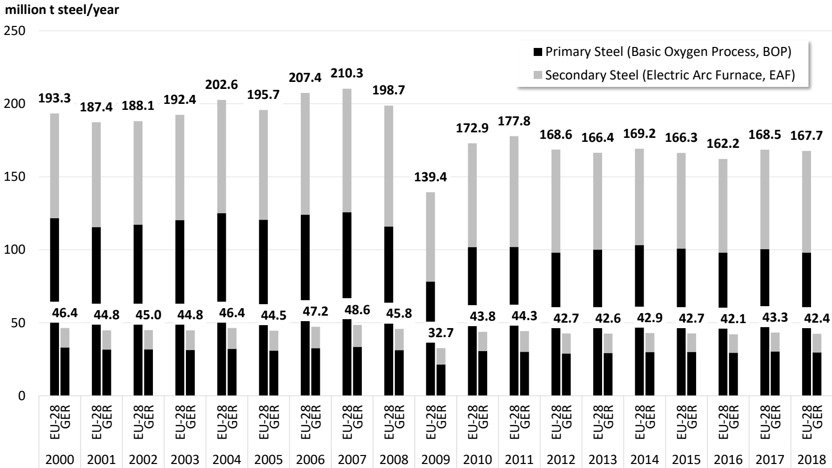


Figure 2-9: Crude steel production in Europe (EU-28) and Germany, 2000-2018 (based on World Steel Association (2018a, 2018b))

2.3.1 Production process in integrated iron and steel mills

The production of crude steel is primarily conducted in integrated iron and steel mills. This so called 'primary steel making' is characterized by a very high complexity in production processes and the re-usage of a variety of by-products. This is especially due to the high interdependency of single process steps, later in the model development addressed as ps_x, material and energy flows as well as the fact that some part of the production are located offsite and run by another operator (European Commission, 2013; European Environment Agency, 2019b). In addition, there exist an intercompany trading (purchase and sale) of diverse intermediate products among steel manufacturers. In Figure 2-10, the production process of primary steel including material and energy flows is illustrated in form of a process diagram, focusing on the directly considered process steps for the model development (see section 4.3).

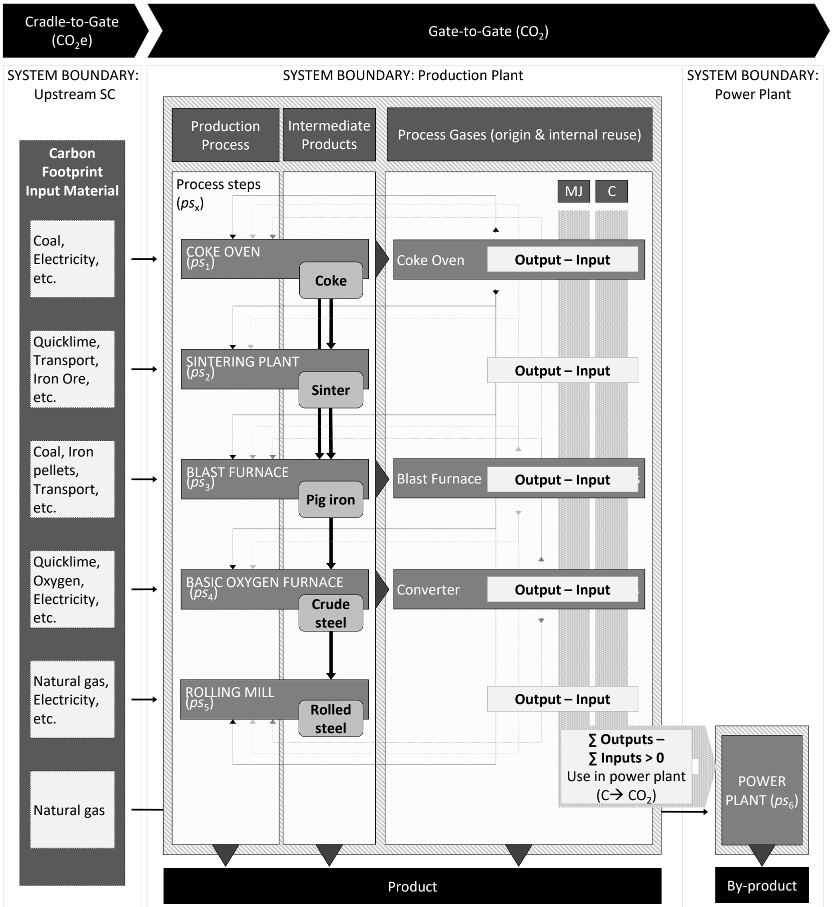


Figure 2-10: Process steps of an integrated iron and steel mill including designated system boundaries and the contemplated material as well as energy flows

In integrated iron and steel mills, which include blast and basic oxygen furnaces, steel is produced from iron ore. Raw or respectively crude steel (ps_4), relies on pig iron (ps_3), which itself depends on the upstream production of intermediate products coke (ps_1), and sinter (ps_2).

Initially, metallurgical coke is produced in the coke oven (ps_1) by the carbonization of high quality bituminous coal respectively coking coal in thermal decomposition under high temperature. During the coke production, the by-product coke oven gas (COG) is produced. This so-called process gas can be burned within the coke plant for energy recovery or used as energy source for on-site, downstream production process steps at an integrated plant. On the contrary, the coke production process relies on process gases from downstream production steps, such as the blast furnace, as energy source (see Figure 2-10).

In sintering plants (ps_2), iron ore as well as other iron-containing materials are agglomerated to sinter by using the process material coke breeze, small-grade coke from the coke oven as fuel. Coke breeze has a significant impact on the performance and efficiency of the sintering process depending on the size distribution of coke particles (Zhou et al., 2015). Process gases from upstream or downstream process steps are reused as energy source in interconnected sintering plants (European Environment Agency, 2019b).

The production process of steel centers on the blast furnace (ps_3), where oxidic iron ore is converted to pig iron by means of carbon in a prior process step. Metallurgical coke is therefore introduced into the blast furnace and serves not only as reducing agent but also as energy source. Instead of coking coal, other forms of carbon, such as wood-based charcoal, can also be used. By the injection of hot air into the bottom part at approximately 1,200°C, the carbon is gasified and reacts with the oxygen of the injected air to carbon monoxide, while high temperatures of up to 2,200°C are generated. While the carbon monoxide rises to the top, it binds the oxygen of the iron ore resulting in the creation of carbon dioxide, and thus reduces the ore. During the combustion of coke, blast furnace gas (BF gas) is generated as process gas. In an interconnected transfer among process steps, the gas is reused as energy carrier for upstream or downstream processes (see Figure 2-10). Hot metal as well as certain waste and by-products, such as blast furnace slag, dust or sludge, remain after the reduction of iron ores (Das et al., 2007).

After taping the hot metal and slag, which is gathered at the bottom part of the furnace, these materials are separated by means of refractory lined runner systems. The metal is directed to the hot metal torpedo ladle and the slag to the slag ladle. The secondary by-product blast furnace slag, for example as granulated blast furnace slag (GBFS), finds a widespread application in various areas and other industries, such as in the cement production (Huang et al., 2016; Siddique, 2014).

In the downstream process in the basic oxygen furnace (ps_4), the remaining carbon content is reduced by the injection of oxygen (refining) to less than 1% (Worrell et al., 2009). Therefore, the vessel is initially charged with molten iron (approximately 70-90%) and steel scrap (approximately 10-30%), in order to adjust, respectively cool down, the reaction heat. Then added high purity oxygen combines with the remaining carbon in the pig iron and leads to the creation of an exothermic reaction. Thus, the carbon content is reduced while the charge is melted. This process results in oxidation of impurities and isolation of unwanted tramp elements in the pig iron, such as silicon, sulfur and phosphor, forming a swimming layer of slag. In order to support the formation of slag, additional lime is introduced. The swimming layer of slag is finally separated when crude steel is tapped and directed to a steel ladle (VDEh, 2020). Again, process gas, so-called basic oxygen furnace gas (BOF gas), is created during the process, fed to BOF gas recovery installation if available and then reused as energy source for other process steps (European Commission, 2013).

According to customer requirements and material specifications (e.g. a car manufacturer), alloying elements can deliberately be added in ladle furnaces in a secondary metallurgy treatment to adjust the chemical composition (VDEh, 2020).

The still-liquid crude steel is then processed to semi-finished products and prepared for downstream finishing operations, such as forming and rolling (ps_5). This is primarily done in continuous casting which represents more than 96% in Europe (World Steel Association, 2013) or in ingot casting processes.

The generated processes gases, such as coke oven, blast furnace and basic oxygen furnace gas can provide more than 60% of the entire energy demand of steel production processes in integrated plants (World Steel Association, 2019). An existing surplus of gases, which is not directly re-used in the production process, can be used for power generation (ps_6) in connected power plants (see Figure 2-10).

2.3.2 Production process in electric arc furnaces

In comparison to the highly interconnected steelmaking process in the basic oxygen route, the secondary steel manufacturing process in electric arc furnaces illustrates a lower complexity. In general, EAFs, which rely on recycled scrap, are stand-alone solutions even though they might be located in integrated steel mills (European Environment Agency, 2019b). The process consists of five main steps, raw material preparation, recycled steel scrap preheating, scrap charging, melting as well as refining and tapping of steel (European Commission, 2013; European Environment Agency, 2019b). The process of steelmaking in EAF starts with the purchase of recycled scrap with a minimum of non-metallic inclusions, based on international specifications. During the initial preparation and handling, non-ferrous and non-magnetic materials, such as wood or stones, are filtered out in order to avoid impurities and hazardous contaminations. With the aim of reducing the energy usage in the downstream melting process, scrap is often preheated. With rising frequency, steel manufacturers use off-gas recovery systems as energy source for the preheating process. Some manufacturers however use additional fossil fuels as energy source for the preheating. This process step takes place in scrap charging baskets, in charging shafts in case a shaft furnace is used or in specially constructed conveying systems. For example finger shaft furnaces provide an efficient solution to assure a 100% preheating of the recycled steel scrap (European Commission, 2013; European Environment Agency, 2019b). The electric arc furnace is then charged by baskets loaded with steel scrap and additional lime or limestone. In order to facilitate a good slag formation with the aim of enabling the removal of phosphorus as well as sulfur, lime is used as fluxing agent. It thus provides a safer platform in order to resist arc plasma with a high intensity. Hence, the quality and quantity of lime added to the process has a direct effect on the output quality of steel (metallurgical properties) and the process efficiency (Manocha and Ponchon, 2018). At some plants additionally lump coal is added in order to adjust the carbon content of the steel to be produced (European Commission, 2013). The actual charging process depends on the according type of furnace installed. In conventional top-charge furnaces, the graphite electrodes are lifted into top position before the retractable roof is swung away. In a repeating process, the refractory-lined vessel is filled with approximately 50-60% in the first run. An electric arc is struck right above the loaded scrap (200-300mm) and the charge is melted. In a second or third cycle, the remaining scarp is loaded to the furnace. In contrast, shaft furnaces enable a vertical charging process without opening the EAF roof. In a so called CONSTEEL process the roof remains also closed while scarp is continuously fed into the furnace by means of a horizontal conveyor system (European Commission, 2013). The preheating process described above is conducted for each filling cycle in conventional furnaces as well as for the other two furnace technologies described. In the initial melting period a lower power is applied, in order to prevent furnace damages from radiation and to achieve a shielding of the arcs by surrounding scrap. Afterwards the temperature is continuously raised to approximately 1600-1700°C (European Commission, 2013; European Environment Agency, 2019b). Due to both, metallurgical aspects as well as productivity reasons, oxygen is introduced to the melting process, for example via oxygen lances (European Commission, 2013). Before tapping the melted steel, slag is removed at the end of the heating process while fume and dust is generated. Prior to steel casting, in a secondary metallurgical treatment the required temperature for casting operations is adjusted, and the final chemical composition is achieved by the addition of deoxidizing agents or alloying elements (European Commission, 2013). Finally, down-stream finishing operations are either conducted in internal rolling plants or the steel is sold directly to end-customers, or to external providers for rolling operations.

2.3.3 GHG emissions of the iron and steel industry

Global greenhouse gas emissions showed an extremely high increase of 36.6% from the year 2000 (35,962.5 Mt CO_2e/year) to 2015, with an all-time high of 49,113.0 MT CO_2e/year (Crippa et al., 2019). On a global level, the iron and steel industry plays an important role in terms of environmental impact. It accounts for approximately 7 - 9% of global greenhouse gas emissions (World Steel Association, 2018d, 2020b). In 2017, total European greenhouse gas emissions for all sectors counted for 4,333 Mt CO_2e/year. These emissions are mainly driven by the source and sink category 1 ‘Energy’ (3,372 Mt CO_2e/year), which have significantly been reduced by approximately 23% in comparison to 1990. However, these emissions alone represent more than three quarters (77.8%) of overall European emissions in 2017. In this sector, the CRF category 1.A.2 ‘Manufacturing Industries and Construction’ belongs to the three biggest key sources for emissions related to energy consumption (500.17 Mt CO_2e/year, 15% share of CRF 1). The iron and steel sector in Europe, with approximately 163 Mt CO_2e emissions in 2017, accounts for roughly 4% of the overall European greenhouse gas emissions. The calculation is based on the combination of the energy related CRF category 1.A.2a ‘Iron and steel’ and relevant emissions from industrial processes included in CRF category 2.C.1 ‘Iron and steel production’) (European Environment Agency, 2019a). From a historic perspective, the development in the European steel producing segment from 1990 until 2017 shows a significant decrease in GHG emissions of 34% (European Environment Agency, 2016, 2019a), while production volumes remained stable over the last twenty years (see section 2.3, Figure 2-9).

The general production process for steel leads to the creation of GHG emissions, which primarily comprise CO_2 emissions (see section 4.3.2) (Ecofys, 2000; EPA, 2012). These emissions are generated as process emissions, in which both, raw material and combustion, are contributing to the emission of CO_2, as emissions from combustion as separate source, or as indirect emissions from electricity consumption, primarily for finishing operations conducted in rolling plants. In integrated iron and steel mills, approximately 43% of the GHG emissions result from blast furnace stoves, 30% from diverse combustion sources burning natural gas and process gases, 15% from other process units and 12% from electricity usage. In the secondary steel production process approximately 50% of the GHG emissions stem from electricity usage, 40% from the combustion of natural gas, and 10% from the steel production in electric arc furnaces (EPA, 2012).

2.4 The aluminum industry[8]

The global aluminum industry, which has been growing over the last decade by approximately 50%, produced around 64 thousand metric tons of primary aluminum in 2019 (World Aluminium, 2020).

The European Aluminum industry accounts for a share of 12.77% of primary aluminum produced application of electrolysis. The German aluminum production makes up for 0.82% of globally produced aluminum (World Aluminium, 2020; World Bureau of Metal Statistics, 2019a, 2019b). In Europe, the overall production volume has shown a relatively stable development over the last decade (see Figure 2-11), with only a slight increase from 2009 to 2018 by 6.6%. The same trend applies for the ratio of primary aluminum from electrolysis and secondary aluminum, produced by remelting or refining of aluminum scrap. In 2018 the ratio in Europe was 74% of primary aluminum production in comparison to 26% of secondary aluminum. In contrast, the German Aluminum production, for both primary and secondary steel, has been growing significantly by 51.4% in the same period. Almost half of the aluminum produced in Germany is used in various applications in the mobility sector (WMV, 2019).

[8] Parts of this section were previously published in Schiessl et al. (2020a) and some passages are transferred without citation as they were exclusively prepared by the author of this research contribution.

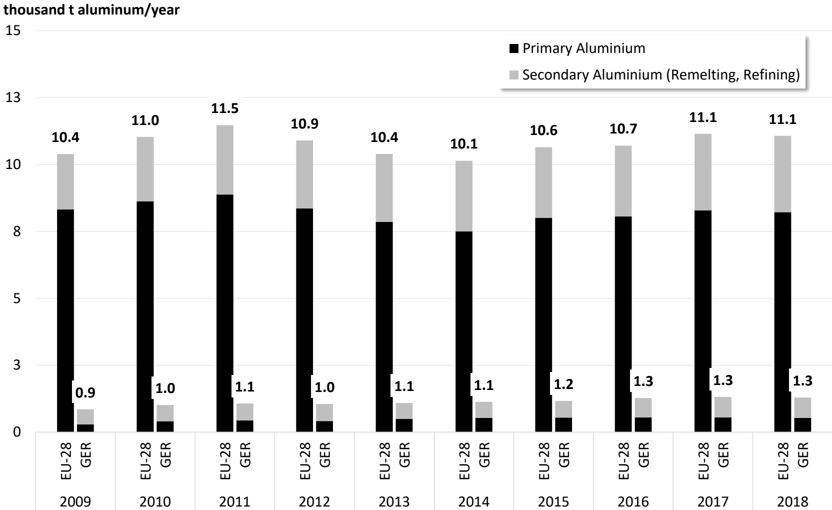


Figure 2-11: Aluminum production in Europe (EU-28) and Germany, 2000-2018 (based on World Bureau of Metal Statistics (2019a, 2019b))

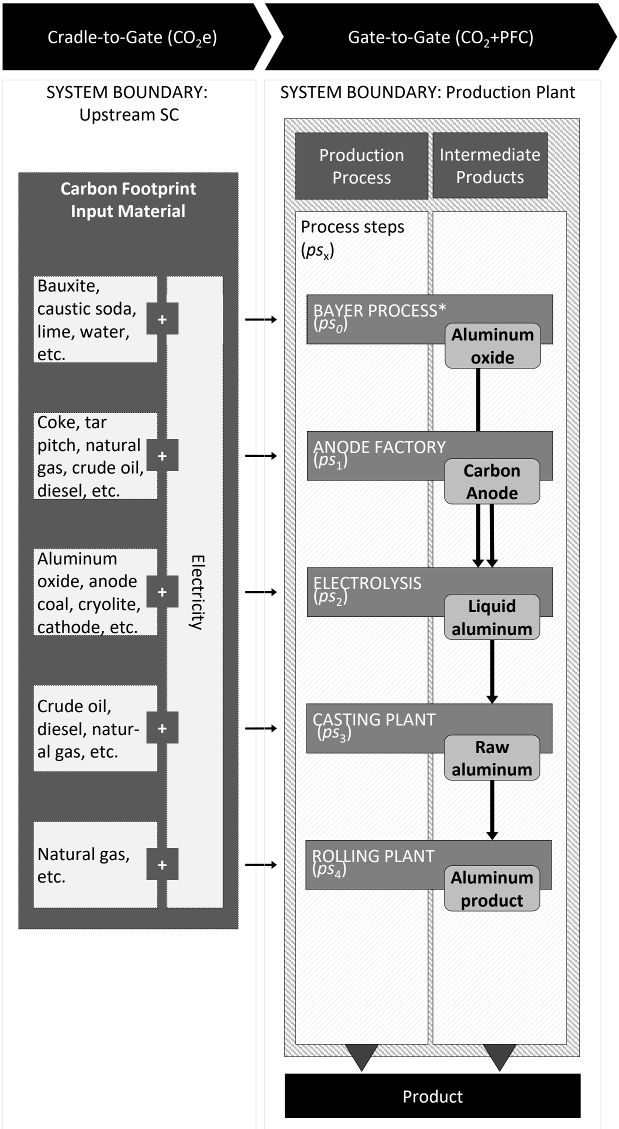
2.4.1 Production process in electrolysis plants

The aluminum production, which is part of the non-ferrous metal industry segment, found its origin only at the beginning of the 19th century. The manufacturing process of primary aluminum consist of five principle process steps (ps_x): alumina production (Bayer process) (ps_0), anode production (ps_1), electrolysis (Hall-Héroult process) (ps_2), casting (ps_3) and further processing (ps_4) (European Commission, 2014, 2017; European Environment Agency, 2019c). The process flow diagram in Figure 2-12 illustrates the aluminum production process, with a focus of the subsequent aluminum model to be developed, and especially the directly considered process steps, which are conducted on-site (see section 4.4).

The metallic element Aluminum (AL) makes up for approximately 8% of earth's solid surface in terms of weight. In nature it is found in various compounds bound in ores, but never as a free element. After the elements oxygen and silicon, it represents the third most abundant element (Totten and Mackenzie, 2003; Tsakiridis, 2012). The production of primary aluminum is relying on bauxite ore, as primary source, respectively initial raw material, which is converted to alumina as input material for the electrolysis. For one ton of aluminum, two tons of alumina and consequently four to six tons of bauxite are necessary (European Commission, 2014, 2017; World Steel Association, 2018c). Bauxite ore, with an approximate global resource of 55 to 75 billion tons, can be found especially in tropical and sub-tropical areas (Africa, 32%; Oceania, 23%; South America and Caribbean, 21%; Asia, 18% and other countries, 6%). Among others, Australia, China, Guinea, Brazil and India are the top five global countries in terms of bauxite reserves and actual bauxite production, representing more than 80% (U.S. Geological Survey, 2020). It is largely used for the refinement into alumina, which is used for the production of aluminum (85% of globally mined bauxite) (World Steel Association, 2018c). In an intermediate process step, alumina will be produced from bauxite prior to the production of aluminum. In the Bayer process (ps_0) bauxite is initially ground in order to increase the material surface for the extraction process. By means of the addition of caustic soda, alumina is extracted from bauxite under high pressure and under elevated temperatures in digesters, resulting in a bauxite slurry. Thickeners and/or filters are used to separate metal oxides, bauxite residues respectively red mud, from the dissolved sodium aluminate (European Commission, 2014, 2017; European Environment Agency, 2019c). Red mud is a hazardous waste by-product which contains toxic heavy metals. Especially the high degree of alkalinity poses a risk to life forms and soil. It is either deposited in sealed ponds next to the production sites or further processed by high-pressure filtration technologies and used as input material for other industries, such as the cement or ceramic production and road construction (European Commission, 2014).

In order to induce crystallization, the aluminate solution needs to be cooled and seeded with aluminum hydrate (aluminum oxide trihydrate) in form of fine particles. In the precipitation area the aluminum hydrate crystallizes and is then removed by filters. In the final process step of the Bayer process, a conversion from aluminum hydroxide to alumina (aluminum oxide) is conducted by means of calcination in rotary kilns or fluid bed/fluid flash calciners (European Commission, 2014, 2017; European Environment Agency, 2019c).

The production of aluminum relies on the technique of electrolytic reduction. The process is conducted under high temperature in electrolytic cells (ps_2), at approximately 960 °C, in a molten bath which predominately consists of cryolite (sodium aluminium fluoride). In so called pot lines (electrical reduction lines), these cells are directly connected in series, and direct current is passed via so called husbars (current conductors) from cell to cell. These cells, consist of carbon cathodes, which are located in a rectangular steel shell and are isolated by refractory brick walls inside as well as carbon anodes. The anodes are suspended and hold in place by electrically conductive anode beams. In electrolytic cells there are mainly two type of methods applied, and according types of anodes used. In Søderberg cells, which are mainly found in older production plants, one continuous anode made from a paste of calcined petroleum coke and coal tar pitch, is used, and bakes from the arising heat. It is regenerated by periodically adding carbon materials at the top of the cell. In contrast, modern aluminum plants apply the prebake technology based on anodes made from calcined petroleum coke, coal tar pitch, and anode butts. These are produced, formed into a block and prebaked in a separate anode plant (ps_1) which is often located on-site at the aluminum plant. In the process, oxygen is extracted from alumina as it is attracted to the positive graphite anodes. These anodes are thus continuously consumed, resulting in carbon dioxide as well as monoxide. The positive aluminum ions are attracted to the negative graphite cathodes forming pure aluminum. By continuously adding alumina, an alumina content of approximately 2-6% in the molten bath is assured. In order to lower the operating temperature and the melting point, as well as to neutralize sodium oxide impurity on alumina fluoride compounds, especially aluminum fluoride (AlF3) is added. From an environmental perspective, especially the anode effect is critical. A decomposition of cyrolite into metal and fluoride ions, in reaction with the carbon anodes, leads to a formation of gaseous PFC emissions when the alumina content decreases below 1-2% (European Commission, 2014, 2017; European Environment Agency, 2019c). The molten aluminum is periodically tapped by vacuum siphons and transported in crucibles to the casting plants. The liquid metal is then stored in holding furnaces, which can be of an induction or reverberatory type. Additionally scrap, internal company scrap or externally purchased scrap which is free of paint, plastic or oil, is fed into the process. In these furnaces, aluminum is refined according to the metallurgical properties required by the customer, by means of the addition of master alloying elements (such as Ti, Cr, Fe, Mn, Ni) or metal (such as Si, Mg, Pb, Sn, Zn, Cu, Zr, Sr). In order to homogenize the melt, it is moved with stirring machines or stirrers. Moreover, by means of adding fluxing salts and injecting gas, metal impurities and hydrogen are removed. Finally, in these furnaces the temperature of the aluminum melt is controlled and the melt is then filtered prior to the casting process (European Commission, 2014, 2017). The produced aluminum, is finally formed during the casting process (ps_3) according to the customer requirements. For example, vertical direct chill casting machines are used to produce ingots, slabs, billets or T-bars by means of water-cooled moulds made from metal. The usage of continuously moving or static metal moulds is another casting technology which finds widespread application. Horizontal direct chill casting technology can be applied for products with a smaller profile respectively cross-section. Moreover, continuous casting techniques are consulted for the production of wire rod or thin aluminum sheets (European Commission, 2014, 2017; European Environment Agency, 2019c). Similar to steel operations, the intermediate cast products are either further processed in on-site rolling plants (ps_4) or sold directly to customers.



*The Bayer process is not conducted on-site at the examined primary aluminum production plants. The respective emissions are however considered in the model within the 'Upstream SC' system boundary.

Figure 2-12: Process steps of a primary aluminum plant including designated system boundaries and the contemplated material flows

2.4.2 Production process in smelting plants

Secondary aluminum is manufactured in a simplified, but similar process to the production of primary aluminum. Secondary aluminum smelters are used to produce aluminum alloys relying on bearing scrap or materials. A variety of melting furnaces and input scraps can be applied (European Aluminium, 2016; European Commission, 2014; Schmitz, 2006).

In so called remelters, clean pre-consumer scrap and materials are melted in reverbatory and induction furnaces, in order to produce wrought alloys for industrial castings and ingots. In refiners, which use rotary furnaces, tilting or horizontal furnaces, post-consumer scrap with a higher degree of contamination is used for casting alloys and deoxidation aluminium (European Aluminium, 2016; Schmitz, 2006). Depending on the scrap quality, an integrated pre-treatment may be applied, as for example de-coating for used beverage cans. Similar to the primary production process in holding furnaces or inline reactors, the aluminum will be refined and then processed in casting and rolling plants (European Commission, 2014).

2.4.3 GHG emissions of the aluminum industry

The metal industry accounts for approximately 21% of the globally emitted greenhouse gas emissions. In this sector, only the production of primary aluminum is responsible for approximately 1% of these emissions (EPA, 2016; Gautam et al., 2018; Tyabji and Nelson, 2012). In Germany, the aluminum production sector alone accounts for 1% of the overall GHG emissions (BMWi, 2020).

The process to produce aluminum is highly energy intensive and is primarily driven by the usage of electricity. From an environmental perspective with a focus on CO_2e emissions, over 80% of the total GHG emissions result from the demand of electricity considered as indirect emissions (IPCC, 2014).

For example in Europe, an approximate average of 15 kWh per kg produced aluminum in terms of electricity consumption in smelters shows the crucial role of electricity for environmental considerations.

Remaining, there are direct (on-site) GHG emitted during the production process. These emissions comprise CO_2, CF_4 and C_2F_6 associated with the consumption of carbon anode and the anode effect in the electrolysis as well as CO_2, CH_4 and N_2O from fuel combustion (World Aluminium, 2018). The polyfluorocarbons CF_4 (tetrafluoromethane) and C_2F_6 (hexafluoroethane), which are very potent and stable greenhouse gases, are formed during the anode effect in an approximate ratio of 10:1. (Ecofys, ISI, Öko-Institut, 2009; European Commission, 2014). Due to their high greenhouse gas effect, special attention is laid upon these polyfluorocarbons. Considering the global warming potential (GWP) with a 100-year time horizon, CF_4 with a GWP of 7,390 t CO_2e/t raw aluminum, and C_2F_6 with 12,200 t CO_2e/t raw aluminum (industrial designation or common names PFC-14 and PFC-116) clearly illustrate the powerfulness of PFCs in terms of environmental impact (IPCC, 2007). In Europe, the PFCs which are emitted during the production process of primary aluminum (CRF Source Category 2C3) individually account for 0,01% of total European greenhouse gases (European Environment Agency, 2014, 2017). Due to publicly restricted access in the greenhouse gas inventory report of the European Environment Agency (2016) to a more detailed level of data regarding direct emissions created during the aluminum production process, no further breakdown can be provided.

In the secondary production process of recycled aluminum, during the remelting (clean) and refining (mixed scrap) process, CO_2 emissions are exclusively created in indirect form due to the usage of fuels for the melting process. The according electricity demand represents roughly 5% of the required energy necessary for the production of primary aluminum (European Aluminium, 2016; European Commission, 2014, 2017).

3 Sustainable decision making and environmental performance assessment[9]

The main research questions center on how a new criteria such as CO_2e can be integrated in existing decision-making processes and how a therefore necessary transparency can be created (see section 1.2).

In this section the current state of research on these questions shall be presented. Due to the initially described design of this research contribution in form of two consecutive sub-models (see section 1.2), the literature research in this section follows this structure. In section 3.1, an overview of existing decision support models and approaches in a multi-criteria decision environment is presented, with a focus on green supplier selection. Moreover, the phase of criteria formulation as part of a supplier selection process is highlighted and the current state of applied supplier selection criteria is illustrated. In section 3.2, models for the assessment of environmental performance with an emphasis on LCA and the application on raw material production are analyzed and described. Within this context, additional in-depth evaluation models based on material and energy flows are reviewed.

Both sub-sections aim at revealing and discussing the strengths and weaknesses of the respective models and methods. Finally, they conclude with the identification of the research gaps.

[9] Parts of this literature review were previously published in Schiessl et al. (2020a) and Schiessl et al. (2020b).

3.1 Decision support models for sustainable decision making

In reference to the main research question as well as the according sub-questions (1) and (2) illustrated in section 1.2, in this section the current state of science in regard to the sub-model for decision support is analyzed.

Therefore, in section 3.1.1 a general overview of existing models, mainly focusing on the core processes of green purchasing and especially the supplier selection phase, is given. In the following sections 3.1.2 and 3.1.3, the focus is laid upon models and methods used for the criteria formulation phase as basis for the later integration of the new criteria, as well as upon an overview of existing selection criteria. Moreover, in section 3.1.4, an extract of decision support models, which make use of LCA based results for the decision-making process, is presented. The overall section concludes in section 3.1.5 with the identification of the research gaps against the background of the research questions to be answered.

3.1.1 Models for green supplier selection

"It is probable that of all the responsibilities which may be said to belong to the purchasing officers, there is none more important than the selection of a proper source. Indeed, it is in some respects the most important single factor in purchasing" (Lewis, 1940, p. 249).

As it can be seen, the crucial role of supplier selection goes back for decades. Ever since, its importance in scientific literature has continuously increased and new concepts have arisen. This also confirms the important role for corporate operations and business competitiveness (Rezaei et al., 2016). Besides the high amount of publications in the field of supplier selection and evaluation, diverse literature review studies were conducted (Rezaei et al., 2016; Wetzstein et al., 2016; Zimmer et al., 2016). The same accounts for publications with a specific focus on sustainable, especially environmental aspects in the supplier selection process. Moreover, a wide variety of models which support the decision-making process in green supplier selections have been identified and discussed in literature. Literature reviews in this field, focusing on quantitative and qualitative models for decision support, are rather scarce. Only in recent years, comprehensive reviews focusing on the environmental dimension in supplier selection, covering the last three decades, have been published (see Table 3-1).

Table 3-1: Related literature reviews on green supplier selection

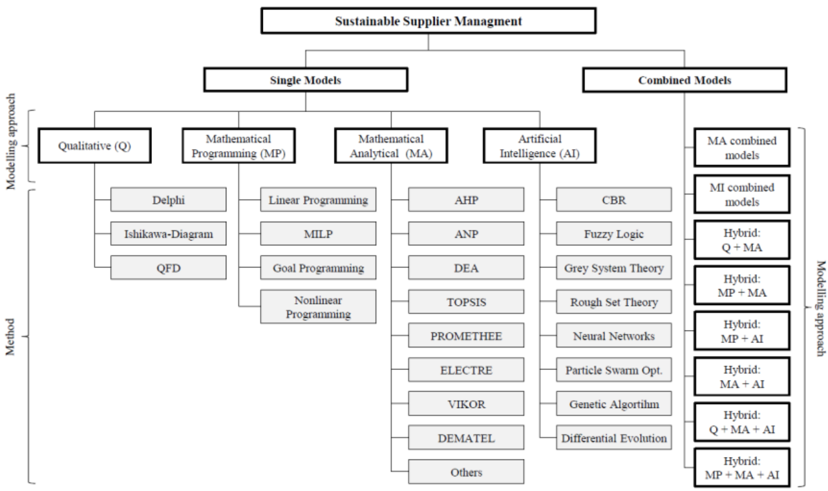
Review			Focus		
Authors (year)	Time range	Articles reviewed	Dimension(s) of sustainability	Content	Methods
Wetzstein et al. (2016)	1990-2015	221	Environmental	Supplier selection	Empirical/normative analytical, framework development
Zimmer et al. (2016)	1997-2014	143	Environmental & Social	Sustainable supplier management	Normative analytical, supplier selection criteria, framework development
Nielsen et al. (2014)	1997-2014	57	Environmental	Green supplier selection	Normative analytical, supplier selection criteria, framework development
Villanueva-Ponce et al. (2015)	2007-2013		Environmental	Green supplier selection	Empirical analytical (MCDA), supplier selection criteria
Govindan et al. (2015)	1997-2011	32	Environmental	Green supplier evaluation / selection	Normative analytical (MCDA), supplier selection criteria
Igarashi et al. (2013)	1991-2011	60	Environmental	Green supplier selection	Empirical/Normative analytical, framework development
Genovese (2013)	1997-2010	28	Environmental	Green supplier selection	Normative analytical, case study, framework development

All listed reviews which cover the field of supplier selection as part of sustainable supplier management respectively sustainable purchasing include environmental perspectives. However, only the review of Zimmer et al. (2016) shows an extended scope and additionally comprises social aspects. The review of Wetzstein et al. (2016), which focuses on supplier selection in general and not only sustainable supplier selection, deals with a broad spectrum of issues: general approaches for supplier selection, supplier selection criteria, green/sustainable aspects, as well as strategic, R&D and operations orientation. In contrast, Zimmer et al. (2016), performed a comprehensive content analysis on formal decision support models concentrated on an in-depth sustainable perspective. It covers all three pillars of sustainability, not only for the supplier selection phases but also the other two phases of sustainable supplier management, supplier monitoring and development. A specific focus is also laid upon the investigation of social aspects in supplier management, which has not been extensively investigated in review studies before. Furthermore, a thorough criteria analysis for sustainable supplier management was carried out. It can be considered as the most profound and detailed review study on sustainable aspects in supplier management and supplier selection which can currently be found in literature. In the further course of this research, reference is made primarily to the results of the two most recent and comprehensive literature review studies of Zimmer et al. (2016) and Wetzstein et al. (2016).

In a supplier selection process, a decision is made based upon various selection criteria and upon the capabilities of suppliers to meet the defined requirements. As described in section 2.1.4, either a single sourcing or a multiple sourcing approach can be applied to meet the quantitative or diverse strategic requirements (Ghodsypour and O'Brien, 1998). This issue is addressed and an investigation is carried out in both reviews of Zimmer et al. (2016) and Wetzstein et al. (2016). The study of Wetzstein et al. (2016) revealed a rather balanced ratio of papers dealing with single sourcing approaches, 81 papers, and multiple sourcing approaches, 77 papers. Among the identified 25 studies on sustainable supplier selection no differentiation was made in this regard. As described above, this review deals with supplier selection in general and not exclusively concentrated on sustainable approaches. Zimmer et al. (2016), who only investigated papers with a sustainable perspective, however revealed a strong predominance of 126 papers dealing with single and only 17 with multiple sourcing. On the one hand, this discrepancy might be traced back to the differences regarding the amount of papers in the field of sustainability investigated. On the other hand, both reviews reason that single sourcing approaches might have been in the focus in the past. This was due to the lower complexity and the goal to find a way of systematically handling the sustainable supplier selection problem at first. According to Wetzstein et al. (2016) only in 2011 the first paper adding more restrictions in form of multiple sourcing was published.

As described in section 2.1.4, the sustainable supplier selection process can in general be divided into four phases: ‘identification of needs and specifications’, ‘criteria formulation’, ‘qualification and evaluation’ and ‘final selection and evaluation’ (see Figure 2-2). In these two most recent literature studies, a distinction of the four phases in terms of quantity of papers published is made in order to illustrate the scientific coverage of the supplier selection process phases. Although Wetzstein et al. (2016) covered supplier selection not with an exclusive focus on sustainable approaches, the phase of ‘final selection and evaluation’ was identified as the most frequently covered category in scientific literature with 95 publications. In terms of sustainable supplier selection, 25 papers were investigated but no specific categorization into the supplier selection process phases was made. The identified widespread consideration of the final selection phase in literature goes in line with the sustainability driven reviews of Igarashi et al. (2013) and Zimmer et al. (2016), who investigated 118 papers dealing with this phase of supplier selection.

Based on Brandenburg et al. (2014), Bruno et al. (2012), Chen (2011), and Kannan et al. (2013), Zimmer et al. (2016) developed a framework for the classification of modelling approaches and methods (see Figure 3-1). The 143 revised publications were firstly divided in two categories: single models, which make use of one method only, and combined models, which apply a combination of methods. Among single models a distinction can be drawn between qualitative, mathematical programming, mathematical analytical and artificial intelligence approaches. Combined models illustrate a variety of combinations of approaches listed within the category of single models.



AHP: Analytic Hierarchy Process, ANP: Analytic Network Process, CBR: Case Based Reasoning, DEA: Data Envelopment Analysis, DEMATEL: Decision-Making Trial and Evaluation Laboratory, ELECTRE: Elimination et choix traduisant la réalité, MILP: Mixed Integer Linear Programming, PROMETHEE: Preference ranking organization method for enrichment evaluation, QFD: Quality Function Deployment, TOPSIS: Technique for Order Preference by Similarity to Ideal Solution, VIKOR: VlseKriterijumska Optimizacija I Kompromisno Resenje

Figure 3-1: Classification of models for sustainable supplier management (Zimmer, 2016; Zimmer et al., 2016)

According to Zimmer et al. (2016) more than half of the reviewed papers applied combined models, with hybrid combinations of mathematical analytical and artificial intelligence approaches being the most preferred approach. In terms of single models, mathematical analytical approaches, which have been widely studied for the last three decades, stand out clearly and represent almost one quarter of all papers studied. More specifically in terms of methods, Fuzzy Logic, followed by AHP and ANP are the most used methods, which are not only applied in the 'final selection and evaluation' phase but also for the determination of criteria weightings. In contrast to Igarashi et al. (2013) who consider the weighting determination as part of 'criteria formulation' and automatically assign related papers to the formulation phase, Zimmer et al. (2016) do not follow this procedure (see section 3.1.2). From a process perspective, the related approaches remain within the last phase of decision making (final selection). These are however separately investigated and illustrated in a more detailed analysis of decision situations. In line with the research objective (see section 1.2), the phase of criteria formulation is further emphasized in the following section 3.1.2.

Since 2010 research studies with a focus on the application of integrated TOPSIS approaches for the final selection stage have aroused much interest in scientific literature (Karsak and Dursun, 2016; Zimmer et al., 2016). Among the revised studies, Zimmer et al. (2016) identified and clustered the data used in the modelling approaches into three groups: expert opinion, supplier's data and combined data. Whereas data generated from expert interviews is very strongly represented, real quantitative supplier data is rather rarely used. A so far not established common understanding on performance indicators between focal companies and suppliers, and a restricted access to validated data in terms of completeness and uncertainty, were identified as two possible reason for that development (Azadnia et al., 2015; Zimmer et al., 2016).

3.1.2 Models for green criteria formulation

As described in section 2.1.4, after having defined the need of a purchasing company in line with the strategic targets, the formulation and definition of criteria plays a significant role in the supplier selection process and lays the groundwork for the final selection phase (see Figure 2-2). The formulation respectively definition of selection criteria relies on the assessment of experts in the field of business operation (Deng et al., 2014), which are not exclusively located in the purchasing department. Among others, experts from quality or environmental management can be involved in the complex process of selecting accurate criteria for the supplier selection. These criteria may also serve for the post selection supplier monitoring or development (Igarashi et al., 2013). Moreover, changes in political framework conditions or in sustainable characteristics can lead to a adjustments of criteria over time (Sagar and Singh, 2012).

Against the background of the initially stated purpose to integrate CO_2e in the supplier selection process in order to reduce emissions and comply with potential future governmental regulations (see section 1), an investigation on according literature was carried out. In reference to the literature studies of Zimmer et al. (2016) and Wetzstein et al. (2016) (see section 3.1.1), who also made a distinction between criteria formulation and criteria weighting, publications dealing with the formulation phase or criteria selection are very scarce.

In the review of Wetzstein et al. (2016) only nine papers with a main focus on criteria formulation in general and not specifically concentrated on a sustainability perspective could be investigated. No further in-depth analysis about models and methods used for this phase of the supplier selection process was carried out. In the review on sustainable supplier management, Zimmer et al. (2016) identified 15 papers dealing with the phase of criteria formulation within a supplier selection context. However, only eight papers were revealed which explicitly apply specific methods for the criteria formulation. The other seven publications only discuss the use of diverse criteria from a more generic perspective. Among the methods used, qualitative approaches predominate in this phase, represented by five approaches using the Delphi method and one using the Ishikawa-diagram. The remaining two can be found among the artificial intelligence approaches, applying Fuzzy logic or rough set theory as method to support the criteria formulation phase.

In the following, a brief excerpt of papers which apply the listed methods for criteria formulation is presented. The focus was laid upon the most recently published studies which are most related to the objective of this research project. The aim of the study from Enarsson (1998) was to evaluate new, or to reevaluate existing suppliers in a more structured way as well as from an environmental angle. This is because a lot of industrial companies integrate supplier selection parameters in their own way, especially environmental criteria. In reference to the production processes of suppliers, the following environmental criteria were used: type of energy, use of energy, waste release, local environment and products' environmental danger. Therefore, a structured tool was developed in Microsoft Excel based on the Ishikawa fishbone diagram, which belongs to the category of qualitative approaches. The basic idea, which relies on the visualization and structuring of the parameters, was to use it as a general screening and evaluation tool and not to select a supplier. The structured approach shall help to adjust parameters according to the evaluation situation and to develop as well as formulate environmental parameters.

Among these studies on qualitative approaches there is one developed by Banaeian et al. (2014) who created a hybrid model combining the Delphi method with Green Data Envelopment Analysis (DEA) in order to identify the most preferred supplier from a holistic point of view. The first part of the developed approach serves to formulate and identify the main decision criteria by help of the Delphi method in order to generate a consensus of opinions among a set of experts. The goal in this study is in particular to at first investigate new and existing criteria which are necessary to consider, and then to evaluate these criteria in terms of importance for the decision situation.

Out of the group of artificial intelligence approaches two studies are illustrated, one applying the Rough Set Theory method and one using the Fuzzy Logic method. Bai and Sarkis (2014) developed a methodology to identify key performance indicators (KPI) for the evaluation of the sustainable performance of suppliers. In a two-stage hybrid approach, the neighborhood rough set method is applied for the formulation and identification of criteria which are then used in the Data Envelopment Analysis method for the suppliers' performance evaluation based on single unified, integrated measures. The rough set method is a non-parametric data-mining approach which determines core relations between various factors by means of an information theory based attribute reduction algorithm. This method is used to create reduced data sets which focus only on the most important criteria and also results in a reduction of operative effort for managers.

Bhattacharya et al. (2014) developed a framework for the measurement of performance in green supply chain, using the application of a collaborative decision-making approach (CDM) with an inter-company scope. Within the CDM, a green balance scorecard (GrBSc) based on a fuzzy analytic network process (ANP) was used and served to test the causal relationships between the identified constructs. Five constructs respectively criteria categories were identified for green supply chain performance measurement which are then further sub-structured: organizational commitment, eco-design, green supply chain process, social performance and sustainable performance. The developed approach thus supports the criteria identification and formulation in line with the collaborative requirements of supply chain partners.

3.1.3 Existing supplier selection criteria

In the 1960s, research on criteria for supplier selection started with a publication of Dickson (1966) and the interest in this area has strongly grown ever since. This study and the developed set of criteria still constitute the basis for criteria selection in current supplier selection situations (Weber et al., 1991).

The focus on cost in various forms and factors such as quality and lead time respectively logistics has remained for many years (Rezaei et al., 2016; Villanueva-Ponce et al., 2015). In the 2000s the scope has strongly been extended by diverse criteria, among others, satisfaction of customers, responsiveness, cycle time and flexibility (Rezaei et al., 2016). Despite this evolvement of criteria, the traditional criteria of cost, quality and delivery maintain to be the most important criteria (Büyüközkan, 2012; Rezaei et al., 2016; Villanueva-Ponce et al., 2015).

In the last two decades, several researchers have extensively dealt with the examination of supplier selection criteria, from different fields and industries, as well as in terms of environmental and social aspects in the context sustainability (Ahi and Searcy, 2015; Govindan et al., 2015; Hashemi et al., 2015; He et al., 2017; Humphreys et al., 2003; Igarashi et al., 2013; Karsak and Dursun, 2016; Nielsen et al., 2014; Suraraksa and Shin, 2019; Villanueva-Ponce et al., 2015; Zimmer et al., 2016).

Within the extensive criteria analysis conducted by Zimmer et al. (2016), which includes and further extends the scope of the reviews of Nielsen et al. (2014) and Govindan et al. (2015), 448 unique criteria among 2661 in total, could be identified. The total amount of criteria revealed is distributed over the three pillars of sustainability as follows: 52.8% economic criteria, 38.1% environmental criteria and 9.4% social criteria. This confirms the currently still leading role of economic aspects (Rezaei et al., 2016). The literature review of Villanueva-Ponce et al. (2015) however focuses exclusively on green supplier selection criteria as sub-category of environmental aspects and presents no further classification into the general sustainability context.

3.1.3.1 Economic criteria

Even though the considered literature reviews differ slightly in the ranking and frequency of use of criteria, price/cost, product quality, technical capabilities and delivery performance are still always represented in the top selection of economic criteria. This goes hand in hand with other studies published in this field of research (Ahi and Searcy, 2015; Karsak and Dursun, 2016; Lee et al., 2011). Among various other criteria, flexibility, reliability, and relationship gain increased attention in supplier selection processes (Karsak and Dursun, 2016; Thiruchelvam and Tookey, 2011).

3.1.3.2 Social criteria

The research on criteria in the context of social criteria for suppler selection is very scarce. Only the three reviews of Ahi and Searcy (2015), Kumar and Rahman (2015) and Zimmer et al. (2016), which comprehensively deal with social criteria in a supply chain context, could be identified. Criteria concentrating on employment, training, community, wage, accidents as well as health and safety were identified in both reviews as key criteria for this category, whereas child and forced labor, the abuse of human rights and discrimination were treated rather rarely (Ahi and Searcy, 2015; Zimmer et al., 2016).

3.1.3.3 Environmental criteria

Starting in the 1980s and 1990s, first attention was drawn on the concept of green purchasing, which includes environmental considerations in the selection of adequate suppliers. Since then its importance has constantly grown (Dowlatshahi, 2000; Igarashi et al., 2013). Among the environmental respectively green criteria, which are in the focus of this research project, the majority of studies identified environmental management systems as the most widely used criteria in supplier selection decision making (Govindan et al., 2015; Suraraksa and Shin, 2019; Zimmer et al., 2016). Zimmer et al. (2016) additionally identified the following criteria as part of the top ten used for environmental supplier selection: resource consumption, eco-design, recycling, controlling of ecological impacts, waste water, energy consumption, reuse, air emissions and environmental code of conduct. In addition, several studies on green criteria for supplier selection were published in recent years (Hashemi et al., 2015; He and Zhang, 2018; Rezaei et al., 2016; Suraraksa and Shin, 2019), but do not present a classification of relative importance respectively quantity of application of criteria with respect to others. Further environmental decision criteria investigated in these studies comprise among others, cost of environmental amelioration, green R&D, green image, environmental training for staff, commitment of management, and the implementation of ISO 14001 certifications, either as a separate criteria or as a sub-criteria of environmental management systems.

A statistical data evaluation developed by Zimmer et al. (2016) illustrates an average application of 18.6 criteria among the approaches reviewed within the field of sustainable supplier management. Moreover, it was identified that in the majority of publications a hierarchical structure based on three levels was applied, in order to better organize and structure the decision-making situation.

Researchers developed different concepts of classifying criteria, especially environmental or green criteria. For example Lloyd (1994) proposes two categories of distinction, supplier/organization-related criteria and criteria-related to the product/material. The classification into quantitative as well quantitative criteria is another type of categorizing criteria which is also applied in scientific research (Humphreys et al., 2003; Nielsen et al., 2014). Along with the highly growing interest in sustainable supply chain management, especially the consideration of a product's entire life cycle increased. Hence, for example Nielsen et al. (2014) promote a classification of criteria according to the single phases of a product life cycle.

In terms of a distinction between quantitative and qualitative criteria, before 1990 the main focus was laid upon quantitative criteria which could be measured in numerical figures. Since then, the incorporation of non-numerical evaluations in form of qualitative criteria has gained importance as it was found out that this type of criteria creates a lot of benefits, despite the difficulty of quantification (Dowlatshahi, 2000). When it comes to environmental criteria, often qualitative ones such as the most widely used criteria of environmental management, which require a subjective decision-making, are applied. However, as green supplier selection criteria are generally less specific and can pose a risk of ambiguity (Govindan et al., 2015; Rezaei et al., 2016), the operationalization into practically applicable and measurable criteria, poses a strong challenge for practitioners from both customer and supplier side (Igarashi et al., 2013).

Due to the crucial role and responsibility of focal companies in a supply chain context, the selection of criteria for a final decision making needs on the one side to assure that the needs of the focal companies' are fully met. On the other side, the interests of all supply chain key players (see Figure 2-1 and section 2.1.3) should also be incorporated in the criteria selection process. This aspect is however not yet strongly represented in scientific research (Ahi and Searcy, 2015; Giunipero et al., 2008). As various different motifs are pursued when suppliers are additionally evaluated and selected based on environmental aspects (see section 2.1.1), it is impossible to create a specific and generally valid framework for criteria (Igarashi et al., 2013). In real supplier selection situations compromises have to be made when environmental criteria are included (Rezaei et al., 2016). Due to a direct connection to the cost structure of the product or the supplier, the addition of environmental criteria needs to be carried out carefully in order to avoid negative effects on price negotiations (Zimmer et al., 2016). However, green practices can also positively affect economic criteria. For example increased efficiencies in operations resulting from higher requirements regarding recycling can lead to reductions in product costs and avoidance of environmental costs (Azevedo et al., 2012).

3.1.4 Models for green supplier selection based on life cycle assessment

Only in recent years, research studies were published which treat environmental criteria in a more quantitative way. Approaches were developed which combine the method of life cycle analysis (LCA) with specific modelling approaches for supplier selection in a multi-criteria environment.

Boosothonsatit et al. (2012) proposed a model based on generic simulation in order to support the selection of the most sustainable supplier against the background of minimizing cost and lead time. Therefore, two methods, fuzzy goal programming (FGP) and min-max operator and system dynamic (SD) simulations were combined. Besides classical criteria, as for example cost and lead time, the environmental impact is included. It is derived from a simplified LCA database using the Eco-indicator method. The applicability and potential benefits of the developed green supplier selection approach are tested on a boat manufacturing case with a focus on four entities (manufacturer, supplier, material as well as transportation mode).

Kumar et al. (2014) developed a novel approach based on carbon footprint monitoring and data envelopment analysis (GDEA). The results from a company specific LCA were consulted in order to define the carbon footprints of suppliers. At this point a special focus was laid upon the assurance of consistency among all considered suppliers. Against the goal of enabling an environmentally friendly supplier selection process, the model, which considers the annually produced footprint for multiple products, was tested on an Indian spare part manufacturer in the automotive industry.

Yoshizaki et al. (2014) developed a model for supplier selection with a focus on low-carbon emissions of material and low cost. A bill of materials with estimations for CO_2 emissions and cost was used, in combination with an integer programming formulation together with an optimization by a mathematical programming package. Two life cycle inventory databases for China and Japan, which are based on country specific input-output tables, are consulted for the estimation of carbon emissions of purchased parts. It includes raw materials, material transport and material production. The goal is to investigate the country specific differences in a supplier selection process for a vacuum cleaner. A similar approach was published by Urata et al. (2016), which can be considered as further development or extension of the model of Yoshizaki et al. (2014). The same methodological principles are applied in this study. In the previously described model, the selection of a part was either limited to the entire quantity purchased from a supplier located either in the one or the other country. In contrast, in this approach arbitrary combinations between the locations can be considered. In addition, market specific supplier locations are incorporated and considered in form of transportation cost for parts. In this context not only purchased parts but also the levels of production are covered.

In a recently published study of Dong et al. (2018), the generic applicability of the life cycle assessment method as basis for an integration of environmental aspects into supplier selection was analyzed. The investigated results, indicate a general suitability of LCAs for use in decision-making processes, more specifically to select adequate suppliers based on the integration of environmental impacts. This further endorses the findings of the literature review of Igarashi et al. (2013), presented in section 3.1.3. However, it is pointed out that attention needs to be paid on several aspects in order to assure a comparability across suppliers. Different variations in scope, variations in system boundary definition and methodological differences constitute hurdles which need to be overcome at first.

The mentioned principles go in line with a publication of Butt et al. (2015), who investigated the general applicability of and methodological choices applied in life cycle analysis as well as the importance of the definition of technical features respectively attributes of the system. This was done based on a case of procurement of roads. In addition, a framework was created which shall support decision makers in defining the extent as well as the focus of LCA studies and in choosing of a design alternative. According to Butt et al. (2015), the methodological approach can be determined depending on where the decision problem can be located in the two dimensional matrix framework, which consists of decision levels (network or project level) and decision stages (early planning or late planning/design stage).

3.1.5 Research gaps

The supplier selection process has been intensively dealt with in scientific literature for more than 50 years. Foremost the last phase of final supplier selection has been most excessively covered among research studies. The same accounts for sustainable or green supplier selection processes which have aroused a lot of interest in the last decades. A great range of approaches has been developed using diverse single methods in this context, individually or in a combined form (see Figure 3-1). Despite the development and the growing attention on sustainable supplier selection, the analysis of the current state of research has however revealed that the criteria formulation phase has not been widely explored and investigated yet (Igarashi et al., 2013; Wetzstein et al., 2016; Zimmer et al., 2016). Moreover, specific research on carbon emissions as explicit criteria in environmental respectively green supplier selection processes remains rather scarce (Govindan et al., 2015; Karsak and Dursun, 2016; Nielsen et al., 2014; Zimmer et al., 2016). Considering the goal of this research to integrate CO_2e as valid decision criteria against the background of a practical applicability in real life decision-making situation, in this section existing research gaps are identified.

Among the few discovered publications, which primarily focus on the formulation of criteria and apply distinct methodological approaches, only methods from the categories of qualitative (Delphi and Ishikawa diagram) and artificial intelligence approaches (rough set theory and fuzzy logic) were applied (Zimmer et al., 2016). The majority of approaches makes use of data generated from expert judgements. The approach of Bai and Sarkis (2014), which makes use of actual quantitative data, however only consults illustrative, simulated data. This matches with the investigation of Zimmer et al. (2016), who state that the use of real supplier data is rather scarce and should be further investigated. According to Azadnia et al. (2015), one limitation with this proposition exists, the accessibility of validated data which is very restricted. Moreover, the application of sensitivity analysis within multi-criteria models for supplier selection, which is highly relevant to test the robustness of criteria and models, has so far been rather neglected (Belton and Vickers, 1990; Zimmer et al., 2016).

In recent years, some studies were published treating environmental criteria in a more quantitative way. First models were presented which combine the method of LCA with specific modelling approaches for supplier selection in a multi-criteria environment. The conducted literature research shows that LCA approaches can be beneficial for the integration of quantitative evaluations into sustainable supplier selection decisions. Various methods such as linear programming, goal programming, data envelopment analysis and fuzzy logic are applied. However, the focus was primarily laid on the supplier selection phase. In terms of data, either average data for regional considerations was applied or non-disclosed company-specific data for more specific investigations. Even though a first, tangible step forward is made for integrating CO_2e performances into the criteria portfolio for supplier selection, compliance with the requirements for making a supplier selection based on site-specific performances, is not given. More in-depth information on this topic and on the methodologic approaches for the conduction of LCAs is presented in section 3.2.

In the majority of scientific literature on green supplier selection, qualitative criteria, such as the most widely used criteria of environmental management system, are applied. This criteria may however pose a risk of ambiguity for suppliers as well as purchasers and may lead to rather subjective decision, as it is not clearly defined and not accurately measurable (Govindan et al., 2015; Igarashi et al., 2013; Rezaei et al., 2016). In addition, Butt et al. (2015) conclude that a certain transparency should be provided when criteria are defined, and that it has to be assured that the calculation is consistently carried out in order to enable reproducible results. Due to the comparative nature of supplier selection decisions, attention needs to be paid to the comparability of results. The definition of scope and the system boundaries constitutes a crucial hurdle which needs to be overcome (Dong et al., 2018).

Most of the existing approaches developed a fixed set of selection criteria concentrated on a specific company or industry. In contrast, a higher efficiency can be generated, if supplier or situation specific criteria sets are applied (Bai and Sarkis, 2014; Zimmer, 2016). In that respect, the success of environmental supplier selection is strongly dependent on the integration of supply chain members in the criteria selection process (Dou et al., 2014). According to Ahi and Searcy (2015), most studies however focus on the focal company and miss to address other members in the supply chain, such as suppliers.

A very important aspect, especially from a corporate perspective, is the economic effect resulting from the integration of an additional, environmental criteria into a supplier selection process. According to Ahi and Searcy (2015) and Igarashi et al. (2013), research on the effects of green supply chain management respectively green supplier selection from an economic perspective is missing.

3.2 Assessment of environmental performance in the metal industry

As basis for an integration of site-specific environmental performance indicators in a supplier selection process, a certain level of transparency of upstream supply chain operations is crucial. In this section the current state of literature referring to the sub-model for environmental performance assessment, with regard to the main research question respectively sub-questions (3) and (4) illustrated in section 1.2, is reviewed.

In section 3.2.1 the LCA method is examined and general advantages and disadvantages for an application are highlighted. In section 3.2.2, exemplary works on LCA with application in the steel industry, which represents the principal case of application in this research contribution, are analyzed followed by section 3.2.3, in which exemplary works in the aluminum industry are evaluated. In addition, an extract of extended methods to define the environmental performance based on material and energy flows is presented in section 3.2.4. Against the background of transferring the developed model to other commodities, in section 3.2.5 exemplary works on LCA in the aluminum industry are discussed. The final section 3.2.5 concludes with the identification of the research gaps.

3.2.1 Life cycle assessment for environmental performance

The evaluation of the environmental performance of consumer products has gained importance in scientific literature since the 1980s and has also been brought to the forefront for practitioners (Bilec et al., 2006; Guinée et al., 2011). In this context, especially the LCA method finds a widespread application. The method of LCA is applied to evaluate product and service designs, and can thus be used as basis for decision making in order to find improvement opportunities for environmental impact reduction and to define eco-labelling. It is used both in business as well as political environments (Breun, 2016; Hendrickson et al., 1997; Zamagni et al., 2013). LCA presents a holistic method which takes the entire life cycle of products or proses into account, reaching from raw material exploitation until the end-of-life recycling phase. The goal is to not only quantify inputs and outputs of material and energy flows but also environmental effects and burdens (Guinée et al., 1993; Hendrickson et al., 1997; Kndungu and Molavi, 2014; Roy et al., 2009; Sonnemann et al., 2004; Suh et al., 2004). In line with the principles of sustainability, LCA can be applied within all three pillars from economic, social and environmental perspectives (Guinée et al., 2011; Zimmer, 2016).

3.2.1.1 Process of life cycle assessment

“LCA addresses the environmental aspects and potential environmental impacts (e.g. use of resources and the environmental consequences of releases) throughout a product’s[10] life cycle from raw material acquisition through production, use, end-of-life treatment, recycling and final disposal (i.e. cradle-to-grave)” (International Standards Organisation, 2006a, p. 4).

The International Organization of Standardization (ISO) introduced a global standard procedure including respective guidelines within the context of the Environmental Management Standards (EMS) (Suh et al., 2004). The ISO standard 14040 defines the principles on life cycle analysis and the ISO 14044,

[10] E.g. services are also covered under the term product.

which forms the foundation for LCA studies, provides the requirements for the performance of a LCA.

The standardized ISO process for life cycle assessment, illustrated in Figure 3-2, is structured in four stages (Bilec et al., 2006; Guinée et al., 1993; International Standards Organisation, 2006a, 2006b; Klöpffer, 2012):

a) The goal and scope definition phase,

b) The inventory analysis phase (LCI),

c) The impact assessment phase (LCIA), and

d) The interpretation phase.

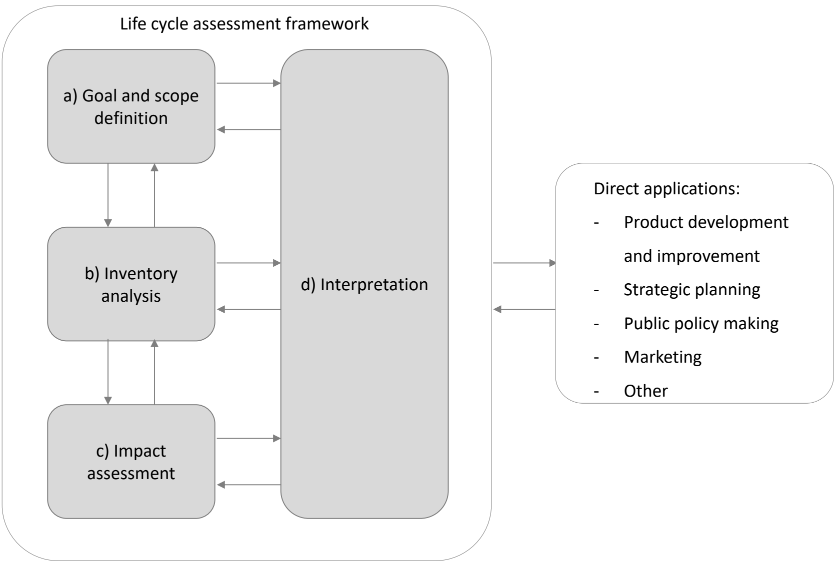


Figure 3-2: LCA phases according to ISO standard 14040 (International Standards Organisation, 2006a)

In the initial step, the goal and scope will be defined which is often considered a crucial step in life cycle analysis (Roy et al., 2009). It deals with the definition of the purpose and intended application of the study, the setting of system boundaries and the derivation of the functional unit. Especially, the process of definition of the functional unit in combination with the setting of system boundaries is of high relevance. It provides the basis for a valid analysis and comparison of products (Kndungu and Molavi, 2014). Within the system boundaries all operations contributing to a product's life cycle need to be taken into account. The FU provides a quantitative reference value to which the life cycle inventory (LCI) data set will be normalized, described in the following step of LCA (International Standards Organisation, 2006a; Roy et al., 2009).

In the LCI, all necessary data for the life cycle analysis need to be collected (see section 3.2.1 and 3.2.2). All input and output materials for a production process, in reference to the functional unit, need to be included. In terms of a consideration of environmental loads, inputs comprise among others raw materials, energy and water. The product and co-product, emissions to air, water- and solid, as well as the generation of solid waste are considered as outputs (Roy et al., 2009). This phase requires the most effort in a LCA due limitations in data availability and the resulting high time consumption (Bieda, 2014; Heijungs et al., 1992; Roy et al., 2009). The collected data set constitutes the basis for a subsequent analysis of environmental impact.

Based on the previous step, the input and output data is evaluated for the severity and dimension of its potential impact on the environment. The life cycle impact assessment phase (LCIA) consists of three main steps (International Standards Organisation, 2006b; Scientific Applications International Corporation, 2006):

- Definition and selection of relevant impact categories and according category indicators as well as characterization models,

- Classification and categorization of LCI data according to the contribution to diverse impact categories, and
- Characterization of impacts by means of science-based category indicators, respectively characterization factors.

In the initial step of selecting an impact category, midpoint and endpoint categories have to be distinguished. At first, so called midpoint categories, which consider problem oriented impacts on the environment prior to the endpoints, are calculated. The different midpoint categories comprise among others: climate change, ozone depletion, acidification and eutrophication (ILCD, 2010).

The damages resulting from the environmental impacts can be assigned to different areas of protection such as human health, natural environment and natural resources (Capaz and Seabra, 2016; ILCD, 2010).

Subsequently, the elementary flows gathered in the LCI such as, for example, greenhouse gases (CO_2, NO_2, CH_4, CFCs, HCFCs and CH_3Br), are organized into impact categories according to the contribution to environmental problems (ILCD, 2010; Scientific Applications International Corporation, 2006). Finally, in the characterization phase, the environmental impacts of the emissions and the consumption of resources are quantitatively calculated by means of characterization factors. In case of the impact category climate change, the categorization factor global warming potential (GWP) is recommended for application at midpoint (ILCD, 2010). Global warming potential, developed by the Intergovernmental Panel on Climate Change (IPCC, 1990) is "an index, based on radiative properties of greenhouse gases, measuring the radiative forcing following a pulse emission of a unit mass of a given greenhouse gas in the present day atmosphere integrated over a chosen time horizon, relative to that of carbon dioxide. The GWP represents the combined effect of the differing times these gases remain in the atmosphere and their relative effectiveness in causing radiative forcing. The Kyoto Protocol is based on GWPs from pulse emissions over a 100-year time frame." (IPCC, 2013, p. 1455). Besides additional time horizons of 20 and 500 years, the 100-year time frame for GWP is the most widely applied approach without a specific scientific argumentation (Sarofim and Giordano, 2018). One of the generally very few explanations is provided by the WMO (1992): "The GWPs evaluated over the 100-year period appear generally to provide a balanced representation of the various time horizons for climate response. This is a time scale that includes due consideration of the ocean thermal inertia and its impacts on the global mean surface temperature. In addition, carbon cycle models also indicate that this time period broadly represents the time scale over which a significant fraction of CO_2 is removed from the atmosphere" (p. 5).

Hence, LCI data for greenhouse gas emissions are converted to, and expressed in an equal unit of kg CO_2 equivalents, CO_2e (Capaz and Seabra, 2016; Scientific Applications International Corporation, 2006). In reference to climate change, the characterization factor for CO_2 is 1 GWP100, while for example CH_4 has a higher effect of 28 GWP100 (IPCC, 2013).

In the context of assessing the impact of the inventory data by means of characterization factors, several impact assessment methods were developed in order to facilitate as well as optimize the impact assessment phase, and to facilitate comparisons of alternative products. The methods can be categorized into midpoint approach methodologies (problem oriented), endpoint approach methodologies (damage oriented), combined approaches and other LCA based approaches. For more in detail information, reference is made to the studies of Jolliet et al. (2003) and Menoufi (2011).

When selecting an impact assessment method, LCA practitioners should choose the best suited model for the individual life cycle inventory. There is no universally suitable method for all impact categories and requirements. The selection should be based on the importance of the investigated emissions and midpoint categories (Landis and Theis, 2008).

In case of the midpoint category climate change, the IPCC approach, which determines and expresses the environmental impact in GWP, is applied in the majority of the established impact assessment methods. Hence, no differences in results are apparent and each method can be consulted (Cherubini et al., 2018; ILCD, 2010; Landis and Theis, 2008; Renouf et al., 2015). This holds true for methods such as, for example, the CML-Method, which was developed in 1992 by the Centre of Environmental Sciences at the University of Leiden (CML, 2020; Guinee, 2002).

In the final interpretation phase, both, the results from the inventory analysis and the impact assessment are jointly considered. It is used to reach conclusions and derive recommendations, which are aligned with the initially defined goal and scope. The goal is to present the results of a LCA in a comprehensive, complete and consistent form. Hence, the findings of the interpretation phase can be provided to decision makers in order to support the decision-making process (International Standards Organisation, 2006a).

Based on the application of life cycle analysis, two types of approaches, attributional and consequential LCAs can be distinguished (Weidema, 2003). Attributional LCAs are used to describe an isolated product system. All material and energy flows which are directly linked to a defined system respectively inventory boundary, are covered. In contrast, consequential LCAs are dealing with the quantification of emission changes as a result of a decision and a consequent action (Bauer and Poganietz, 2007; Brander, 2017; Weidema, 1993). From a time perspective, both approaches can be consulted for a retrospective assessment of past actions and for prospective considerations of possible, future actions (Bauer and Poganietz, 2007; Weidema, 2003). According to Weidema (2003), the selection of the type of LCA approach has to be transparently placed in step of goal and scope definition.

3.2.1.2 Methods of life cycle assessment

In the scientific field of life cycle assessment analysis, mainly two methods were distinguished and frequently discussed in the past: bottom up calculations using the process based LCA and top down approaches applying the input-output analysis (Feng et al., 2011; Guinée et al., 2011; Huang et al., 2009; Minx et al., 2009; Wiedmann, 2009). Since the start of the twenty-first century, combinations of the two mentioned methods have occurred more frequently and gained strongly in importance (Guinée et al., 2011; Islam et al., 2016; Suh and Huppes, 2005). In order to overcome the limitations of the two single methods, the advantages of the bottom-up and the top-down methods are combined. All three methods pursue the same objective of systematically analyzing economic, social and ecologic effects of products throughout the entire lifecycle. However, not only the level of detail varies significantly among these methods but also the scope of analysis (Guinée et al., 2011; Zimmer, 2016).

In the late 1960s, the foundation for process based approaches as a methodological framework for the measurement of energy requirements and the prevention of pollution was laid (Islam et al., 2016). This net energy analysis and a study from Smith (1969), which represents one of the first studies in this field, are considered to be the predecessor and origin of process based LCAs (Ayres, 1995; Islam et al., 2016). In this straight forward method, the inventory is compiled via a process analysis. According to Suh and Huppes (2005) and Islam et al. (2016) two types can be distinguished: modelling based on process flow diagrams and on matrix inversion.

In the modelling approach with process flow diagrams, the entire input and output flows of specific processes for a product system are identified and quantitatively expressed according to a defined functional unit (Kndungu and Molavi, 2014; Sonnemann et al., 2004). It shows the interconnectivity of processes via commodity flows in a diagram. Processes are illustrated with boxes and commodity flows. Ratios of inputs and outputs define single process steps (Suh and Huppes, 2005). A LCI for a product is calculated by means of plain algebra, multiplying the necessary quantity of commodities for a product with the quantity of environmental interventions, which occur during the production of a chosen functional unit (Islam et al., 2016). The matrix representation of a product system constitutes a more computational method for life cycle inventory analysis. Introduced in 1994 by Heijungs (1994), a broad range of linear equations is solved simultaneously and used to illustrate the entire product system. It can be a suitable method, if several input output relations, specific internal production loops or recycling processes are considered in a product systems (Islam et al., 2016). Both process based methods offer the advantage of providing a necessary level of detail to analyze processes of a product system. Whereas the process flow method produces the best results for a single product system and is more easily comprehensible, the matrix inversion method, which requires mathematical expertise, can be applied for more complex systems. Whilst the two process methods offer a variety of opportunities, some limitations come along, as for example in terms of quality of available data (Bilec et al., 2006; Hendrickson et al., 1997; Yellishetty et al., 2011). Moreover, as there is no method standardization when it comes to the definition of system boundaries, a certain subjectivity occurs. This can lead to truncation errors which prevent a comparability of results and restrict policy decision-making (Islam et al., 2016). The high requirements of data for a detailed modelling of processes leads to an associated high time and cost effort (Bilec et al., 2006; Guinée et al., 1993). As in-depth primary data is very scarce, often life cycle databases, which provide average values for specific processes, are consulted.

The originally in 1936 developed top-down input output approach by Leontief (1936) was in 1970 for the first time used for environmental analysis (Leontief, 1970). Since then, the economy wide input output approach has found strong appeal in environmental application (Islam et al., 2016). The approach assumes an interdependency among different sectors in one economy and makes use of a nation's economic input-output data combined with sector-level environmental impacts (Bilec et al., 2006; Leontief, 1936; Suh et al., 2004). As the entire supply chain of a product system in an economy is taken into account respectively the system boundaries are defined as the whole economy, truncation errors are avoided and results are reproducible. Furthermore, as no unit process data is required, the acquisition of data requires a minor expenditure as publicly available input output databases, such as national economic accounts, can be used. In this context, indirect impacts on the environment and upstream activities can easily be integrated (Bilec et al., 2006; Islam et al., 2016). On the contrary, the aggregated level of data on sector-level does not provide the necessary level of detail and process specificity for a direct comparison of specific product systems (Bilec et al., 2006; Suh et al., 2004; Zimmer et al., 2017). In addition, data uncertainty and the issue of not being able to accurately provide data for upstream processes, which depend on imports, illustrate a limitation. The actuality of data cannot always be guaranteed as the compilation of input output datasets often goes along with a time delay of up to three to five years.

Hybrid LCAs apply the process based and the input output LCA methods in a combined manner (Islam et al., 2016; Minx et al., 2009; Suh and Huppes, 2005; Wiedmann, 2009; Wiedmann and Minx, 2008). Several types of hybrid LCAs can be differentiated and categorized in tiered hybrid analysis, input output based analysis, integrated hybrid analysis and augmented process-based hybrid analysis (Bilec et al., 2006). All types of hybrid LCA aim at combining the strengths of both methods, but make use of a varying ratios of process and input output data. The goal is to achieve an ideal relation between precision, accuracy and efficiency (Wiedmann, 2009). For example, the augmented process-based hybrid method makes use of the largest part of process data in contrast to the tired hybrid method which relies primarily on input output data (Bilec et al., 2006). The combination of methods allows for preserving the necessary level of detail for main processes by the application of bottom-up process approaches, while covering the less important steps by an input output model (Wiedmann, 2009). Thus, a higher precision of results and completeness of system boundaries can be achieved. However, the approach shows a high mathematical complexity and poses a risk for double-counting of data (Islam et al., 2016).

3.2.2 Life cycle assessment in the steel industry

In order to evaluate the direct and indirect emissions from the steel production process in China, Li et al. (2016) developed an economic input-output LCA model. Within cradle-to-gate system boundaries, ranging from raw material extraction to the use phase of steel products, the industry life cycle is analyzed, with focus on CO_2 emissions. In terms of data sources, the study makes use of average data from China's input–output extension table for the reference year 2010, China's Energy Statistical Yearbook for 2011, the national Electrical Power Yearbook from 2013 and from the Xiamen energy saving Center.

Scaife et al. (2002) carried out a process based LCA to investigate the effects of new production technologies and the re-usage of by products on the environmental impact of steel. The cradle-to-gate study comprises all activities from raw material extraction to casted steel and concentrates on the assessment of the environmental impact in form of greenhouse gas emissions. In the approach, a credit scheme was introduced, which considers the reuse of interworks gases as well as slags for other products, as for example cement. The focus is set on the Australian steel production industry on an average country level. The life cycle inventory for the selected reference year 1999 is based on an Australian LCA study, conducted by Australian Coal Industry's Research Program.

Norgate et al. (2007) conducted a cradle-to-gate study for various metal production processes in Australia. The goal was to analyze the main contribution processes to the environmental impact based on an average, national scope. In terms of data gathering for the life cycle inventory, Norgate et al. (2007) rely on averaged process data retrieved from various sources. The problem-oriented life cycle impact assessment makes use of the IPCC characterization model and concentrates on the midpoint categories of GWP and acidification potential (AP).

After a previous publication on the general importance of the LCA method for the iron and steel industry in 2011 (Burchart-Korol, 2011), in 2013, Burchart-Korol (2013) performed a LCA on steel produced in Poland. The target was to conduct LCA on a national, average level with a focus on steelmaking in integrated steel works and electric arc furnaces (EAF) in order to point out the emission hotspots in the production process and to propose methods for pollution prevention. The LCA study sets the system boundaries as cradle-to-gate, comprising the processes in the sinter plant, the blast furnace, the lime production plant, the basic oxygen furnace, the casting and the rolling plant. It is conducted according to the ISO 14044 standards. The life cycle inventory for 2010 relies on averaged data from Polish steel plants, which were checked against the Best Available Techniques reference documents from the European Commission and diverse literature sources. It covers raw materials, fuels, additives, electricity and additional auxiliary materials for the operating processes of steel manufacturing, however excludes the internal flow of intermediate products. The life cycle impact assessment is carried according to the IPCC (2007) GWP 100a, the cumulative energy demand (CED), and the ReCiPe Midpoint method, by help of the SimaPro software (SimaPro, 2020) based on the ecoinvent database (Ecoinvent, 2007-2013).

In Huang et al. (2010) several factors which influence the emissions from the steel production process in integrated steel mills are identified. Against the background of reducing CO_2 in the production process according reduction measures are suggested. The geographic scope is limited to China and more specifically, the focus is laid upon the examination of one single integrated steel production plant. In terms of environmental burdens, the study exclusively investigates CO_2. In the cradle-to-gate consideration, the system boundaries are set for all operations from the exploitation and production of raw materials to the rolling of steel products. In terms of a product life cycle perspective, all upstream processes, material transport, the production phase at the steel plant itself, as well as recycling of by-products are covered.

In the life cycle inventory, company specific data gathered from the selected steel plant are consulted. The transport of raw materials is calculated according to the identified transportation modes and distances. To complete the cradle-to-gate boundaries, average industry data for upstream processes, provided by GaBi LCA database and software (GaBi, 2020), are included. At first a classical process-based LCI is conducted. With the help of the Tornado Chart Tool, the effects of variations of the LCI input variables on the CO_2 emission of the selected Chinese steel plant, are then calculated and analyzed. The tool is integrated in the Crystal Ball Software and enables a sensitivity analysis of the variables (existing and target forecast variables), with the aim of prescreening and selecting the best choice of decision variables. As a result the most important CO_2 emission factors influencing the integrated steelworks are disclosed.

Bieda (2012a) developed an approach for the life cycle inventory phase with a focus on basic oxygen steelmaking. The geographic scope is limited to Krakow, Poland and one steel production site from ArcelorMittal is exclusively investigated. The LCI study, which is carried out for the year 2005 and follows the International Standards ISO 14040: 2009 guidelines, presents, according to Bieda (2012a), the first of its kind for Poland. It covers input materials and energy sources and a wide range of outcomes such as emissions of SO_2, NO_2, CO, CH_4, CO_2, dust, and heavy metals, as well as several types of waste (gas cleaning sludge and slag). The goal of the study is the development of a generic LCA method for Poland with a focus on the creation of a LCI dataset limited to a specific company, ArcelorMittal, in order to support and solve both technical as well as environmental aspects. A process-based bottom-up calculation is applied on a specific stage of the steel manufacturing process. The gate-to-gate system boundaries include processes from pig iron produced in the blast furnace to the end-product basic oxygen steel, which is defined as functional unit. Several company specific data sources, such as company specific measured and calculated data as well as internal information obtained from interviews with company experts are consulted.

In addition, two studies from polish universities as well as diverse, peer-reviewed literature is used. In the following years several papers, examining additional upstream process steps of the ArcelorMittal steel plant in Poland were published. In 2012, Bieda (2012b) presented an LCI study for the blast furnace operations on site and in 2015 for the coke making process (Bieda et al., 2015). The additional studies follow the same basic principles of the first publication described above. Similar data sources and the same methodological process-oriented approach were applied. All studies, which cover different gate-to-gate system boundaries, deal exclusively with the inventory phase and focus on environmental loads, without considering the subsequent environmental impact phase. In 2014, Bieda (2014) developed a new approach and applied stochastic assessment for life cycle inventory. It was conducted on a process chain for steel production with the help of the Monte Carlos simulation software. The study aims at promoting the general application of uncertainty analysis in life cycle assessment as well as inventory studies. It also shows that an integration can support the interpretation of the LCA results in a decision-making context.

In Olmez et al. (2016) a process-based life cycle analysis for Turkey was carried out by means of the SimaPro software tool (SimaPro, 2020). The objective is to compare impacts of intermediate processes and final products, such as for example hot rolled wire rod and hot rolled coil. The IMPACT 2002þ methodology, which combines advantages of IMPACT 2002, Ecoindicator 99, CML 2002, ecoinvent and IPCC, was used to assess the impact on environment for four damage categories. Therefore, a plant specific inventory analysis is derived from one out of three steel manufacturing sites (35% of national steel production) in Turkey. The plant was considered as representative sample for Turkey and thus used as average production site. With a cradle-to-gate focus, the study relies on average data from the ecoinvent database for raw materials, auxiliary materials and energy. Hereby a distinction is made if data is specific to the country of origin. In case of electricity, the calculation is adjusted respectively extended, and country specific energy sources for electricity production, which reflect the conditions in Turkey, are taken into account.

In Renzulli et al. (2016), an analysis of the environmental impact of steel making in one specific integrated steel making plant in Italy is carried out. It aims at identifying process improvements and options for emission reduction. The study is carried by the requirements of the ISO 14040 (2006) and includes all for stages (goal and scope determination, the inventory as well as impact assessment and interpretation). The selected system under study focuses on raw material extraction, coke and sintering operations as well as the iron and steel making process (cradle-to-gate). The process-based LCI relies on several sources of data. Site-specific foreground data was mainly collected on site at the Ilva steelworks in Taranto, Italy. In case of unavailability of data, the Best Available Techniques Reference documents for steel sector (BAT) from the European Commission (European Commission, 2013), were consulted. Information on emissions were obtained from a local environmental protection agency and for the assessment of background data, the SimaPro software (SimaPro, 2020) was applied. In terms of environmental loads, several outputs were examined as for example emissions to air, emissions to water and output of solid waste. Subsequently the studied process steps were analyzed according to their contribution to various impact categories. In total sixteen impact categories were selected for the impact assessment phase. Concluding, Renzulli et al. (2016) point out that interconnection of the integrated steel plant and the neighboring power plant can illustrate a potential field for future research. Whereas, the reuse of process gases as internal energy providers for diverse process steps is taken into account, the exchange between the steel and the power plant is not in the scope of the study.

3.2.3 Life cycle assessment in the aluminum industry

Several publications were published on the environmental impact assessment of the aluminum production process by means of LCA. Tan and Khoo (2005) conducted a cradle-to-gate LCA for the primary aluminum industry in Australia with a focus on a refinery, a smelter and a casting plant. They analyzed the environmental impact via GWP, human toxicity for air (HTA), bulk wastes and acidification (Ac) with SimaPro LCA software (SimaPro, 2020) in four scenarios based on technological approaches and sustainable practices to improve the production process and thus reduce the environmental impact.

Similarly, Norgate et al. (2007) used LCA to assess the environmental impact of metal production processes in Australia. Among others, the environmental impact of Aluminum was investigated in a cradle-to-gate consideration, relying on various non-disclosed literature sources. The study covers the two impact categories of acidification gas emissions (Acidification Potential, AP) and greenhouse gas emissions (expressed in GWP).

Ciacci et al. (2014) combined life cycle analysis and material flow analysis (MFA) in order to analyze the GHG emissions in the aluminum industry in Italy. In a cradle-to-gate approach the development of the environmental impact (GWP) is analyzed on country level over a period of approximately 50 years (1960 until 2009) in order to provide support for political stakeholders for the orientation of industrial policies towards cleaner manufacturing of aluminum. Data on a national level was retrieved from the Italian Institute for Environmental Protection and Research (ISPRA), the Italian electricity transmission grid operator TERNA, from the International Aluminium Institute, the European Aluminum Association and the International Energy Agency was used in conjunction with primary information from expert consultation.

Similar to the study of Ciacci et al. (2014), Suciati and Goto (2014) applied a combination of MFA and LCA for the evaluation of the environmental impact of the primary aluminum production in Indonesia. They analyzed the current situation and provide future projections on carbon dioxide emissions (CO_2) in reference to the Indonesian roadmap for national aluminium development. Therefore, they assess CO_2 emissions in a cradle-to-gate scope. The used data is mainly derived from the Statistical Yearbook of Indonesia and on unspecified literature sources as well as publicly available reports.

Korneliúsdóttir (2014) conducted and compared two cradle-to-gate LCAs (reference year 2012) for an average European smelter and for the aluminum production process at the Norðurál plant in Iceland. The necessary inventory data for the site-specific consideration is composed of publicly available data as well as internal information from Norðurál, supplemented by information from the Environmental Agency of Iceland. For the calculation of the average European smelter, an industry average dataset provided by the European Aluminium Association is consulted. The GaBi LCA software (GaBi, 2020) is used for the impact assessment based on the CML 2001 methodology assessing GWP and six other impact categories.

Kovács and Kiss (2016) carried out a comparative analysis based on LCA in order to reveal the GWP hotspots in the aluminum production process. In a simplified cradle-to-gate consideration, the process steps of bauxite mining as well as alumina refining, production of anode, aluminum smelting, ingot casting and power generation are investigated for the reference year 2010. The examination is based on two types of anodes used for the aluminum production: conventional (Soderberg and prebake) and inert anodes. Additionally, a scenario analysis with eight scenarios is conducted applying either fossil, coal-based energy supply or a renewable energy mix with hydro power being the key source. The life cycle inventory comprises average data from LCA studies of the International Aluminium Institute, the Aluminium Association and the European Aluminium Association in general. For the scenario analysis, exemplary the composition of the fossil energy mix is taken from China and for the hydro based energy mix the Canadian composition is consulted. In addition, company-specific data from the Russian aluminum manufacturer Rusal is used for the calculation of the production process of inert anodes and applied in the scenarios. The impact assessment is based on the CML method with emphasis on GWP and primary energy demand (PED).

Nunez and Jones (2016) performed a LCA to test and challenge the LCI data published by the International Aluminium Institute and to emphasize the need for up-to-date and robust data sets for practitioners in general. The study relies exclusively on average industry data for direct process steps.

The data set is supplemented with average background data from the GaBi database (GaBi, 2020) for indirect processes. In a cradle-to-gate model, the environmental impact of the primary aluminum production is evaluated with datasets on a global level and on an adjusted, so called rest of the world level without China. The LCIA comprises six CML midpoint impact categories: GWP, ozone depletion potential, acidification potential, depletion of fossil energy resources, photo-oxidant creation potential and eutrophication potential.

Paraskevas et al. (2016) applied the LCA method to assess and compare the environmental performance of primary aluminum production on national level. The scope comprises 29 countries which are particularly active in the aluminum production business and reaches from raw material mining, via refining to primary aluminum smelting. The comparison among investigated countries focuses on the underlying energy mix as well as the technology mix. The inventory data for the reference year 2012 is derived from publicly available sources such as the United States Geological Survey (USGS), the ecoinvent database and the International Energy Agency's (IEA). The impact assessment, which is performed in the SimaPro software (SimaPro, 2020), concentrates on the midpoint indicator GWP and is based on the ReCiPe method.

Yang et al. (2019) carried out a LCA for the primary aluminum production process in China relying on the lime soda Bayer process. The study with reference year 2017 concentrates on two modes of energy inputs' for power generation: thermal power and hydropower. It covers the processes from bauxite mining to ingot casting but explicitly excludes transportation. The underlying inventory data for direct processes is derived from company-specific field surveys and other, not disclosed information from the aluminum industry in China. For the evaluation of indirect processes, average data from China's Life Cycle Database (CLCD) and the online LCA tool eFootprint, developed by IKE Environmental Technology Co. Ltd. is consulted. In terms of environmental impact assessment, they focus on four of the 13 impact categories from the product environmental footprint (PEF) methodology: GWP, primary energy demand (PED), freshwater eutrophication potential (FEP) and water use (WU).

Farjana et al. (2019) analyzed the environmental impact of the aluminum production process in the United States by means of LCA within the scope of the defined cradle-to-gate system boundary. Average data from the ecoinvent database is consulted for the inventory analysis. Various impact categories (ozone formation, GWP, eutrophication, acidification, human toxicity and ecotoxicity) were assessed by the SimaPro software (SimaPro, 2020) using the International Life-cycle Reference Data System method (ILCD), the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts method (TRACI) and the Cumulative Energy Demand method (CED). In addition, Farjana et al. (2019) conducted a sensitivity analysis based on a variety of scenarios in order to analyze how the type of fuel as energy input for the aluminum production process affects the overall environmental impacts.

In contrast to the reviewed retrospective approaches above, Schmidt and Thrane (2009) conducted a prospective LCA to analyze the future environmental impact of a planned aluminum smelter in Greenland. The cradle-to-gate analysis is conducted in SimaPro software (SimaPro, 2020) and is based on company-specific data from Alcoa complemented with average industry data from the European Aluminium Association (EAA). In accordance with the requirements of the Government of Greenland, the study provides decision support in terms of granting or not granting approval for the launch of a new smelter.

Liu and Müller (2012) reviewed diverse LCA studies (36 peer-reviewed publications and gray literature studies) in order to analyze and discuss the current state of practice as well the weaknesses and strengths of LCA for the evaluation of aluminum production. Special emphasis is put on the limited scope of geographical coverage, the definition of scope, the setting of system boundaries and the practical use of average industry data. The examined widespread range of results (5.92 to 41.10 kg CO_2e/kg primary aluminum) can be traced back to not only temporal and geographical factors but also data uncertainties and varying method applications (e.g. with respect to definitions of system boundaries, inventory data sources, technological assumptions and types of allocation methods).

Das (2014) uses LCA to model the effects of different material compositions of passenger vehicles' components from an environmental impact perspective. For this, cradle-to-gate LCAs for steel and aluminum were conducted according to the ISO standards 14040 and 14044, within the geographical scope of North America. Das (2014) relies on primarily North American average data from 2010, which is derived from the Steel Recycling Institute, the Aluminum Association, the U.S. Environmental Protection Agency and the ecoinvent database.

3.2.4 Extended environmental performance assessment models based on material and energy flows

In He et al. (2017) a three layer material flow analysis (MFA) was constructed with the goal to analyze and assess operations in integrated steel production plants in terms of energy consumption and carbon emitted during the production of steel. The layers include flows of material, ferrum and energy. The First Law of Thermodynamics and the principal of mass conservation constitute the basic principles for the analysis. MFA relies on the law of conservation of mass and constitutes a procedure for quantifying and evaluating flows and stocks of goods as well as substances, which are transferred between a system and its surrounding environment. The developed approach follows the process of life cycle inventory and serves to estimate the intensity of energy and carbon emissions for Chinese steel making plants. The system boundaries cover the four processes of coke and sinter production as well as iron and steel making in a gate-to-gate consideration. The inventory comprises data from Chinese environmental institutes and ministries, such as for example conversion rates of fuels and energy carriers or carbon emission factors.

It is supplemented with diverse scientific sources if data was not available. In closing, He et al. (2017) point out the difficulty of comparing the results of different research studies on carbon emissions. This can be traced back to the variations in system boundaries, technological development, continuous growth in production volumes and the general complexity of the steel making process.

Iosif et al. (2009) developed a methodological framework considering the environmental LCA in correlation with a flow sheeting approach for process simulation. With the help of a physiochemical model, processes are simulated in the Aspen Plus software tool (Advanced System for Process Engineering) based on thermodynamic principles, material properties and diverse unit operation models (Aspen Plus, 2020). The goal of the model is to create LCIs which can be used as basis for the optimization of energy usage, the calculation of emissions and to monitor heat and mass balances, for example in integrated steel making plants. The selected system boundaries reach from the coke and sinter production to hot rolling with a focus on foreground processes and the according interconnection of process. In a gate-to-gate consideration, electricity produced from internal usage of process gases is incorporated and assumed to meet the total demand of electricity of the steel plant. In order to enable a comparability of results, the functional unit is defined as one ton of hot rolled coil from the integrated steelmaking route. Upstream activities such as raw material extraction and transport are not included. The data used rely also on the industrial information of a selected European integrated steel plant. In order to validate the results as well as to promote the application of the developed approach for modelling breakthrough technologies, the results are finally analyzed and compared to data from the ULCOS project (Ultra Low CO_2 Steelmaking) as benchmark, and to a reference LCI provided from the International Iron and Steel Institute (IISI).

Flow sheeting, which is a widely used instrument and belongs to the group of process engineering-based models, found a broad application in several studies in the field of metal producing and processing industry (Fröhling et al., 2010; Fröhling et al., 2012; Fröhling et al., 2013; Schultmann et al., 2004).

Starting in 2007, a group of researchers from the Karlsruhe Institute for Technology developed a National Integrated-Assessment-Model (IAM) named otello (Breun et al., 2011; Comes et al., 2010a; Comes et al., 2010b; Ilsen, 2012). Within the otello project, a tool was developed to assess environmental and macroeconomic effects of the application of environmental-political instruments. The goal of the model is to support political decision makers in national ministries and agencies to improve the strategic alignments in order to cope with emission targets, and to reveal emission reduction potentials. The model combines a technology based bottom-up approach with a macroeconomic input-output approach which covers four sectors over a planning horizon of ten to twenty years: production industry, supply of energy, residential properties as well as transport.

In terms of emissions, it covers not only diverse pollutants such as SO_x, NO_x, NH_3, VOC but also CO_2 and dust. Production processes are modelled with the help of multi-stage sequences of reference processes. Intermediate products are defined as references based on the identified manufacturing processes, as well as the reference facilities for the involved process steps. A sequential connection of reference facilities thus allows the representation of a particular production processes (Ilsen, 2012). In an actor-oriented, production-theoretical approach, the activity rate, reflecting the frequency of emitting from a process, is addressed to determine emissions. It is often based on production rates and according emission factors which describe the emissions per unit of activity and depending on the used technology. Facility specific input factors, which are assumed to be equal for all considered plants, are consulted to calculate the overall demand of a plant’s production factors. A particular emphasis is laid on the iron and steel production industry as it represents one of the main drivers for emission from the industrial sector in Germany.

Therefore, production processes and respective emissions are at a plant level. The approach assumes that every plant consists of the defined sequence of reference processes, meaning that each plant is assumed to be equipped with facilities from coke production to rolling plants. Plant-specific data for the technical process steps is derived from the BAT (European Commission, 2013), specific literature from the steel sector and from a techno-economic database. For information on emissions the European Pollutant Release and Transfer Register (E-PRTR) is consulted (European Environment Agency, 2012). The derived results are used as basis for simulations on the implementation of technologies for pollutant reduction and efficiency enhancement and how according decisions affect the emission output of the considered actors respectively plants.

In Breun (2016) an integrated assessment model is developed to simulate ideal decisions for investment under varying political conditions. Therefore, an actor-oriented, plant-specific approach was developed, which is used as basis for the simulations in a macro-economic input-output model, based on the approach developed from Leontief. With this model, macroeconomic, cross-sectoral effects can be simulated both from an economic as well as ecologic perspective. The dynamically extended input-output-model, which includes private consumption, depreciations, investments and climate policies, allows to depict indirect effects of decisions and technological developments on greenhouse gas emissions as well as the consumption of fossil resources. The goal is on the one hand to derive forecasts of future changes of prices and consumption expenditure as well as investment decisions, and on the other to enable carbon accounting in order to support the evaluation of climate policy instruments and respective premises.

The model from Breun (2016) follows the general principles of the previously described otello approach, however incorporates fundamental adjustments as well as extensions in terms of the scope and the degree of detail. The technical sub-model also applies multi-stage sequences of reference processes but enables the illustration of actual plant configurations as not all plants have reference facilities on-site. It furthermore allows the variation of input and emission factors of similar types of facilities due to the important role of the mode of operations which differs between plants. Especially the steel industry is characterized by complex levels of integration of production systems, and exchange as well as reuse of process gases. Therefore, Breun (2016) refined the production-theoretical approach described above and developed an extension by means of a process engineering-based approach, including material and energy balances.

Due to the fact that information regarding material and energy flows is not publicly available, a nonlinear programming approach (NLP) was used to estimate the missing data on a plant-specific level (Breun et al., 2014). The NLP is based on a carbon balance, as in the steel production process high quantities of CO_2 are emitted, and high quantities of fossil fuels are consumed. In addition, with the help of an energy balance, plant-specific amounts of process gases and the resulting fuel consumption is considered.

In a simultaneous calculation technical restrictions are included and plant-specific coefficients are estimated, while minimum and maximum limits for inputs and outputs for intermediate products are observed. The limits are predefined in the BAT from the European Commission (European Commission, 2013). Additionally a carbon balance is used to model dependencies of in- and outputs for carbonaceous material and energy flows within the production process network.

The reported CO_2 emissions from the plants under investigation, which are derived from the E-PRTR (European Environment Agency, 2012), affect this calculation and are included. The same holds true for individual production volumes and plant-specific capacities for production process steps. In a gate-to-gate consideration, the geographical scope is laid upon Germany and not only steel but also aluminum production plants are covered. The nonlinear programming approach was implemented in the Generic Algebraic Modeling System (GAMS) under the usage of the Ipopt solver (GAMS, 2020).

The individually modelled efficiencies and resulting reduction potentials of emissions constitute the basis for the above described simulations of effects for investment decisions and climate policy instruments.

3.2.5 Research gaps

In recent years several studies on the assessment of environmental impacts of steel production have been published. The developed models have often been used for a general assessment of environmental burdens of manufacturers' steel production processes and for entire steel industries. Furthermore, discovering the critical process steps in order to define and exploit reduction potentials of emission in the production process is a frequently occurring goal. More comprehensive models have even addressed the simulation of effects of new technologies for steel production on climate policy instruments and vice versa, as well as on investment decisions for plant operators. Despite the described widespread field of application, research on environmental performance assessments in the context of decision making for supplier selections is however scarce in scientific literature (see section 3.1.3). Specifically the assessment on site-specific level of suppliers, which is crucial for an in-detail supplier selection decision and simultaneously allows for a comparison of performances among different suppliers in a competitive tendering procedure, is so far not existent.

The presented models and methods exhibit different strengths and weaknesses, which will be discussed in the following with respect to the categories of 'site-specific transparency and assessment', 'comparability and widespread application', as well as 'availability of data and model complexity'.

Site-specific transparency and assessment

With regard to the 'site-specific transparency and assessment' several models using life cycle analysis were presented, however show different emphasis. The process-based approaches developed by Bieda (2012a; 2012b) and Bieda et al. (2015) follow a plant specific consideration which is however based on the investigation of single process steps exclusively and focus on one specific production plant in Poland. Similar process-based models, which take the entire steel making process in a cradle-to-gate investigation into account, such as the one by Olmez et al. (2016) for Turkey, Renzulli et al. (2016) for Italy and Huang et al. (2009) for China, focus on selected plants only. In addition, process-based LCAs from Scaife et al. (2002) and Norgate et al. (2007), which focus on an average national scope for Australia, and from Burchart-Korol (2013) for Polish steel plants, do not differentiate between specific plants. The same goes for the developed economic input–output life cycle assessment (EIO-LCA) for China's steel making industry from Li et al. (2016).

Among the presented extended assessment models for environmental performance based on material and energy flows, the approaches developed by Iosif et al. (2009) and He et al. (2017) present a very in-depth, complex analysis of one European steel making plant and of average Chinese steel manufacturers. In contrast, the otello model (Breun et al., 2011; Comes et al., 2010a; Comes et al., 2010b; Ilsen, 2012) and the extended and even more complex, in-detail NLP approach developed by Breun et al. (2014) covers all steel making plants from Germany.

Comparability and widespread application

In line with the 'site-specific transparency and assessment', the application of results for supplier selection decisions is strongly dependent on a 'comparability' of the defined system boundaries of the product system and a facilitation for a 'wide-spread application'. Only the two models otello and the NLP allow a comparison of various suppliers due to a universal calculation approach which nevertheless includes company-specific differences in manufacturing processes. In contrast to the otello model, which does not incorporate the frequently occurring trading of intermediate products between steel manufacturers, diverse extensions and additionally integrated, more in-depth process characteristics in the NLP (Breun et al., 2014) help to overcome this hurdle. One of the mentioned characteristics comprises the treatment of process gases for the internal electricity production and a resulting credit procedure. These aspects are also picked up in two of the reviewed process-based LCA studies. Scaife et al. (2002) already put an emphasis on displacement credits for avoidance of environmental burdens in another sector which are led by activities in the production of steel. For example the reuse of process gases for the production of electricity on-site can lead to a replacement of externally sourced electricity from the local power grid. In Olmez et al. (2016) average data from databases is consulted for the energy demand in the production process under study. The data is modified by taking country specific energy sources for electricity production into account and thus indicates a possibility for a partial comparability across national borders. The other approaches described are either too specific to the production process of a certain plant or generally too aggregated on a regional respectively national level.

Availability of data and model complexity

Against the background of 'availability of data and model complexity', the approaches discussed show high variances. The models from Bieda (2012a; 2012b; 2015), Olmez et al. (2016), Renzulli et al. (2016) and Huang et al. (2009) make use of inventory data based on company internal data which require an extensive effort of data gathering and can often not be reproduced respectively not be used for other studies. More aggregated approaches, such as from Scaife et al. (2002), Norgate et al. (2007) and Burchart-Korol (2013) offer the advantage of a higher availability of and accessibility to data, for example from national industry statistics and reports, however do not permit a site-specific investigation of production plants. Besides the advantages of the process method to achieve detailed results, depending on the intended purpose of use and the generally lower mathematical complexity, a high cost and time effort is required. The aggregation problem is even more pronounced for rather low effort requiring input output models such as the one by Li et al. (2016). Going along with the in-depth investigation of single process steps, the in-depth process flow models based on thermodynamic principles, such as from Iosif et al. (2009) and He et al. (2017), require a very high effort and expertise in modelling as well as in data collection, and are thus not suitable for the investigation of a larger number of plants.

In terms of data availability, both - the otello and the NLP model - make use of publicly available data which shall generally serve to enable a reproducibility of the results of application. However, especially the NLP illustrates a high mathematical elaboration and complexity in modelling, while simultaneous calculating several non-linear equations and dependencies. Despite the achieved rather high accuracy of results, the complexity of the model does not allow for easy data updates and integration of primary data. Furthermore, due to the required mathematical know how, a practical application is restricted. In addition, extensions of the scope, as for example from a geographical perspective, are complex and involve a rather high effort.

4 Development of an integrated CO_2e assessment and decision support model for supplier selections

In the following section 4, the sub-model for decision support (sub-model A) and the sub-model for environmental performance assessment (sub-model B) are described. In section 4.1, the structure of the entire model including the interaction of the two sub-models is illustrated. In sections 4.2 and 4.3, the concept, the mathematical fundamentals and the development of both sub-models are presented.

4.1 Model structure

As initially described in section 1.2, the proactive model[11] for integrating site-specific environmental impact assessment in supplier selection is comprised of two consecutive sub-models. Based on the described current state of research and the consecutively identified research gaps (see section 3.1 and 3.2), in this research an environmental performance estimation model and a criteria formulation respectively supplier selection model is developed. It shall in particular support environmental decision-making and the introduction of performance based environmental supplier selection, as well as the creation of transparency along supply chains.

[11] In comparison to reactive approaches a proactive approach appears promising due to better risk mitigation strategies in terms of possible environmental as well as economic risks. Moreover, proactive efforts to increase sustainability can also result in competitive advantages (Giunipero et al., 2012; Gopalakrishnan et al., 2012).

In the first step, a decision support model (sub-model A), which also includes the economic aspects of a decision to be made, is developed in order to enable the integration and formulation of a new environmental decision criteria based on real life decision situations. By means of a technical model (sub-model B), a transparency and comparability of environmental performance - CO_2e - of raw material manufacturers are created without the application of scarce and strongly restricted company internal data. The results of sub-model B, are afterwards integrated in sub-model A, representing the coupling point for the sub-models (see Figure 4-1). Both sub-models are hence merged to an integrated techno-economic model.

In order analyze the stability of the derived results and thus test the robustness of the model, a thorough sensitivity analysis is performed subsequently to the coupling of both sub-models. This additional analysis is crucial for the decision-making process in multi-criteria environments and shall support decision makers with the identification of the most critical criteria derived from the expert based AHP approach, and shall help to reveal possibilities for improvement.

By means of ‘what-if’ scenario simulations, the dynamic behavior of the model is finally investigated. It enables the analysis of how already made decisions (retrospective consideration) may change when a new criteria, such as CO_2e, is formulated and implemented. Hence ecological as well as economic effects can simultaneously be considered, the according formulation of CO_2e as adequate decision criteria be enabled, and prospective estimations of implications for upcoming decisions be derived.

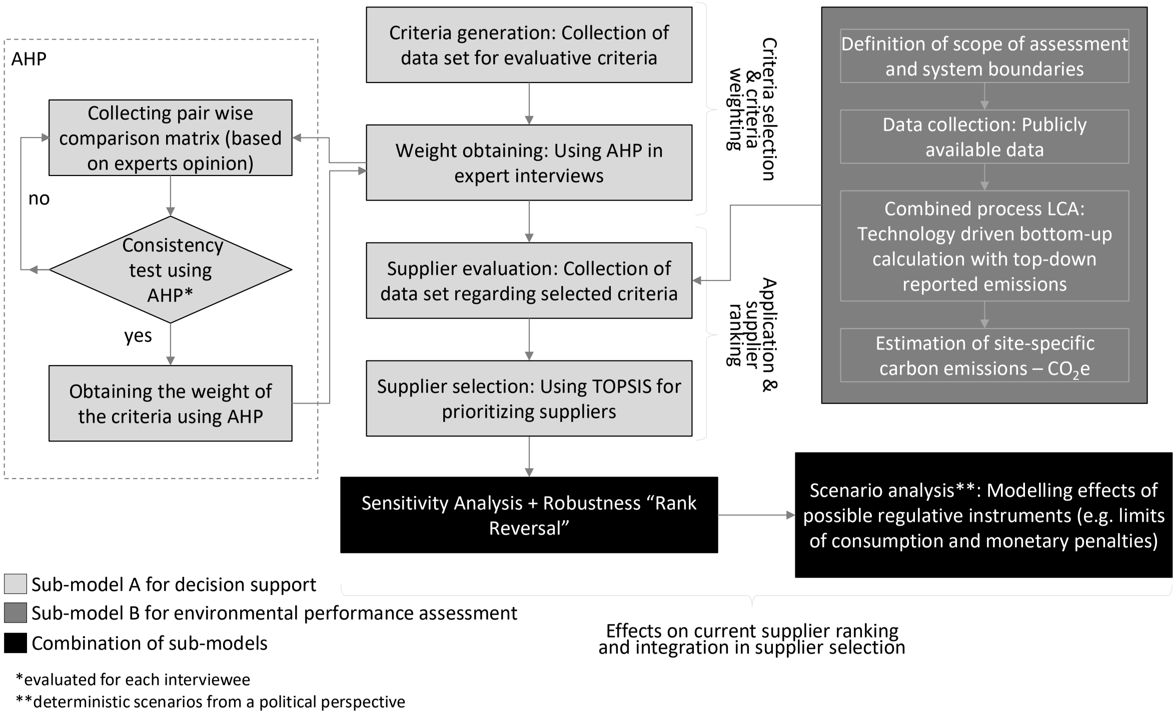


Figure 4-1: Structure of the outlined model to integrate CO_2e in the supplier selection process

In order to allow for a large-scale practical application and an easy handling of practitioners, the integrated model is implemented in Microsoft Excel. It allows for adjustments according to user specific preferences and the specific decision environment, such as changes of selection criteria and refinement of supplier performance data as well as parameters for scenario simulation. Sub-model B is programmed and implemented in Microsoft Visual Basic and then coupled with the Microsoft Excel model. The created simplicity of the model as well as the tool creates a user-friendly, practical application in an industrial environment without a significant loss of data accuracy. It allows on the one hand for regular data updates (e.g. for a new time frame of the study, for plant modifications, etc.), and on the other hand for the completion of increasing data accuracy by manually integrating a variety of industry or site-specific primary data (e.g. material conversion rates), if available.

4.2 Sub-model A for the integration of new criteria in supplier selection[12]

In this section, initially the requirements and the concept of sub-model A are described in the section 4.2.1. It is followed by the illustration of mathematical fundamentals in section 4.2.2. These present the basis for the development of the sub-model for decision support which is described in section 4.2.3. In a partial, exemplary application of the decision support sub-model in section 4.2.4 the need for the subsequent development of sub-model B shall be further substantiated.

[12] Parts of this section were previously published in Schiessl et al. (2020b).

4.2.1 Requirements and concept

On the basis of the initially illustrated research objective in section 1.2 and the identified research gaps in section 3.1.5, the following model requirements arise:

(1) At first, relevant decision criteria for supplier selection need to be defined and a method to evaluate their relative importance and their relations with each other need to be determined.

(2) A method needs to be identified, which allows for the creation of a supplier ranking according to their performance with regard to the selected set of criteria, including the new environmental decision criteria.

(3) The model needs to be able to analyze and simulate environmental and economic effects of the selection decision simultaneously, from a retrospective and prospective point of view, in order to support the formulation of the new criteria against the background of being consistent with environmental as well as economic requirements.

To meet the obligations of the first requirement, existing literature on supplier selection criteria according to the targeted sustainable dimensions needs to be reviewed thoroughly for qualitative and quantitative indicators, and then streamlined as well as matched with the considered case of investigation. Expert consultation can be very valuable to increase efficiency and accuracy of the criteria selection processes, if a real-life case is examined. Currently, most of the identified environmental criteria are of qualitative nature due to the difficulty of quantification, resulting from the unavailability of data and the complexity of comparability of results. In order to increase the objectivity of environmental evaluations, another sub-model is developed to quantitatively express the environmental performance on supplier site-specific level (see section 4.3).

In reference to the two identified, yet less covered areas of criteria formulation and application of actual supplier data in modelling approaches (see section 3.1.2 and 3.1.5), these gaps shall be closed by the development of a decision support model which allows for the consideration of qualitative expert judgments combined with crisp supplier performance data. As supplier selection decision are made with respect to a simultaneous consideration of various criteria (see section 3.1.3), single-criteria preferences need to be aggregated to a consolidated, global preference, while trade-offs between criteria are considered (Kim and Wagner, 2012). Hence, the selection of a multi-criteria decision analysis approach (MCDA) appears to be expedient. This is especially due to the advantages of MCDA compared to alternative approaches, which do not only emphasize on the development of procedures to analyze data sets and to construct classification models, but also set the focus on the development of preference modeling methodologies which enable the incorporation of the experience and preferences of decision makers (Zopounidis and Doumpos, 2002). Therefore, with respect to the defined second and third requirement, a mathematical analytical, multi-criteria decision analysis approach, consisting of the analytical hierarchy method (AHP), developed by Saaty (1980), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, developed by Hwang and Yoon (1981), has been chosen. It furthermore serves as foundation for the subsequent conduction of what-if scenario simulations. In this research, the combination of AHP and TOPSIS, which has already been applied several times for the final selection of suppliers (see Fox et al. (2015), Hanine et al. (2016), Önder and Dag (2013), Sarwar et al. (2017)), is used for the initial phase of a supplier selection process, the criteria formulation phase.

In the first part of the decision support model to be developed, an aggregation of relative importance of the selected criteria on a supplier level is realized by means of the analytical hierarchy process (AHP) method. The method allows for a prioritization of conflicting criteria (tangible and intangible) or alternatives in a multiple criteria environment achieved by pair-wise comparisons. It supports decision makers by converting normally complex decision problems in the form of a structured and simplified problem hierarchy. AHP, which is based on expert judgments of individuals or groups in a certain field, makes the integration of expert opinion and incorporation of their experience possible and thus contributes to the targeted practical applicability of the overall model to be developed. It is a widely used and validated approach not only in scientific research but also in corporate environments to evaluate suppliers as objective and subjective opinions are expressed in a quantitative manner. In addition, the AHP method provides a methodical mechanism to support practitioners to check and monitor the consistency of decision makers' judgements. Besides the described simplicity of application some disadvantages come along. The model generally requires a thorough preparation as well as introduction to the interviewees and can thus be very time and cost intensive. Inconsistent judgements demand for a re-evaluation by the interviewed experts and can lead to complications in conduction and acceptation by experts due to the generally limited availability of practitioners (Bruno et al., 2012; Singh, 2014). However, it presents an approach which enables an efficient and simple measurement of the importance of especially new criteria, based on decision makers' personal experience and opinion from the according field of expertise. These drawbacks are explicitly addressed and considered in the development process of the presented approach, as well as in the phase of application (see sections 4.2.3 and 5.6).

For the ranking of different alternatives respectively suppliers as basis for the final selection, another mathematical analytical approach, the TOPSIS method is used in combination with AHP. In AHP a ranking is produced by means of evaluating suppliers' performance with pair-wise comparisons of two alternatives at a time (cardinal ratio measurement), similarly to the criteria weighting and prioritization process. The execution is thus extremely time intensive, and a practical application as well as implementation are very difficult if several alternatives are considered. In contrast, in TOPSIS all suppliers are evaluated and ranked simultaneously, according to their quantitatively expressed performance score (cardinal absolute measurement) and in reference to the selected set of criteria (Shih et al., 2007).

As one possible disadvantage of this method, the appearance of the rank reversal phenomenon is listed (García-Cascales and Lamata, 2012). It considers the relationship between new and old alternatives in the light of each criteria. Similar to the drawbacks of the AHP method, a special emphasis is laid upon this issue during the development of the method in section 4.2.3 and in the course of conducting sensitivity analysis in section 5.6. This approach, which makes use of objective, quantitative performance data of suppliers in a time efficient manner, appears suitable for the integration of CO_2e as quantitative performance criteria as well as for a practical application including expert involvement.

However, as TOPSIS does not include a methodology to elicit criteria weights and to check for consistency of judgements, the advantages of both methods are combined and used in a hybrid AHP/TOPSIS approach.

A case study in the automotive industry is conducted to illustrate the functionality and applicability of the model, using case-specific selection criteria and real-life supplier performance data. Later in section 5.5, the results from the sub-model for the estimation of site-specific CO_2e performance, are integrated in the hybrid approach.

4.2.2 Mathematical fundamentals for the multi-criteria decision approach

In the following section, the mathematical principles and the process of implementation for the selected multi-criteria decision analysis methods are described.

4.2.2.1 Analytical hierarchy process (AHP)

The analytical hierarchy process developed by Saaty (1980) is an important discrete multiple criteria decision-making (MCDM) method. The widely used method in research as well as in practice, still gains increasing attention (Ossadnik et al., 2016) and offers a variety of advantages (see section 4.2.1).

The structure of the process can be divided into six steps (Lee et al., 2009; Lee et al., 2011):

1) Definition of the problem and establishment of the hierarchy structure,

2) Construction of a pair-wise comparison matrix,

3) Calculation of the priority vector,

4) Determination of the maximum eigen value,

5) Examination of the consistency, and

6) Ranking and evaluation of criteria respectively criteria weights.

Step 1: Initially the decision problem is stated, selection criteria are defined and then structured by means of a multi-level criteria hierarchy, which consists of 'goal', 'criteria', 'sub-criteria' and 'alternatives' (see Figure 4-2).

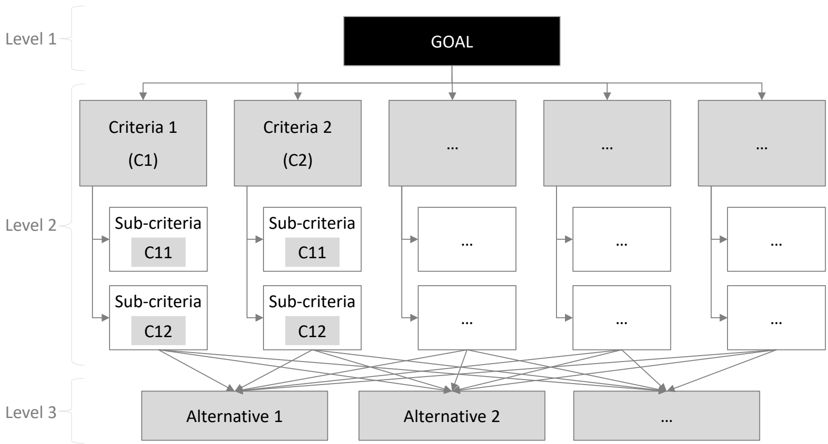


Figure 4-2: The hierarchical structure of the problem (Saaty, 1990b)

Step 2: Pairwise comparisons are applied to derive preferences of criteria, analyzing how much more or less a criteria is weighted compared to the other. Therefore, in the corresponding hierarchy level, each criteria is evaluated with all other criteria on a numerical evaluation scale, which is explained in Table 4-1. The use of odd numbers is suggested, but in case there exist doubts in the preference settings, even numbers can be consulted (Miller, 1956; Saaty, 1977).

Initially, a $m \times m$ dimensional criteria preference matrix PM is constructed, with m being the number of criteria C to be compared:

$$\mathrm{PM} = \begin{array}{c} \\ C_1 \\ \cdots \\ C_i \\ \cdots \\ C_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_m \end{array} \\ \begin{bmatrix} c_{11} & \cdots & c_{1j} & \cdots & c_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{i1} & \cdots & c_{ij} & \cdots & c_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{m1} & \cdots & c_{mj} & \cdots & c_{mm} \end{bmatrix} \end{array} \tag{4-1}$$

with,

$$c_{ij} > 0 \qquad \forall i = 1, \dots, m \; \forall j = 1, \dots, m \tag{4-2}$$

$$c_{ij} = 1 \qquad \forall i = j \tag{4-3}$$

$$c_{ij} = c_{ji}^{-1} \quad \forall i = 1, \dots, m \; \forall j = 1, \dots, m \tag{4-4}$$

Criteria C on row i is compared to a criteria in column j by means of the previously described evaluation scale (see Table 4-1), in order to express the relative preference between the i-th criteria and the j-th criteria. Thus, c_{ij} represents the relative importance resulting from the pairwise comparison of two criteria. A total quantity of $m(m-1)/2$ pairwise comparisons is required. $c_{ij} = 1$ is used to express the equal importance, meaning that no preference between two compared criteria is determined, or in case if the comparison is between the same criteria $i = j$. Consequently, the values along the main diagonal of matrix PM are 1.

The preference matrix is assumed to be reciprocal, meaning that diagonal criteria preferences are reciprocals of previous comparisons, $c_{ij} = c_{ji}^{-1}$.

Table 4-1: Scale of relative importance (Saaty, 1977)

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed

Step 3: Based on the previous steps, priorities from the paired comparisons matrix are derived in order to create criteria weights.

According to Saaty (1990b, 2003) and Saaty and Hu (1998) the eigenvector method illustrates the best access to derive priority weights. It has been mathematically proven that the calculated eigenvector of the preference matrix C has to be equal to the vector of the relative priority weights. Furthermore, it is stated that the eigenvector method is the only valid approach to derive a priority vector, especially when inconsistency in judgements exist. For a more detailed understanding of other methods to derive priorities reference is made to Saaty (1988; 1998).

Therefore, the criteria preference matrix PM is raised to a sufficiently large power and then the eigenvector, respectively priority vector, which represents the criteria weights, is calculated (Saaty, 1990b; Saaty, 2000).

It is assumed that the preference matrix PM has a dominant eigenvalue and corresponding eigenvectors.

The matrix is iteratively squared and multiplied by a nonzero vector $x_0 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$

to calculate the row sums x_k (Larson, 2016):

$$x_k = C^{2^{(k-1)}} * x_0 = \begin{bmatrix} c_{11} & \cdots & c_{1j} & \cdots & c_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{i1} & \cdots & c_{ij} & \cdots & c_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{m1} & \cdots & c_{mj} & \cdots & c_{mm} \end{bmatrix}^{2^{(k-1)}} * \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \tag{4-5}$$

Finally, the priority vector $w^k = \left[w_i^k\right]$ is derived by normalizing the row sums (Saaty, 1990a), as follows:

$$w_i^k = \frac{x_i^k}{\sum_{i=1}^{m} x_i^k} \tag{4-6}$$

After each iteration of matrix PM, the priority vector w^k is calculated. The matrix is squared until for example the differences of the single components of the priority vector at the *k-th* power, and the next iteration is smaller than a predetermined value ε (Saaty, 1990a; Saaty, 1990b):

$$\Lambda_{i=1,\ldots,m}\left(max\left|w_i^k - w_i^{k-1}\right| < \varepsilon\right) \tag{4-7}$$

According to Cabała (2010), the total quantity of iterations k of the matrix PM equals the number of criteria c ($\forall k = 1, \ldots, m$).

Step 4: In AHP a consistency index $(C.I.)$ and consistency ratio $(C.R.)$ was introduced to investigate inconsistencies in expert judgements which are based on pairwise comparisons (Saaty 1980).

These measures rely on the assumption, that in case of precise results and a totally consistent preference matrix PM, there exists a maximum eigenvalue $\lambda_{max} = m$ of the preference matrix with an associated eigenvector w^k:

$$PM \times w^k = \lambda_{max} \times w^k \tag{4-8}$$

In order to obtain λ_{max}, the row sums of the preference matrix PM are multiplied with the priority weights w_i^k, and the single components of the resulting vector are summed up (Saaty, 1990a):

$$\lambda_{max} = \sum_{j=1}^{m} \left(\left(\sum\nolimits_{i=1}^{m} c_{ij} \right) * w_i^k \right) \tag{4-9}$$

Step 5: Based on step 4, the consistency index $C.I.$ can be calculated as follows:

$$C.I. = \frac{\lambda_{max} - m}{m - 1} \tag{4-10}$$

The $C.I.$ enables a verification if a preference judgement needs to be adapted or revised by the consulted expert.

The previously calculated consistency index is divided by an average random consistency index $(R.I.)$, which is derived from a sample of 500 randomly generated reciprocal matrices (see Table 4-2), using the scale of relative importance (see Table 4-1):

$$C.R. = \frac{C.I.}{R.I.} \tag{4-11}$$

Table 4-2: Random consistency index (Forman, 1990; Saaty, 2001)

Size of matrix (m)	1	2	3	4	5	6	7	8	9	10
Random consisteny index R.I.	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

In AHP, two types of inconsistency, ordinal and cardinal inconsistency, can occur during the pairwise comparison of two criteria and negatively affect the rational ranking respectively evaluation of the investigated criteria.

In order to preserve the order of in which the criteria are arranged, an ordinal consistency of a preference matrix $PM = [c_{ij}]$ is ensured if the following condition holds true: $c_{il} > 1$ and $c_{lj} > 1$ then $c_{ij} > 1$. Due to the ratio scale used in the analytical hierarchy process, not only the order of criteria has to be taken into account but also a consistency regarding the exact values of the relative importance resulting from the expert judgements need to be consistent. The preference matrix $PM = [c_{ij}]$ is cardinally consistent if for any of the three preference judgement rations c_{ij}, c_{il}, c_{lj} the following condition holds true: $c_{ij} = c_{il} \times c_{lj}$ (Kulakowski, 2018; Li and Ma, 2007).

As an absolute consistency is often not achievable in practical applications, due to errors in judgements which can be traced back to for example trembling, rounding or other unpredictable events (Bernasconi et al., 2014), minimal consistency violations, $C.R. < 10\%$, are acceptable and allowed (Saaty, 1980; Saaty, 2001).

The previously illustrated steps 1 - 5, are initially conducted for the main, respectively parent criteria in the problem hierarchy (see Figure 4-2). Equally for the sub-criteria under each main criteria, the process is carried out in order to derive local priorities. With regard to the overall goal (see Figure 4-2), the local priorities are then weighted, respectively multiplied, with the priorities of the main criteria in order to obtain global priorities. These are in sum always equal to the weights of the main criteria (Saaty, 1987; Saaty, 2001).

Step 6: In a final step, the alternatives, which were defined and structured in the problem hierarchy, are ranked and thus provide the basis for a selection decision. Therefore, the same methodological procedure based on pairwise comparisons, which was described above for the calculation of criteria weights, is conducted. As illustrated in section 3, in the process step of ranking of alternatives, the AHP methodology is substituted with the Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS), which is further illustrated in the following section 4.2.2.2.

It is often assumed that decisions made by a group of experts in a collective decision-making process are better or more objective than decisions by individuals due to possible, natural cognitive restrictions of individuals. Groups of experts may provide more information and experience, which leads to a better diversification of cognitive restrictions (Ossadnik et al., 2016). In this case, the results of the single pairwise comparisons need to be aggregated. Two techniques are primarily applied, the aggregation of individual judgements (AIJ) and the aggregation of individual priorities (AIP).

The previously described AHP approach, illustrates the execution for one individual expert. In case of a group of experts r is consulted, the following applies:

$$PM^{(r)} = \left[c_{ij}^{r}\right]_{m \times m}, \; r = 1, \dots, l \qquad \text{(4-12)}$$

If there exist different gradations of the importance of a decision makers opinion, the relative importance α of the decision maker r will be included, $\alpha_r \; for \;\; r = 1, \dots, l$ with, $\alpha_r > 0$ and $\sum_{r=1}^{l} \alpha_r = 1$ (Grošelj et al., 2015).

The procedure of aggregating individual judgements (Saaty, 1989) is used for a homogenous group of experts from the same field (Grošelj et al., 2015).

It relies on the single pairwise comparisons of each expert and the resulting preference matrix (see Eq. (4-12)). The individual judgements c_{ij}^{r} are aggregated by means of either the arithmetic or geometric mean method.

According to Aczél and Saaty (1983), the geometric mean is the only approach which satisfies the pareto principle (unanimity condition) and the homogeneity condition. Homogeneity in a multi-criteria decision-making context means that, if a criteria is judged by each individual as t times larger than another criteria, the aggregated judgement should also show the same condition.

In order to include different importance of decision makers' evaluations, the weighted geometric mean $(WGMM)$ is calculated as:

$$c_{ij}^{WGMM^{AIJ}} = \prod_{r=1}^{l} \left(c_{ij}^{r}\right)^{\alpha_r} \tag{4-13}$$

Finally, the aggregated priority vector $w^{WGMM^{AIJ}}$, representing the criteria weights, is derived by the application of the eigenvector method (see Step 3).

Another approach to aggregate the results of various expert opinions is the aggregation of individual priorities (Forman and Peniwati, 1998; Ramanathan and Ganesh, 1994), which is primarily used when inhomogeneous groups of experts from different fields are taken into consideration (Grošelj et al., 2015). For each expert or decision maker the AHP process is conducted and the individual priority vector derived (see AHP step 1-5):

$$w_i^{k,r} = \frac{x_i^{k,r}}{\sum_{i=1}^{m} x_i^{k,r}},\ r\ = 1, \dots, l \tag{4-14}$$

The weighted geometric mean is again selected for the final aggregation of individual priorities:

$$w_i^{WGMM^{AIP}} = \prod_{r=1}^{l} \left(w_i^{k,r}\right)^{\alpha_r}, \qquad i = 1, \dots, m \tag{4-15}$$

For this method an additional normalization procedure is necessary (Bernasconi et al., 2014), and can be described as:

$$wn_i^{WGMM^{AIP}} = \frac{\prod_{r=1}^{l} \left(w_i^{k,r}\right)^{\alpha_r}}{\sum_{i=1}^{m} \prod_{r=1}^{l} \left(w_i^{k,r}\right)^{\alpha_r}} \quad (4\text{-}16)$$

The resulting vector $wn^{WGMM^{AIP}} = \left[wn_i^{WGMM^{AIP}}\right]$ hence fulfills the additive normalization condition $\sum_{i=1}^{m} wn_i^{WGMM^{AIP}} = 1$, which is required for further calculations in the analytical hierarchy process (Sun and Greenberg, 2006).

4.2.2.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS method, which was developed by Hwang and Yoon (1981), belongs to the category of compromise methods. The goal is to identify the alternative which represents the closest to the ideal solution, while a compromise is made based on mutual concessions by means of linear normalization (Chai et al., 2013). The performance of an alternative is compared to the ideal best and ideal worst solution, for example least and most cost intensive, in order to determine a ranking of alternatives. The alternative with the shortest Euclidean distance to the positive ideal solution and longest distance from the negative ideal solution is hence placed first. Due to the fact that the TOPSIS method does not provide a methodology for weight elicitation (Shih et al., 2007), the results from the previously described AHP method are consulted at this stage. The process of the TOPSIS method is structured in the following steps (García-Cascales and Lamata, 2012):

Step 1: Initially, a performance data matrix is established. In a discrete multi-criteria decision problem, n suppliers ($S_i, i = 1, \dots, n$) are analyzed and evaluated with regard to m criteria ($C_j, j = 1, \dots, m$). Hence, in the resulting $n \times m$ data matrix D, the elements sd_{ij} represent the deterministic performance values (supplier data) of the considered supplier alternatives S_i associated with the respective criteria C_j.

These criteria are derived by means of AHP and are illustrated in the problem hierarchy (see Figure 4-2).

$$D = \begin{array}{c} \\ S_1 \\ \cdots \\ S_i \\ \cdots \\ S_n \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_m \end{array} \\ \begin{bmatrix} sd_{11} & \cdots & sd_{1j} & \cdots & sd_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ sd_{i1} & \cdots & sd_{ij} & \cdots & sd_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ sd_{n1} & \cdots & d_{nj} & \cdots & sd_{nm} \end{bmatrix} \end{array} \quad (4\text{-}17)$$

Step 2: Due to possibility of expressing the various performance criteria in various measurement units, a normalization of the decision matrix is required. Therefore, each performance value element sd_{ij} of the performance data matrix D is converted and normalized into non-dimensional values on a single scale:

$$DN = \begin{array}{c} \\ S_1 \\ \cdots \\ S_i \\ \cdots \\ S_n \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_m \end{array} \\ \begin{bmatrix} u_{11} & \cdots & u_{1j} & \cdots & u_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ u_{i1} & \cdots & u_{ij} & \cdots & u_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ u_{n1} & \cdots & u_{nj} & \cdots & u_{nm} \end{bmatrix} \end{array} \quad (4\text{-}18)$$

with,

$$u_{ij} = \frac{sd_{ij}}{\sqrt{\sum_{i=1}^{n} sd_{ij}^2}} \quad , sd_{ij} \neq 0 \quad (4\text{-}19)$$

$$u_{ij} = 0 \qquad , sd_{ij} = 0 \quad (4\text{-}20)$$

The created normalized data matrix DN with the normalized, uniform data u_{ij} allows for a comparison of suppliers' performance value across different criteria.

Step 3: At this stage, the previously established criteria weights find application in the calculation of the weighted normalized decision matrix. In case a single expert consultation is used as basis for the calculation, the priority vector $w^k = [w_i^k]$ derived in step 3 of the analytical hierarchy process (see Eq. (4-6)), is consulted. In case of a group consolidation of experts' opinions, which is pursued throughout this research, the consolidated group criteria weights $w^{WGMM} = [w_i^{WGMM}]$ from either the AIJ or AIP method find application (see section 4.2.2.1). For further calculations the priority vector is transposed: $wt^{WGMM} = (w^{WGMM})^T$.

Each column of the normalized data matrix is multiplied with the criteria weights to derive the weighted normalized evaluation values e_{ij} and to generate the weighted normalized decision matrix E:

$$E = \begin{bmatrix} e_{11} & \cdots & e_{1j} & \cdots & e_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ e_{i1} & \cdots & e_{ij} & \cdots & e_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ e_{n1} & \cdots & e_{nj} & \cdots & e_{nm} \end{bmatrix} \quad (4\text{-}21)$$

with,

$$e_{ij} = wt_j^{WGMM} \times u_{ij} \quad (4\text{-}22)$$

Step 4: Two virtual alternatives are developed from the weighted normalized decision matrix E, the initially described ideal best, positive solution (PIS) $S^+$and ideal worst, negative solution (NIS) S^-:

$$S^+ = \{e_1^+, \dots, e_m^+\} = \left\{\left(\max_i e_{ij}, j \in BC\right)\left(\min_i e_{ij}, j \in CC\right)\right\} \quad (4\text{-}23)$$
$$\forall\, i = 1, \dots, n, j = 1, \dots, m$$

$$S^- = \{e_1^-, \dots, e_m^-\} = \left\{\left(\min_i e_{ij}, j \in BC\right)\left(\max_i e_{ij}, j \in CC\right)\right\} \quad \forall\, i = 1, \dots, n, j = 1, \dots, m \tag{4-24}$$

with BC being benefit criteria, and CC cost criteria (García-Cascales and Lamata, 2012). In terms of the distinction between benefit and cost criteria, it is the goal of a decision maker to achieve the maximum value for benefit criteria. For cost criteria, the minimum value illustrates the most achievable alternative.

Step 5: By means of the Euclidean distance, which is determined by the quantity of criteria m, the distance between two points in a multidimensional space can be measured. It is applied to define the distances between the score of a supplier and the two virtual alternatives, the positive ideal solution (PIS) and negative ideal solution (NIS):

$$ds_i^+ = \left[\sum_{j=1}^{m}\left(e_{ij} - e_j^+\right)^2\right]^{0,5} \quad \forall i = 1, \dots, n \tag{4-25}$$

$$ds_i^- = \left[\sum_{j=1}^{m}\left(e_{ij} - e_j^-\right)^2\right]^{0,5} \quad \forall i = 1, \dots, n \tag{4-26}$$

Step 6: As basis for the subsequent derivation of a ranking of suppliers, the relative closeness P_i, also called proximity index, of the overall suppliers' performance scores, which lies between 0 and 1, is calculated:

$$P_i = \frac{ds_i^-}{ds_i^+ + ds_i^-} \tag{4-27}$$

The higher the value for the relative closeness P_i, respectively the closer the value is to 1, the higher is the final priority of the i-th suppliers.

Step 7: Concluding, the suppliers are ranked in a descending order, according to the previously developed relative closeness P_i.

4.2.2.3 Sensitivity Analysis

According to Saltelli (2004), sensitivity analysis can be defined as a "study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input" (p. 45). It can provide important information concerning the robustness of a model and its results for a certain decision problem (Leonelli, 2012).

Generally, sensitivity analysis can be divided into three categories (Chen and Kocaoglu, 2008; Leonelli, 2012): numerical incremental analysis, probabilistic simulations and mathematical models.

Numerical incremental analysis, also called one-at-a-time (OAT), functions on the basis of constantly changing one parameter respectively criteria weight at a time, and calculating new results as well as analyzing possible changes in rankings. It is the most widely used method in scientific literature on hierarchical decision making and within associated software solutions, due to its reduced complexity and practical applicability. In probabilistic simulations, local contribution values are replaced with probability distributions by means of extensive simulation runs in order to finally calculate the expected ranking values. Due to the probabilistic input, stochasticity is introduced to the output which determines the model as non-deterministic. Mathematical models can be applied, when the possibility is given to describe the relationship between input and output data, respectively the solution of the problem, by simple closed-form expressions.

Due to the targeted practical applicability of the overall decision support model to be developed, in this research the focus was laid upon numerical incremental analysis. For more information regarding the other two methods of sensitivity analysis and its application in multi-criteria decision situations, reference is made to Chen and Kocaoglu (2008) and Leonelli (2012).

Due to the manipulation of criteria in sensitivity analysis, the non-manipulated criteria is changed.

The criteria manipulation by means of step weights Δ_{ss} results in a proportional adjustment $wt_j^{WGMM'}$ of the remaining criteria. It is calculated as:

$$wt_j^{WGMM'} = \frac{1-(wt_{ss}^{WGMM}+\Delta_{ss})}{1-wt_{ss}^{WGMM}} \times wt_j^{WGMM}; j \neq ss, j = 1, \dots, m \tag{4-28}$$

with wt_{ss}^{WGMM} being the criteria weight to be changed and wt_j^{WGMM} representing the current weight of criteria j. The current criteria weight is consequently influenced by the manipulation (Alinezhad and Amini, 2011; Fox et al., 2015).

In addition, a second sensitivity analysis method is applied to intensify the robustness analysis of the results. Each criteria weight wt_j^{WGMM} is exchanged respectively switched with another criteria weight wt_{j+1}^{WGMM}, while the other criteria wt_j^{WGMM} remain constant (Gumus, 2009; Mousavi et al., 2013).

In general, the manipulation of criteria weights in the course of sensitivity analysis leads to changes of scores and rankings of alternatives (Alinezhad and Amini, 2011). This is especially important during the application of the TOPSIS method and the possible occurrence of the rank reversal phenomenon (García-Cascales and Lamata, 2012), as described in section 4.2.1. A subsequent introduction of an additional alternative to, or the removal of an alternative from the existing set of alternatives in the decision-making process after the initiation of the decision process can lead to a change in alternatives ranking. Hence, a thorough verification of the appearance of this phenomenon needs to be conducted during the sensitivity analysis and if necessary, adjustments need to be made to the modelling approach (see section 5.6).

4.2.3 Model development

With reference to the derived model requirements and the created model concept in section 4.2.1, in this section the model is developed with regard to the selected case study. The set of selection-criteria is defined, the criteria priority weights were derived in personal expert interviews, and a sample part is chosen as basis for the gathering and analysis of performance data on a selected range of suppliers.

4.2.3.1 Criteria selection for the application of AHP

In reference to the identified requirements of the sub-model A illustrated in section 4.2.1, a selection of criteria based on the case of application is made in the course of the model development.

Consequently, a thorough research on existing supplier selection criteria was carried out with an emphasis on application for automotive cases. In order to comply with the application of the selected case-study (company-specific), a first selection was derived from existing scientific publications and then verified by different experts from the purchasing division of the OEM in a personal consultation (see section 3.1.2).

Against the background of the later creation of an AHP problem hierarchy and the consequent conduction of pairwise comparisons, the number of selection criteria plays an important role. According to Miller (1956), humans have a certain capacity (upper limit of seven plus minus two) for the processing of information on elements which are simultaneously interacting, in terms of reaching a dependable accuracy and validity of results.

This restriction in regards to the number of elements is also recommended for the criteria selection phase in the analytical hierarchy process and is consequently applied in the further course of this research project. The consistency of AHP results relies strongly on limiting the level of overstressing the mind of experts. Moreover, a huge number of selection criteria prevents the possibility for a scrutinization, and correction of the relation of the single criteria with the highest impact on the consistency (Saaty and Ozdemir, 2003).

Supplier selection criteria can generally be categorized into two groups, qualitative and quantitative criteria, and need to be selected and applied depending on the selection decision to be made (Taherdoost and Brard, 2019; Wedley, 1990). This aspect is also taken into consideration during the creation of the set of criteria and the selection of the right method for criteria and performance evaluation (see section 4.2.1). Supplier selection criteria consists of both, (negative) cost and (positive) benefit criteria, which are expressed in monetary and non-monetary units. Both types can appear either in form of quantitative or qualitative criteria (Khaki and Shafiyi, 2011).

The selection of decision criteria for the automotive case study relies on scientific publications of Ahi and Searcy (2015), Fazlollahtabar et al. (2017), Galankashi et al. (2016), Jain et al. (2018), Yadav and Sharma (2015) and Zimmer et al. (2016), combined with company specific, case related requirements.

In the following, a brief description of each selection criteria (see Figure 4-3), is given, and if required, the way of calculation is presented. According to the AHP procedure, a problem hierarchy was created (also see Figure 4-2), consisting in this case of five main criteria, cost (C1), quality & production (C2), flexibility (C3), development & innovation (C4) and environmental sustainability (C5). In line with the recommended quantitative limit of selection criteria, for each of the main criteria C1 - C4, which fall under the economic pillar of sustainability, two sub-criteria were selected. For the main criteria C5, which belongs to the environmental pillar, the focus is on one sub-criteria exclusively, as it represents the new selection criteria to be integrated in consisting decision-making structures.

'Cost' (C1):

- 'Parts cost' (C11) is related to externally purchased components including all sub-components from upstream supply chain activities. This criteria is comprised of two cost items, namely material cost and production cost. These in turn consist either of direct or indirect cost. In a full-cost accounting approach, cost associated with the product itself, such as raw material from upstream supply chain and according logistics, scrap, packaging, customs, are included in material cost. Production cost include for example labor cost for the production and assembly of the component, machine costs, energy cost. Additionally overhead costs in administration and sales, as well as profit are included in the parts cost. Finally, downstream logistic cost are added.

- ‘Industrialization cost’ (C12) comprises all cost for the development which are in relation to the component sourced by an upstream supplier (see C11), such as project specific equipment and machines, measurement technologies, test facilities. This type of cost is separately considered to the parts cost, due to requirements in the balance sheet recognition.

‘Quality & production’ (C2):

- ‘Machine conditions and manufacturing technology’ (C21) deals with the conditions of the production machines and the efficiency of the applied manufacturing technology. These are necessary in order to assure the required productivity and according efficiency in process sequences, measured by the overall equipment effectiveness (OEE) in %.

- ‘Testing processes and facilities’ (C22) is measured by means of the level of testing which is performed during the component production process in form of end-of-line (EOL) test stands, and the according degree of automatization. It is measured in a 1-5 point evaluation scale depending on the installed equipment (see Table 4-6). Thus, the quality requirements of customers shall be assured, and a long-term reliability of products guaranteed in line with existing regulations.

'Flexibility' (C3):

- 'Product development/industrialization time' (C31) considers the flexibility of the suppliers to quickly develop a new product or integrated changes in existing developments, depending on the customer requirements and technical capabilities. It also includes the required time for industrialization, meaning the secured launch of the product including all necessary framework activities. It focuses on the according time span and is measured in months.

- 'Infrastructure and supply' (C32) takes the geographic location of the suppliers and the according infrastructure conditions into account. It is applied to analyze the flexibility to react to supply interruptions by the use alternative transport routes. It is measured in a numerical form and relies on an intermediate calculation respectively multiplication of two factors. On the one hand, the geographical distance of the suppliers' production site to the customers' production location is considered. A shorter distance in km has a positive effect the performance evaluation. On the other hand, the existing conditions of the infrastructure as well as transport routes play an important role. It is assessed in a 1-5 point scale depending on the possibility to switch to alternative transport modes (see Table 4-6).

'Development & innovation' (C4):

- 'Development experience' (C41) focuses on the competence and level of experience with the concerned component. It is generally related to the experience in manufacturing with the entire component, sub-components or production technologies and is initially evaluated by means of a 1-5 point scale (see Table 4-6).

- 'Investment in innovation' (C42) considers the investment activities of a supplier in innovation and future technologies. It is considered as indicator for the innovation strength, and thus represents the basis for a securing long-term access to prosperous development of new technologies. It is expressed in € and is measured by the reported figure in the balance sheet of the component manufacturer.

As described in section 3.1.2, the selected set of criteria is not to be considered as fixed for an unlimited time period (Sagar and Singh, 2012). It might be adjusted according to significant changes in the decision environment, triggered by internal or external factors. Hence, due to an increased awareness for environmental effects in business operations (see section 2.1.1), a new environmental performance criteria shall be formulated and integrated.

As most of the current practices in supplier selection processes referring to the environmental pillar are of qualitative nature, a new quantitative criteria - CO_2e - shall be introduced. Thus, the goal is to increase objectivity and to enable a measurability, as well as an objective comparability among suppliers.

'Environmental sustainability' (C5):

- 'CO_2e component manufacturing' (C51) comprises all the CO_2e emissions which are created during the manufacturing of raw materials, in a cradle-to-gate consideration (see Figure 2-3 and see Figure 2-4). Emissions resulting from a subsequent processing of the raw material and related logistics activities were excluded in this research contribution (see section 4.2.4), but are discussed in section 6. Further information about the relation of C51 with the other criteria is firstly presented in section 4.2.4 and then emphasized on in section 5.5.

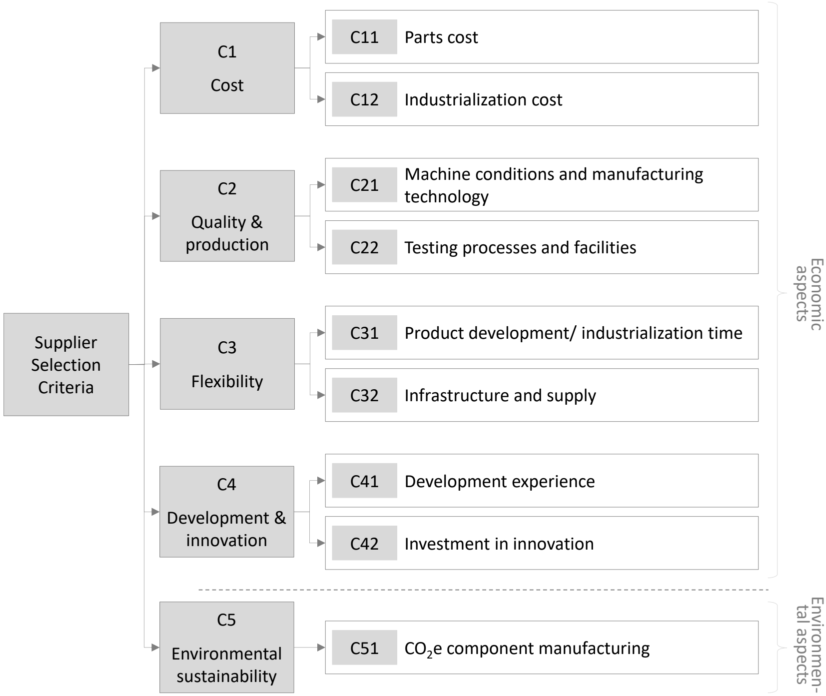


Figure 4-3: Problem hierarchy of supplier selection criteria

4.2.3.2 Expert consultation and interview procedure

Before the start of the main expert consultation for the derivation of criteria weightings, the selected set of criteria and the according problem hierarchy (see Figure 4-3) was tested in trial runs of the AHP pairwise comparison method with five experts in personal interviews. This was to prepare for and to enable an efficient wide-spread application of the method.

The interview follows a structure initially proposed by Kvale (1996). An exemplary application of the structure is illustrated in Drechsler (2007).

It consists of four phases, the briefing and warm-up, the main, the debriefing and the reflection phase (see Figure 4-4).

Initially the 'briefing and warm-up phase' was started off with a mutual, personal introduction and presentation of the work environment including the respective field of responsibility of the interviewer (researcher) and interviewee (purchasing expert). Moreover, the topic and purpose of the study was presented, and the structure as well as framework conditions of the interview were introduced.

Following, in the 'main phase' the principles of the analytical hierarchy process (see section 4.2.2.1) were disclosed and the procedure was exemplarily demonstrated. Therefore, a personalized template was created in Microsoft Excel in order to provide a numerical as well as graphical presentation of the results, and to support the understandability for the interviewees (see Appendix A, Figure A-1). Hence, the experts were asked to evaluate the proposed set of criteria and sub-criteria (see section 4.2.3.1) and perform the pairwise comparisons of criteria scale, from the experts' perspective of individual work environment in the according purchasing sector of employment:

"Is criteria A more important than criteria B or correspondingly the other way around?".

This is done by means of the chosen 9-point numeric evaluation scale (see Table 4-1):

"By how much is criteria A or B more important than the other?".

After the completion of the AHP procedure and the derivation of criteria weights (see section 4.2.3.3), not only the consistency ratio (CR) was calculated for each experts' judgments but also a more in-depth, individual consistency check was performed. The automatism, which was incorporated in the Excel template, was automatically run during the interviews in order to directly highlight the detailed level of consistency/inconsistency of the concerned pairwise comparisons. The consistency check includes both, ordinal consistency, preserving the order of criteria arrangements, as well as cardinal consistency, considering the relative importance of experts' judgements. In case the limit of the acceptable consistency ratio of 10% is exceeded, the experts where asked to review and re-evaluate the specific pairwise comparisons which caused the deviation, or if necessary, the entire set of judgements.

The 'debriefing phase' and the 'reflection phase' started with a graphical and numerical presentation of the criteria weights resulting from the pairwise comparison of the interviewed expert (see Appendix A, Figure A-2). In a fluent transition, the results were finally verified for correspondence to the experts' opinion, and the further use of the results in the research approach was re-verified. In case of unacceptable discrepancies, the experts were offered to make adjustments, to conduct the entire AHP process again, or to withdraw the permission to include the results in the further approach.

In order to get a glimpse about the expectations on the future development of selection criteria, the experts were additionally asked to evaluate the local main criteria from a personal perspective separately from the corporate requirements in the according field of purchasing:

"What will play the most important role in the future?"

respectively,

"How do you expect the priorities to change/develop in the future?".

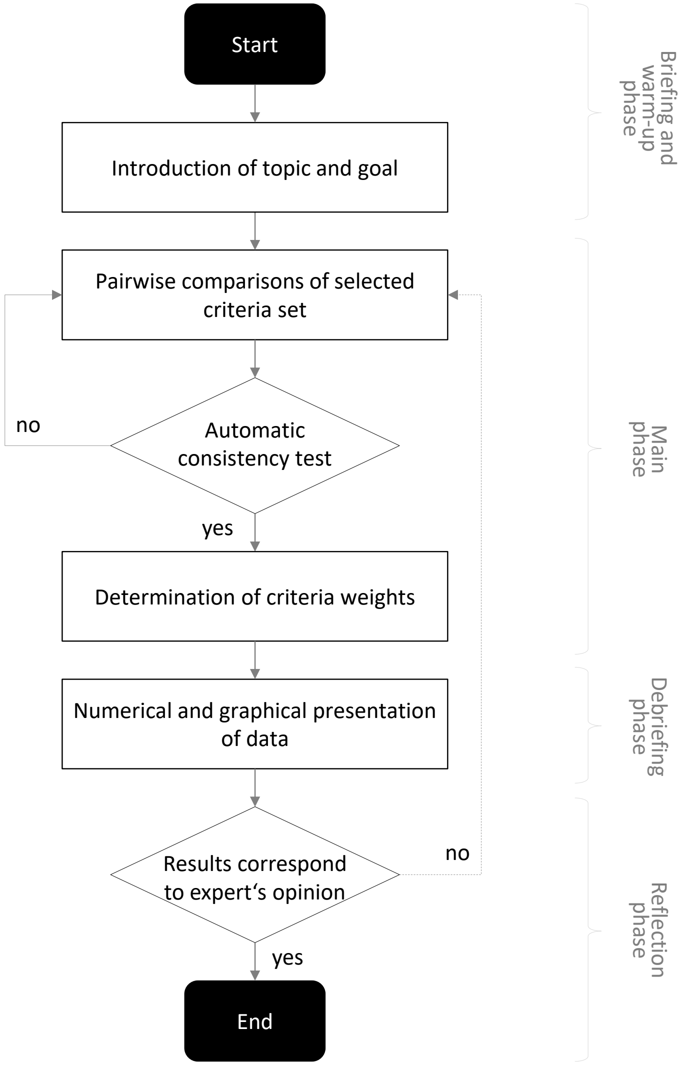


Figure 4-4: Process flowchart of the interview structure

At the end of each interview, the experts were offered a quick presentation of the overall division results in an anonymized format, in order to put the personal point of view into relation with the other purchasing experts consulted.

In total 41 experts from diverse purchasing divisions of a German automotive OEM were consulted in personal face-to-face interviews. In each purchasing division, the experts were comprised of four hierarchy levels ranging from specialist buyer (SB), to team leader (TL), to department manager (DM), to senior department manager (SDM) and to division manager (DIVM). The distribution per hierarchy level is illustrated in Figure 4-5.

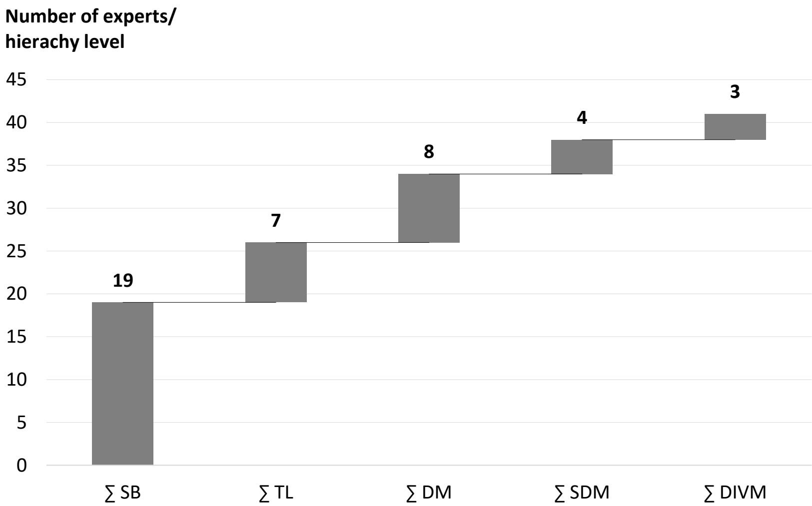


Figure 4-5: Distribution of experts/interviewees per hierarchy level

The investigated divisions cover the areas of purchasing for non-consumable materials, consumable materials and services and strategic purchasing (see Figure 4-6). In this classification, non-consumable materials comprise single components, parts and modules and entire product systems. In contrast, purchasing for consumable materials include goods such as oil, production machines for further processing and assembly, as well as external services. The distribution of experts per purchasing division and the according hierarchy levels are illustrated in Figure 4-6. For each interview a time period between 30 and 60 minutes was scheduled. The conduction of the expert interviews took place at the experts' offices at the OEMs facility.

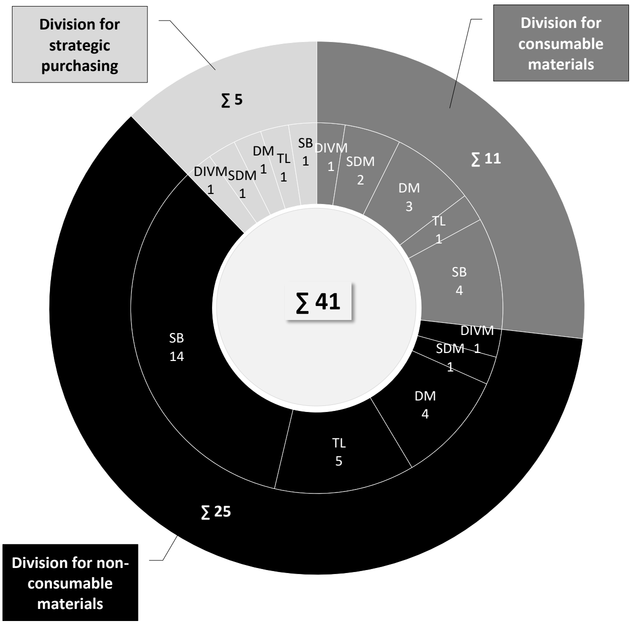


Figure 4-6: Distribution of experts/interviewees per purchasing division and hierarchy level

4.2.3.3 Results of the AHP criteria weight derivation

In this section, the results of all AHP criteria weights, which were derived from the pairwise comparisons in personal expert interviews, are presented. Moreover, certain groups were formed according to the professional specialization of the purchasing experts in the according field of work. This illustrates the basis for a later application in the sub-model of decision support depending on the selected supplier selection case study.

According to the recommended process for the conduction of AHP (section 4.2.2.1), the main criteria were firstly evaluated by the experts, and the derived weights were multiplied with the underlying sub-criteria weights to form global criteria weights. The single judgements of each expert were investigated for judgement consistency. A consistency ration (CR) below 10% is acceptable. The results per expert of the entire interview sample of 41 purchasing experts from the OEM are presented in Appendix A, Table A-1. Consequently, an aggregation of a group preference was carried out (see section 4.2.2.1). Due to the inhomogeneous nature of the sample, experts from three different purchasing divisions, the aggregation of individual priorities (AIP) method was applied. The aggregated results are illustrated in Table 4-3. Moreover, the minimum and maximum priority rankings of the entire sample are disclosed in order to show the large discrepancies about criteria weightings among the consulted purchasing experts. This aspect is discussed in more detail in section 6 in the light of future research.

Table 4-3: AHP results - consolidated criteria weights (priority rankings) for 41 purchasing experts

Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability
Sub-criteria	C11 Parts cost	C12 Industri-alization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development /industrializa-tion time	C32 Infrastruc-ture and supply	C41 Develop-ment experience	C42 Investment in innova-tion	C51 CO_2e component manufac-turing
min	1.98%	1.39%	3.39%	2.37%	1.31%	1.95%	1.68%	1.49%	2.44%
max	44.16%	25.05%	37.59%	41.48%	25.51%	42.16%	23.43%	33.19%	2.66%
geometric mean (AIP)	23.54%	10.20%	14.63%	11.28%	5.81%	12.18%	12.63%	6.58%	3.15%
Porpor-tional ad-justment	24.12%	10.45%	15.29%	11.80%	5.94%	12.44%	13.13%	6.84%	

Against the background of a later application on a real-life case study part, which is sourced in the non-consumable division (see section 4.2.3.4), the derived criteria weights of the sample of experts from the according purchasing division were consolidated (see Table 4-4). Similar to the initially described treatment of the single criteria weights per expert, each judgement is firstly examined for consistency before a group aggregation technique is applied. Due to the homogenous character of this group of purchasing experts, the aggregation of individual judgements (AIJ) method, combined with the geometric mean method is applied (see section 4.2.2.1).

The aggregated criteria weights for the entire sample of all purchasing experts (C11: 23.54%, C21: 14.63%), as well as the selected sample for the non-consumable purchasing division (C11: 20.89%, C21: 16.33%) show a continuing importance of economic and quality aspects (see Table 4-3 and Table 4-4). This goes hand in hand with the current status of research on applied supplier selection criteria, illustrated in section 3.1.3.

Table 4-4: AHP results – single global and consolidated criteria weights (priority rankings) for 25 purchasing experts (Schiessl et al., 2020)

Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
	C11	C12	C21	C22	C31	C32	C41	C42	C51	
Sub-criteria	Parts cost	Industri-alization cost	Machine conditions and manufacturing technology	Testing processes and facilities	Product development/industrializa-tion time	Infrastruc-ture and supply	Develop-ment experience	Investment in innovation	CO_2e component manufacturing	Consistency Ratio (CR<10%)
Exp. 1	8.35%	25.05%	15.18%	3.79%	7.44%	22.32%	7.64%	7.64%	2.58%	4.54%
Exp. 2	44.16%	8.83%	15.81%	5.27%	1.93%	9.65%	10.41%	1.49%	2.44%	9.94%
Exp. 3	43.56%	6.22%	16.09%	3.22%	1.31%	7.84%	2.76%	16.55%	2.45%	9.44%
Exp. 4	6.39%	19.18%	13.17%	4.39%	2.54%	7.61%	11.06%	33.19%	2.46%	9.02%
Exp. 5	24.23%	8.08%	29.87%	9.96%	8.50%	2.83%	10.57%	3.52%	2.44%	9.91%
Exp. 6	33.57%	6.71%	3.69%	14.74%	3.05%	9.14%	19.98%	6.66%	2.46%	9.06%
Exp. 7	2.47%	7.41%	12.87%	38.62%	10.67%	3.56%	16.46%	5.49%	2.45%	9.64%
Exp. 8	5.20%	15.59%	33.87%	11.29%	1.92%	9.59%	16.74%	3.35%	2.46%	9.24%
Exp. 9	40.98%	5.12%	3.39%	10.16%	7.83%	1.96%	23.43%	4.69%	2.44%	9.81%
Exp. 10	29.48%	4.91%	19.74%	19.74%	1.41%	8.46%	10.36%	3.45%	2.45%	9.55%
Exp. 11	8.33%	1.39%	37.59%	5.37%	25.51%	4.25%	12.09%	3.02%	2.44%	9.73%
Exp. 12	39.52%	9.88%	7.96%	15.93%	1.36%	8.18%	12.62%	2.10%	2.44%	9.81%
Exp. 13	16.27%	4.07%	9.80%	2.45%	10.54%	42.16%	2.45%	9.80%	2.48%	8.26%
Exp. 14	19.20%	6.40%	32.77%	10.92%	3.61%	14.43%	8.18%	2.04%	2.44%	9.72%
Exp. 15	1.98%	7.91%	17.16%	34.33%	9.49%	4.74%	16.46%	5.49%	2.45%	9.64%
Exp. 16	35.49%	7.10%	3.40%	13.61%	1.99%	7.96%	4.67%	23.34%	2.45%	9.66%
Exp. 17	21.50%	5.38%	8.73%	8.73%	11.64%	5.82%	17.79%	17.79%	2.62%	3.04%

Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
Sub-criteria	C11 Parts cost	C12 Industri-alization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development/industrializa-tion time	C32 Infrastruc-ture and supply	C41 Develop-ment experience	C42 Investment in innovation	C51 CO_2e component manufacturing	Consistency Ratio (CR<10%)
Exp. 18	27.07%	9.02%	15.31%	5.10%	3.40%	17.01%	10.21%	10.21%	2.66%	1.31%
Exp. 19	34.58%	5.76%	4.68%	23.39%	5.29%	5.29%	14.83%	3.71%	2.47%	8.85%
Exp. 20	3.94%	19.69%	3.60%	10.79%	6.55%	39.31%	11.95%	1.71%	2.47%	8.49%
Exp. 21	24.22%	8.07%	19.85%	9.92%	5.53%	16.60%	9.93%	3.31%	2.56%	5.23%
Exp. 22	40.08%	10.02%	10.47%	3.49%	3.37%	20.22%	7.43%	2.48%	2.44%	9.77%
Exp. 23	19.04%	4.76%	14.06%	14.06%	2.66%	7.99%	23.31%	11.65%	2.47%	8.81%
Exp. 24	11.85%	2.96%	34.20%	6.84%	2.62%	21.00%	2.25%	15.76%	2.51%	7.03%
Exp. 25	5.49%	16.46%	11.86%	2.37%	10.30%	41.19%	8.24%	1.65%	2.45%	9.64%
min	1.98%	1.39%	3.39%	2.37%	1.31%	1.96%	2.25%	1.49%	2.44%	
max	44.16%	25.05%	37.59%	38.62%	25.51%	42.16%	23.43%	33.19%	2.66%	
geometric mean (AIP)	20.89%	9.98%	16.33%	11.45%	5.68%	12.71%	13.14%	7.15%	2.67%	
Porpor-tional ad-justment	21.46%	10.26%	16.77%	11.77%	5.84%	13.06%	13.50%	7.34%		

In terms of the environmental criteria C51, it became apparent during the interviews that CO_2e emissions from the manufacturing phase do currently not play a role in decision making and are not in the focus in supplier selection processes. Due to the application of the pairwise comparison in the AHP method, a weight of 3.15% was assigned to the new decision criteria considering the entire group of 41 experts (see Table 4-3), and a weight of 2.67% for the selected group of 25 experts from the non-consumable purchasing division (see Table 4-4). This indicates and confirms the minor role of C51 in current activities, which are further addressed in the context of sensitivity analysis in section 5.6.

From that point onwards, this sample of 25 experts is used in the further course of this research contribution and is consulted for the application in the case study (see section 5.5), as well as for the subsequent scenario simulations (see section 5.6). Additional information regarding the aggregation per purchasing sector for all three examined purchasing sectors as well as a group aggregation per hierarchy level can be found in Appendix A, Table A-2 and Table A-3 and is further discussed in section 6.

As described in the previous section 4.2.3.3, at the end of each personal interview the experts were asked for an estimation of main criteria evaluation from their personal, business-related perspective. Hence, the derived future main criteria weights were multiplied with normalized, aggregated value per sub-criteria based on the entire expert sample in order to derive global 'future' criteria weights. Therefore, the AIP geometric mean method was again consulted in an intermediate step. A comparison of the current evaluation and future estimation of criteria weights (see Figure 4-7) for the group of experts from the non-consumable section already indicates a discrepancy in terms of the new decision criteria 'CO_2e component manufacturing' (C51). The necessity for a further examination and consideration in supplier selection processes is strengthened.

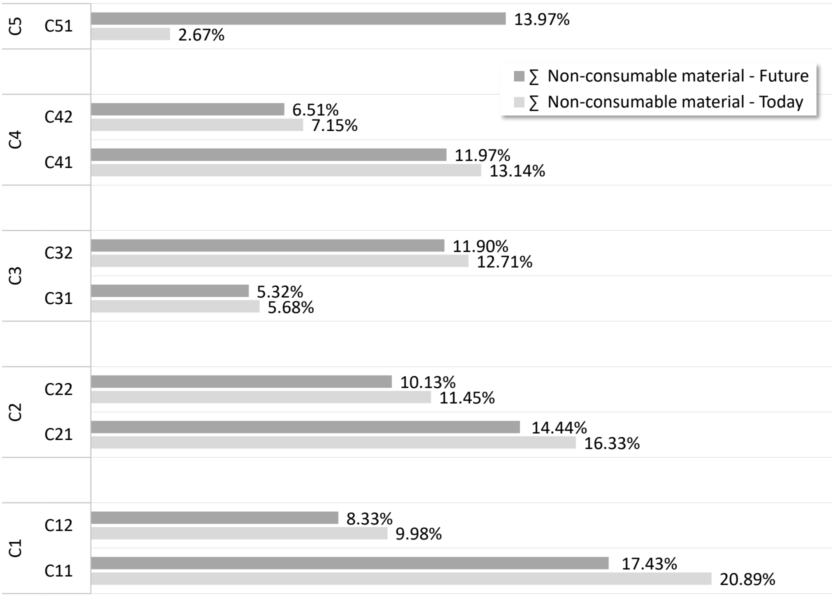


Figure 4-7: Comparison of current criteria weights and according future estimations

Additional information can be found in Appendix A, Figure A-3. In Table 4-5, the consolidated group results per purchasing division, as well as an aggregated result for the entire expert sample is illustrated.

Table 4-5: Consolidated expert estimation for future criteria weights (priority rankings)

Purchasing division	Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability
	Sub-criteria	C11 Parts cost	C12 Industri-alization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development/ industri-alization time	C32 Infrastruc-ture and supply	C41 Development experience	C42 Investment in innovation	C51 CO_2e component manufacturing
∑ Consumable material - Future	AIP - Geomittel (normalized)	30.43%		28.45%		14.68%		17.42%		9.02%
		22.91%	7.52%	13.95%	14.50%	6.15%	8.53%	11.64%	5.79%	9.02%
∑ Non-consumable material - Future	AIP - Geomittel (normalized)	25.76%		24.57%		17.22%		18.48%		13.97%
		17.43%	8.33%	14.44%	10.13%	5.32%	11.90%	11.97%	6.51%	13.97%
∑ Strategy - Future	AIP - Geomittel (normalized)	30.38%		24.11%		20.51%		15.62%		9.38%
		20.41%	9.97%	14.66%	9.45%	4.34%	16.17%	10.65%	4.97%	9.38%
∑ All divisions - Future	AIP - Geomittel (normalized)	27.62%		25.63%		16.94%		17.91%		11.89%
		19.27%	8.35%	14.47%	11.16%	5.47%	11.47%	11.78%	6.14%	11.89%

4.2.3.4 Selection of supplier data for TOPSIS ranking

As basis for a later application of the developed approach in section 5, one sample part was chosen for the case study. The sample part belongs to the powertrain of a vehicle, and is more specifically a part of the drivetrain. The purpose of a powertrain component is to convert power from the engine to the wheels in order to move the vehicle. The sample powertrain part is sourced by the non-consumable division of the purchasing sector of the German OEM. It is composed of mainly of steel, aluminum as well as plastics and weighs 18.36 kg. An indication about the material composition of the sample part, which can slightly differ among suppliers, can be found in Appendix A, Figure A-4. Due to confidentiality reasons, an exact breakdown of the percent share and weight by material could not be published.

In reference to the defined structure of the decision support sub-model (see section 4.1), five example alternatives, representing five supplier cases, were analyzed. From a geographic perspective, the circle of bidders, in this case suppliers, comprises manufacturers with production locations in Austria, France, Spain or Sweden. According to the set of selection criteria (see Figure 4-3), respective performance data is gathered in relation to the sample part (see Table 4-6).

The sub-criteria C11 and C12, which can be designated as classical cost criteria, result in a better performance evaluation from a customer perspective the lower the costs are. The other sub-criteria defined in the main criteria categories can generally be seen as benefit criteria, which normally lead to a better evaluation score the higher the measured numerical performance is. However, not always the highest performance score is considered to be as most favorable from an evaluation perspective. This counts for the sub-criteria C31 and the considered time period for the development and industrialization. A lower duration leads thus to a better performance score. For C32 in the intermediate calculation of the infrastructure/distance rating, the incorporated geographical distance has a negative effect on the performance score, the greater the distance from the customer production site is.

Finally, C42, which is also expressed in a monetary unit in €, has however a positive effect on the performance score of this criteria, the higher the investment in future technologies is.

The performance score per supplier for the new, environmental criteria C51 are not yet included at this stage of the research. The according performance scores expressed in kg CO_2e, result from sub-model B, which are developed in section 4.3.

The summary of the performance evaluation per criteria, illustrated in Table 4-6, serves as basis for the application of the combined AHP/TOPSIS approach which is firstly illustrated in the following section 4.2.4.

Table 4-6: Supplier performance on a powertrain part for the case study

Main criteria	C1			C2		C3				C4	
	Cost			Quality & production		Flexibility				Development & innovation	
Sub-criteria	C11		C12	C21	C22	C31	C32			C41	C42
	Parts cost		Industrialization cost	Machine conditions and manufacturing technology	Testing processes and facilities	Product development/ industrialization time	Infrastructure and supply			Development experience	Investment in innovation
	per part	sum parts	per project	OEE (original equipment efficiency)	Test depth & degree of automation a)	-	Rating (infrastructure /distance)	Geografical distance	Infrastructure assessment b)	Experience of production with part c)	Balance sheet figure
Supplier 1 (S1)	280 €	280,000,000 €	0 €	86%	5	3 Mon.	0.003	2,000 km	5	5	14,490,001 €
Supplier 2 (S2)	285 €	285,000,000 €	6,000,000 €	75%	4	8 Mon.	0.004	1,000 km	4	3	2,000,000 €
Supplier 3 (S3)	280 €	280,200,000 €	10,000 €	86%	5	3 Mon.	0.002	2,001 km	5	5	14,500,001 €
Supplier 4 (S4)	273 €	273,000,000 €	8,000,000 €	91%	3	12 Mon.	0.003	1,000 km	3	3	500,000 €
Supplier 5 (S5)	290 €	290,000,000 €	9,000,000 €	85%	3	12 Mon.	0.001	2,200 km	3	3	16,000,000 €
Number of parts	1,000,000										

a) 5 - fully automated incl. all parts, 4 - fully automated incl. main parts, 3 - partly automated, 2 - manually, 1 - no final testing

b) 5 - very well developed infrasturture and transport alternatives, 4 - well..., 3 - averagely...,2 - below average..., 1 - badly...

c) 5 - same part produced for other OEM, 4 - similar part produced..., 3 - product with same production process..., 2 - product same production process for other industries, 1 - no experience with part or production process

4.2.4 Exemplary model application

At this stage, the sub-model for decision support finds a partial, exemplary application in order to further strengthen the necessity for a more detailed analysis of environmental performance on a site-specific level. It also aims at confirming the initially defined research objective and according research design.

In terms of availability of environmental performance data, currently, only data on regional industry averages for some selected countries can be found in scientific publications (see section 3.2). Moreover, studies on site-specific assessment and according results, only cover a few specific plants. Due to varying levels of detail and not consistent setting of system boundaries, as well as the accordingly limited regional and site-specific scopes, a wide-spread evaluation of European manufacturers is not possible for the chosen supplier selection example. Consequently, the current availability of data is limited to LCA databases which use industry averages. Hence, the highest degree of granularity provided is on a regional, European level (RER). For example for steel produced in integrated steel mills, only one European average value is accessible. The average cradle-to-gate value is 2,408 kg CO_2e/t crude steel, including emissions from all upstream activities (Ecoinvent, 2007-2013).

At this point, the selected sample part, with an overall weight of 18.36 kg, was assumed to be produced exclusively from crude steel. The application of the average European value for all selected suppliers in the bidder circle, described in section 4.2.3.4, leads to an equal environmental performance score of 44.20 kg CO_2e/part (see Figure 4-8, Case 1). Additional emissions from upstream supply chain activities, such as further processing as well as transport emissions to the Tier-1 and from the Tier-1 supplier to the OEM (see Figure 2-3 and Figure 2-4), were not considered in this study due to the generally small share of CO_2e emissions. In case of primary steel supply chains, only an approximate share of 10% of the emissions (Ecoinvent, 2007-2013) stem from the mentioned activities (see section 4.3.2).

A first application of the AHP/TOPSIS model, including equal environmental performance data for all five selected suppliers (see Figure 4-8, Case 1), results in the following supplier ranking, S1 → S3 → S2 →S5 → S4.

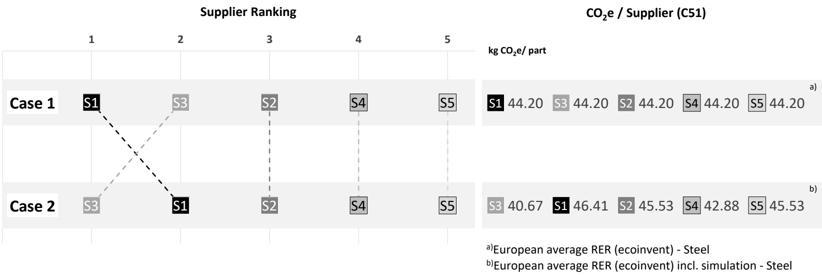


Figure 4-8: Influence of CO_2e (C51) on supplier ranking (Part 1)

The detailed results of the ranking of alternative suppliers respectively performances, derived from the TOPSIS approach, are illustrated in Table 4-7. The best ranked supplier with a proximity index value P_i of 0.751, in this case supplier 1, shows the shortest distance to the ideal best solution and simultaneously the longest distance from the ideal worst solution out of the set of analyzed supplier performances.

Table 4-7: Evaluation and ranking of alternatives (Case 1) based on average emissions (RER)

Supplier	Distance (PIS)	Distance (NIS)	Proximity Index (relative closeness)	Ranking
	ds^+	ds^-	$P_i = \frac{ds^-}{ds^+ + ds^-}$	
S1	0.0310664	0.0937531	0.7511092	1
S2	0.0702235	0.0036655	0.1307666	3
S3	0.0310927	0.0087802	0.1247956	2
S4	0.0892596	0.0013765	0.1263609	5
S5	0.0979896	0.0018781	0.1413270	4

Table 4-8: Evaluation and ranking of alternatives (Case 2) based on average emissions (RER), manipulated

Supplier	Distance (PIS)	Distance (NIS)	Proximity Index (relative closeness)	Ranking
	ds^+	ds^-	$P_i = \frac{ds^-}{ds^+ + ds^-}$	
S1	0.0311051	0.0937531	0.7508766	2
S2	0.0702358	0.0605435	0.4629442	3
S3	0.0310927	0.0937158	0.7508767	1
S4	0.0892616	0.0371136	0.2936782	5
S5	0.0979983	0.0433381	0.3066305	4

Now, the average European performance value, which is currently equal for all suppliers, is randomly and only slightly manipulated for each of the five examined suppliers (see Figure 4-8, Case 2). For supplier 1, the average value of 2,408 kg CO_2e/t crude steel is changed by +5% resulting in

46.41 kg CO_2e/part, for supplier 2 by +3% resulting in 45.53 kg CO_2e/part, for supplier 3 by -8% resulting in 40.67 kg CO_2e/part, for supplier 4 by -3% resulting in 42.88 kg CO_2e/part and for supplier 5 by +3% resulting in 45.53 kg CO_2e/part.

A subsequent application of the manipulated performance scores in sub-model A, already leads to a changed order of supplier ranking, S3 → S1 → S2 →S5 → S4, and ranks supplier 3 in first position as most preferable alternative. A comparison of the performance scores for the newly introduced environmental criteria of supplier 1 (46.41 kg CO_2e/part) and supplier 3 (40.67 kg CO_2e/part) shows a deviation of only 14.13% or 5.75 kg CO_2e/part.

This furthermore confirms and strengthens the motivation of the research to generally integrate CO_2e as a selection criteria. It also illustrates the need to analyze the environmental performance of suppliers on a more detailed level, as real-world supplier selections are based on the performance of suppliers according to the site where the products are manufactured.

4.3 Sub-model B for the assessment of site-specific environmental performance[13]

In the following, the requirements and the concept of the sub-model for environmental performance assessment, sub-model B, are described in section 4.3.1. In sections 4.3.2 – 4.3.4, the aim as well as the related width and depth of the assessment are defined, and information about the conduction of the study is provided, according to the process for life cycle assessment (International Standards Organisation, 2006a, 2006b). Consequently, the model development with a focus on the steel industry is illustrated in section 4.3.5.

[13] Parts of this section were previously published in Schiessl et al. (2020b).

The model was developed within the framework of an industrial project (see section 4.3.2). The goal was to develop a standardized calculation approach on the example of the steel industry, which allows for a transfer to various commodities such as aluminum (see section 4.4) and plastics as well as according secondary production processes. The approach including an application on the steel industry was previously published in Schiessl et al. (2020b).

4.3.1 Requirements and concept

As previously described, the decision support sub-model to be developed, relies on the processing of quantitatively expressed performance measurement data, not only for classical, but also for newly integrated environmental criteria (see Figure 4-1). Hence, a transparency and comparability of carbon emission performance among suppliers' production sites needs to be created. The approach shall support decision makers to reduce the carbon footprint of a product by selecting the most adequate suppliers from an environmental efficiency perspective, while simultaneously meeting general economic targets.

Therefore, derived from the identified research gaps in section 3.1.5 and the defined research questions in section 1.2, diverse additional requirements for a model to quantify the environmental performance of suppliers occur:

(1) A transparency of the environmental performance of raw material manufacturers on a site-specific level must be created without the need for restricted primary data.

(2) The results need to be comparable among suppliers in order to assure that no supplier is preferred or disadvantaged because of the modelling approach.

(3) A widespread and transnational application must be possible in order to cover the broad range of available suppliers to be selected in a real-life environment.

(4) Due to different material mixes of products and strong variances in environmental burdens resulting from the type of raw material used, the possibility to transfer the methodological approach to other commodities must be given.

(5) As basis for a practical application of the model, user friendliness must be taken into account and the possibility for situational refinements by the integration of site-specific primary data, if available, as well as for continuous data updates in order to assure validity of results, must be given.

Among the analyzed published scientific literature in this field, the majority of the investigated approaches only partially fulfill the stated requirements due to the divergent objectives pursued with the studies. No single approach, which meets all the demands necessary for a model to evaluate a broad range of suppliers on a site-specific performance level, with the purpose of integrating the performance results in supplier selection decision-making processes, could be found. In this case of application, this also counts for single LCA methods and according approaches discussed in section 3.2.1 and 3.2.2. The application of a classical process LCA does not appear to be appropriate for making comparisons among different manufacturers, as comprehensive primary data on a site-specific process level is inaccessible. In this context, the usage of process LCA databases does not enable a site-specific consideration of environmental impacts due to the availability of average industry data only (see section 4.2.4). This aspect goes hand in hand with sectoral input–output datasets which represent a too aggregated level of data. The otello model (Breun et al., 2011; Comes et al., 2010a; Comes et al., 2010b; Ilsen, 2012) and the thereupon derived new development in form of a non-linear programming model (Breun, 2016; Breun et al., 2017), were identified as the two single approaches, which satisfy the designated requirements to the largest extent.

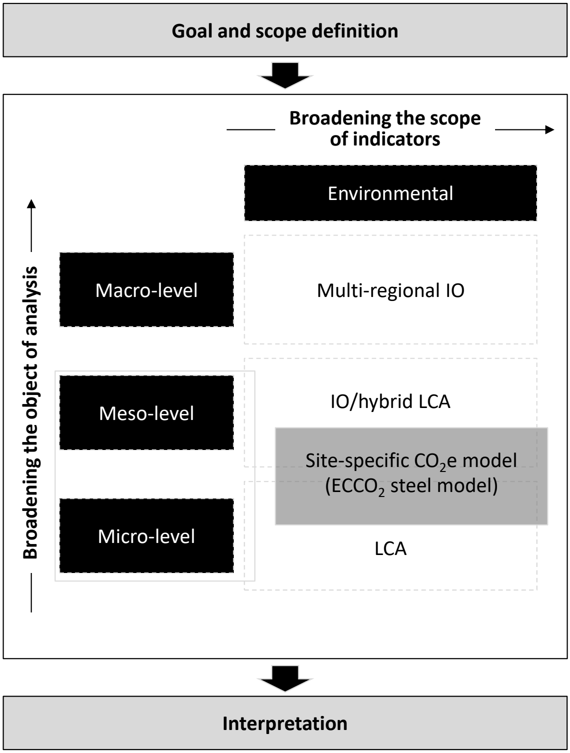
The approach to be developed in the sub-model for the estimation of site-specific CO_2e performance follows the basic principles of the model from Breun (2016), which combines non-linear programming model with an input–output model (Leontief, 1936).

In order to meet the defined requirements, which are based on a different target of application, several adjustments need to be made. Whereas in the NLP approach an exact estimation of carbon emissions on a detailed facility level per location was created, the newly developed approach focuses on estimating the overall amount of carbon emissions of all facilities per location, due to the target application for supporting supplier selection decisions. Therefore, in contrast to a complex simultaneous calculation applied by Breun (2016), a sequential step-by-step calculation (see section 4.3.5) inspired by the otello approach (Ilsen, 2012) is consulted.

In a combined approach based on the process LCA method, bottom-up and top-down site-specific data are applied, without the need for Leontief's input-output model on an economic sector level. In this systematic and modular approach – ECCO_2 steel (Evaluation tool to compare CO_2 emissions of the iron and steel industry), technical process flows are calculated (bottom-up data) and combined with site-specific top-down information on environmental impact (CO_2), while existing technical restrictions are considered. Moreover, the trading of intermediate products between different production sites, which is incorporated in the approach from Breun (2016) but not included in the otello model, is included in the newly developed approach. This hence supports the avoidance of truncation errors (Islam et al., 2016) and allows for a comparability among suppliers.

While a similar accuracy of results for the overall amount of site-specific carbon emissions is targeted, the new approach, which falls into the category of attributional LCAs (see section 3.2.1.1), shows a lower complexity and requires less mathematical in-depth expertise. It thus allows for a practice-oriented implementation and a more wide-spread application through practitioners. This goes in line with the model being designed to rely on publicly available data exclusively and not to be dependent on confidential company internal data. The data availability and the sequential calculation method also give the opportunity to continuously update the data more efficiently. Moreover, if primary data is available, a straightforward integration is supported and considered in the model structure in order to even further improve the accuracy of results of the model. In comparison to the model from Breun (2016), which laid the focus on German policy instruments, and thus the in-depth analysis of German steel manufacturers, the new approach extends the geographical scope on a European scale. This is essential to comply with real-life supplier selection decisions in the selected industrial field which are not limited to national borders. Further considerations of the global supplier market are discussed in section 6. In accordance with the defined target to further complete transparency in upstream value chains from a product life cycle or supply chain perspective, the system boundaries were also expanded compared to Breun (2016), by means of incorporating the carbon footprint for upstream, cradle-to-gate supply chain activities.

The proposed site-specific CO_2e model can be categorized into the existing range of varying LCA approaches by a schematic framework for life cycle sustainability analysis (LCSA). This framework (see Figure 4-9) was originally developed by Guinée et al. (2011), and further revised as well as modified by Zimmer et al. (2017). The developed approach extends the object of analysis as the data availability for the conduction of a site-specific process LCA is not given in comparison to classical process LCA, which is usually found at the product-oriented, micro level exclusively. Especially the inter-company trading of necessary intermediate products and the accompanying CO_2e emissions do not permit the application of a classical LCA approach. On these grounds, the object of analysis was extended to meso, company level (Magerholm Fet, 2002), by integrating the reported environmental data (CO_2) on production site-specific level (see section 4.3.4 and 4.3.5). As the application of methods or data from one level might advantageously be used on another level, the boundaries between these levels are not to be considered as definite.



IO: Input Output Analysis
LCA: Life Cycle Assessment
$ECCO_2$ Steel: Evaluation tool to compare CO_2 emissions of the iron and steel industry

Figure 4-9: LCA framework (based on Guinée et al. (2011); and Zimmer et al. (2017; 2016))

4.3.2 Definition of scope and functional unit

Due to the fact that 98,3% of all greenhouse gases (GHG) emitted in the iron- and steel production are determined by CO_2 emissions (among others, CO with 1,62% and NO_x/NO_2 with 0,06%) (UBA, 2018a), the scope was defined by, and the focus laid on CO_2 emissions.

This includes not only the process related, direct emissions on site (Scope 1[14]) but also all energy-related, indirect emissions (Scope 2). In Figure 2-10, all in the model considered process steps, gas flows and external supplies which have an impact on the site-specific CO_2e emissions are illustrated in a flow diagram. All additional greenhouse gases which are emitted during the production and supply of upstream raw materials (Scope 3) are included in the model.

From a geographical point of view, 22 iron and steel mills in EU-15 countries (see Figure 4-10), which directly or indirectly supply to the European automotive industry, are examined. This specific selection of steel producers was made upon consultation in personal interviews with four experts from leading international Tier-1 suppliers and one OEM, which were part of an industrial project.

The functional unit, which represents the quantitative reference for a normalization of the LCI dataset (Roy et al., 2009; Sonnemann et al., 2004), was determined as one t crude steel in this study. This performance measure is highlighted in the DIN ISO 14044 framework (International Standards Organisation, 2006b) and represents the crucial concept in LCA (Bieda et al., 2015). It allows for a comparison of different products and manufacturing sites (International Standards Organisation, 2006b; Kndungu and Molavi, 2014), as crude steel represents the joint output product of the selected and examined sample of manufacturers. Hence, all emissions, intermediate products, process gases and energy supply, which are directly related to the manufacturing of crude steel, are considered in an attributional approach (see section 3.2.1.1), and can thus be used for a comparison of the environmental performance of steel manufacturing sites.

[14] The consulted classification in scope 1-3 relies on the GHG Protocol Corporate Standard, which provides a guidance for organizations to prepare emission inventories (Scope 1: direct emissions from company owned sources, Scope 2: indirect emissions from purchase energy and Scope 3: indirect emissions from value chain activities) (GHG Protocol, 2004, 2013).

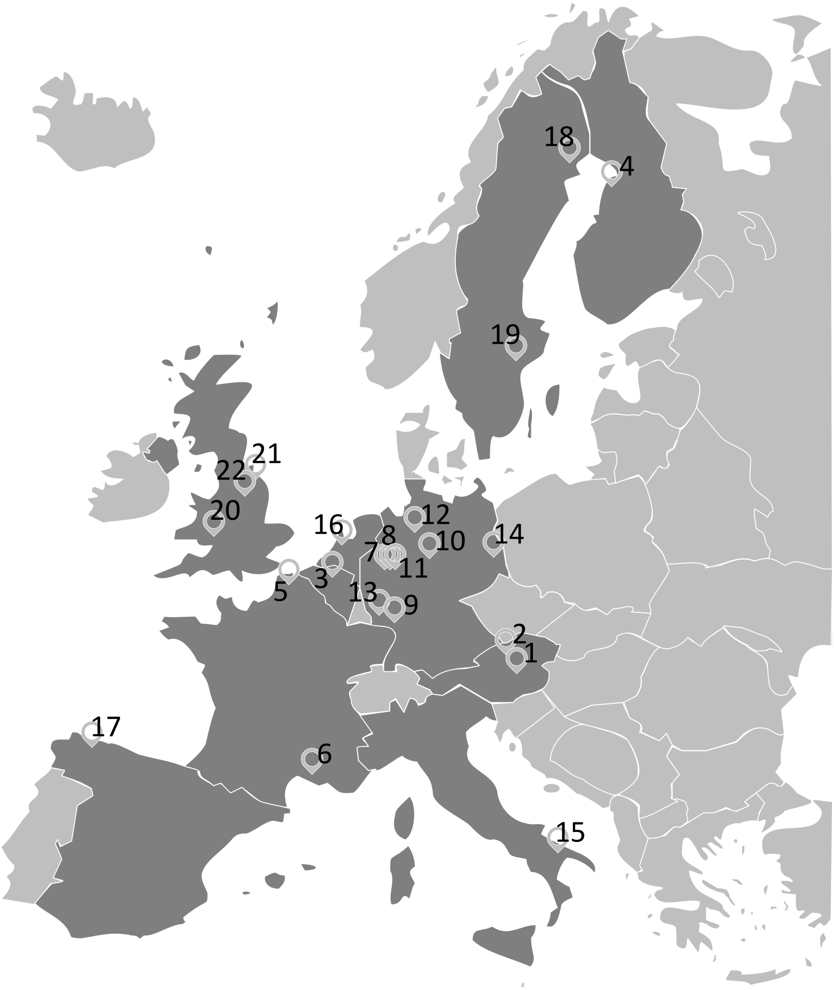


Figure 4-10: Geographic location of the considered integrated iron- and steel mills in Europe

4.3.3 System boundaries

In combination with the functional unit, the definition of the system boundaries is the crucial basis to enable a valid comparability of results (Tanaka, 2012). It plays an important role especially for examinations in the area of primary steel production (Brunke and Blesl, 2014) due to the very complex interconnection/coupling of process steps. Moreover, as not all process steps are located on-site, and the consequently existing trade of intermediate products (see Table 4-9), as well as due to prevailing capacity restrictions, the necessity for a clear definition of system boundaries becomes apparent.

As illustrated in Figure 2-10, the system boundary ‘Production Plant’ (gate-to-gate) comprises all necessary operations for the production of crude steel in relation to Scope 1 emissions. Based on the existence of connected power plants, which generate power and thus Scope 2 emissions from locally produced process gases but are subject to an individual, separate CO_2 emissions reporting scheme, the system is extended by the ‘Power Plant’ boundary.

Against the background of creating a holistic consideration of steel products, the external raw material supply and thus the environmental impact (CO_2e) in form of Scope 3 emissions from the upstream supply chain activities, was included into the product system (cradle-to-gate). Due to the unavailability of more detailed and site-specific information, industry average values from publicly available data bases were consulted (see section 4.3.4).

Additional secondary products, which arise during the steel production process, such as for example blast furnace slag, were not considered in the scope of this study and were thus neglected in terms of system boundaries. This is due to the fact that they are not directly linked to the defined functional unit, and due to the unavailability of detailed information regarding the further processual usage and according trading activities.

Table 4-9: Plant set-up of the 22 integrated iron- and steel mills under study (S&P Global Platts, 2015; VDEh, 2014a)

Prod. site	Coke Oven				Sintering Plant				Blast Furnace				Basic Oxygen Furnace		Rolling Mill		Power Plant [MW]		
	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4	i=1	i=2	i=1	i=2	i=1	i=2	i=3
1	1,38				2,80				0,77	0,79	2,78		6,00		5,65		371		
2					1,40				0,67	0,70			1,57		1,57		11		
3	1,27				1,90	5,30			2,30	2,13			5,00		5,50		616		
4	0,94								1,24	1,24			2,80		2,80		86		
5	0,60	0,80			2,10	7,50			1,48	1,87	3,45		6,75		5,10		730		
6	1,65				6,80				2,50	2,40			5,10		4,80		96	65	
7	2,60				6,48	2,20	3,60		1,62	2,00	3,50	4,30	5,44	6,12	5,30	6,00	172	344	240
8													2,30		1,20				
9													3,25		0,50				
10	1,50				2,45				1,80	0,80	2,00		4,80		4,50		470		
11	1,16				4,95				2,50	2,70			5,67		0,66		618		
12					2,80				1,25	2,60			3,60		4,70		270		
13	1,10				1,70	3,20			2,60	2,20			2,70		1,80		90		
14					2,90				1,58	0,55			2,30		2,15		110		
15	0,87	0,86			5,50	5,50			1,95	2,01	3,55		5,20	6,30	5,20	6,30	1.023		
16	0,36	0,56	0,36	1,04	0,90	1,75	1,75	4,60	2,77	3,54			7,20		7,20		755	316	
17	0,76	0,68	1,03		2,65	3,35			2,26	2,22			3,95	1,20	4,26	1,00	385		
18	0,72								2,30				2,20				191		
19	0,43								0,78	1,05			1,70		1,70		70		
20	0,93				4,60				2,67	1,95			4,90		4,90		41		
21	1,27	0,61			3,50				3,47				3,50				288		
22	0,32	0,36	0,65		2,75	2,75			1,25	1,25			3,50		3,50		54		

i = Number of facilities per process step

if empty, process step of facility not available on site

4.3.4 Data collection

In the life cycle inventory phase (LCI), which illustrates the initial basis for an estimation of environmental performance on a site-specific level, a comprehensive data gathering is required. As the access to primary data from the steel producers and the according production sites is rather limited, the focus was set on data gathering from publicly available sources (reference year 2012). The selection of sources is based on the reliability of the source and the assurance of regular data updates. Hence, continuous extensions of the time horizon under study are enabled.

All installed steel plants in Europe rely on the authorization of a permit for operation, resulting from European regulations which are defined in the Industrial Emissions Directive 2010/75/EU (European Commission, 2010). The regulation assures that steel operations follow the conditions specified in the best available techniques reference documents for the iron and steel industry (European Commission, 2013). This is to achieve and ensure a high level of environmental protection among the installed plants. These documents are published by the European Commission and are accessible for the public. In combination with the limited published site-specific data (see Table 4-10), the reference documents serve as essential framework information for the technology-driven bottom-up calculation (see section 4.3.5).

In addition, the regulation (EC) No 166/2006 of the European parliament and the council (European Commission, 2006) obliges member states to report emissions on a yearly basis. It is comprised of diverse pollutants to air, land and water as well as waste water pollutants and the treatment of waste. It includes the industry sector of metal production. Specifically for the production of pig iron or steel, rolling mills and power plants for combustion, a reporting obligation exists, depending on a certain production volume.

These information are essential for the modelling approach as they represent the basis for the top-down integration of site-specific CO2 emissions (see section 4.3.5). Further details about the data consulted for the site-specific performance assessment model are presented in section 4.3.5.5 and in Appendix B, Table B-4.

Table 4-10: Data sources applied (ECCO$_2$ steel)

Data Scope	Type of data	Source
Plant specific data	Capacities	PLANTFACTS data base (S&P Global Platts, 2015; VDEh, 2014a) World electric power plants database (S&P Global Platts, 2015)
	Production Volumes	Statistical yearbooks (VDEh, 2014b) Company specific reports
	Emissions	European Pollution and Transfer Register E-PRTR (European Environment Agency, 2012)
General technical parameter	Production Process	Best Available Techniques BAT (European Commission, 2013) Non-linear programming approach (Breun, 2016)
Country specific data	Electricity Mix	German Environment Agency (UBA, 2012) ecoinvent Data Base (Ecoinvent, 2007-2013)
Carbon Footprint	Input material steel manufacturing	ecoinvent Data Base (Ecoinvent, 2007-2013)

4.3.5 Model development for steel

As several production sites under study do not have the facilities and respective process step to produce compulsory intermediate products such as sinter or coke on-site, these products are sourced externally at the steel market (see section 4.3.3). Due to capacity constraints, this external procurement can also include products such as pig iron.

As the amount of on-site crude steel production depends on certain amounts of intermediate products (European Commission, 2013), consequently a consideration of according CO_2e emissions is required. These emissions, which are caused during the production of intermediate products at the selling plant, need to be allocated to the purchasing site, where the intermediate products are used and further processed. By means of the introduction of a credit system for procured and sold intermediate products, the hurdle of incomparability of production sites is overcome and a normalization to kg CO_2e/t crude steel per site is enabled.

The modular approach, which illustrates a combination of a bottom-up and top-down LCA based approach (see section 4.3.1), is structured in eight steps (see Figure 4-11[15]). Initially, the technology-driven bottom-up calculation of site-specific material and energy flows is described in Step 1 to Step 4 (S1-S4). The created pre-results are then in Step 5 (S5) combined with the top-down, publicly available CO_2 emissions per production location respectively site. In Step 6 (S6), the modelling of fully integrated production plants is carried out. The development is finalized in Step 7 (S7) and Step 8 (S8) with the credit calculation procedure for intermediate trading and an according adjustment of emissions. The analysis of the production sites to be examined has revealed that several facilities (i) per process step (x) at location (l) may exist ($ps_{x,i,l}, x \in \{1;6\}, i \in \{1, \dots n\}, l \in \{1, \dots m\}$), which are therefore separately considered in the model. In the developed model, the production efficiency of each single facility for an according process step is assumed to be equal. Due to the high dependency of the model development on the defined purpose of the study and the availability of data in the according industrial sectors, in the following, the modelling approach and the application of diverse structural data for the single development phases are combined.

[15] The single steps (S1) to (S8) presented in Figure 4-11 correspond to section 4.3.5 and will be further explained in the text.

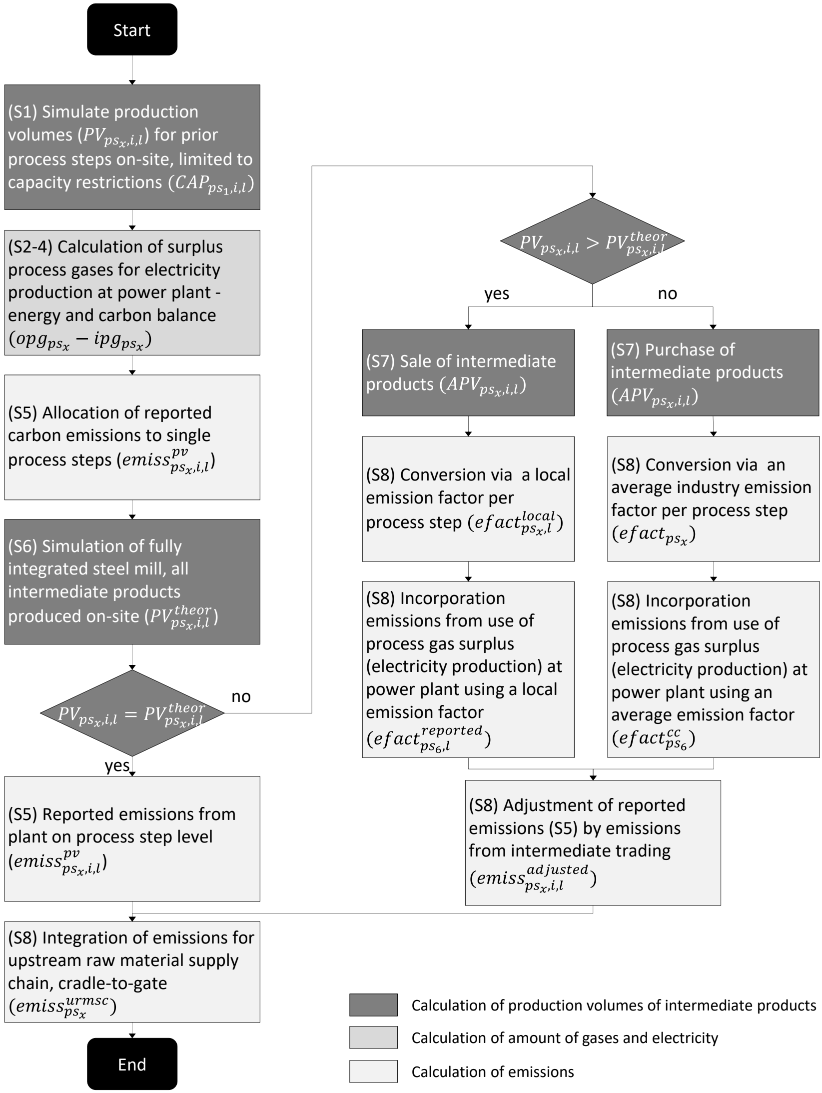


Figure 4-11: Flow chart of the combined LCA approach for the predefined eight calculation steps

4.3.5.1 Step 1: Plant set-up to scale reported production volumes to process steps

In order to define the basis for a later calculation of the internal material and energy flows, initially the plant set-up at the different production locations is examined (see Table 4-9). Thus, the determination of the trading for intermediate products can also be enabled. The focus is set exclusively on the boundaries of the European steel industry.

The capacities for single process steps ($CAP_{ps_x,i,l}$), which are published in the PLANTFACTS data base from the Association of German Steel manufacturers (VDEh, 2014a), were consulted in order to determine if the production process of coke and sinter is located on-site (see Table 4-9). These information also serve for the definition of capacity restrictions on a process step level. Moreover, the external purchase or sale can be derived in combination with the simulated production volumes.

In terms of production volumes, no uniform reporting scheme is established among steel production sites. Hence, various steel manufacturers publish the according information on different levels of process steps ($PV_{ps_x,i,l}$). Within the sample of 22 examined steel producers in Europe, the quantity of pig iron produced in the blast furnace $PV_{ps_3,i,l}$ represents the most detailed level of reporting (see Appendix B, Table B-2). At this stage of the model, the reported production volume of the blast furnace at each examined location (see section 4.3.2 and Figure 4-10) was defined as a reference value, and serves for the determination of the amounts of intermediate products from upstream processes (coke oven $PV_{ps_1,i,l}$ and the sintering plant $PV_{ps_2,i,l}$).

Whenever the actual production volume of a prior, upstream process step is unknown, average material conversion rates (mcr_{ps_x,ps_x}, see Appendix B, Table B-1) were utilized, in combination with the reference value and the capacity restrictions for the simulation of the overall production volumes including all process steps:

$$PV_{ps_1,i,l} = \begin{cases} \left(mcr_{ps_1,ps_3} + mcr_{ps_1,ps_2} \times mcr_{ps_2,ps_3}\right) \times \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_3,\tilde{\imath},l} \times \frac{CAP_{ps_1,i,l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_1,\tilde{\imath},l}} & , CAP_{ps_1,i,l} > 0 \\ 0 & , CAP_{ps_1,i,l} = 0 \end{cases} \tag{4-29}$$

$$PV_{ps_2,i,l} = \begin{cases} mcr_{ps_2,ps_3} \times \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_3,\tilde{\imath},l} \times \frac{CAP_{ps_2,i,l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_2,\tilde{\imath},l}} & , CAP_{ps_2,i,l} > 0 \\ 0 & , CAP_{ps_2,i,l} = 0 \end{cases} \tag{4-30}$$

$\tilde{\imath}$ and $\tilde{n}$ serve as auxiliary variables and correspond to i and n. The auxiliary variables are used throughout the further steps of calculation ($ps_{x,\tilde{\imath},l}, \tilde{\imath} \in \{1, \dots \tilde{n}\}$). The calculation of the conversion rates (in $\left[\frac{t\ ps_x}{t\ ps_x}\right]$) relies on the upper and lower limits for single material and energy flows defined in the BAT documents, published by the European Commission (European Commission, 2013). It follows the approach presented by Breun (2016) based on a German industry average value for eight assessed integrated iron and steel mills (see Appendix B, Table B-1). At this stage, company specific efficiency measures were neglected due to a non-availability of data. However, these measures, which represent company internal process know-how, are later incorporated in the model within the actually reported CO_2 emissions[16], in Step 5.

[16] The emission reporting obligation for industrial facilities comprises various air pollutants, depending on the field of activity and predetermined threshold values. Based on the defined scope in section 4.3.2, this study focuses on the reported carbon dioxide emissions (CO_2).

This aspect is further discussed in the critical appraisal in section 6.2. Downstream processes conducted in the basic oxygen furnace ($PV_{ps_4,i,l}$) and the rolling plant ($PV_{ps_5,i,l}$) were modelled according to the reported production volumes, in proportion to the capacities of the single facilities ($CAP_{ps_x,i,l}$) to the total capacity for each process step.

4.3.5.2 Step 2: Energy balance of process gases for reutilization on-site

During the production of crude steel, several process gases such as coke oven gas (COG) (in ps_1) and blast furnace gas (BF gas) (in ps_3) are produced depending on the process depth located on the considered location. Also specific technologies which have a direct influence on the process gas flows were explicitly incorporated. For example basic oxygen furnace gas recovery ($BOGR_l \in \{1; 0\}$), which leads to the availability of basic oxygen furnace gas (BOF gas) reuse (in ps_4), was considered if the technology is available at the examined site. The reutilization of these gases, former waste products, as energy source during the production process is very common in the steel manufacturing process. In 2012, the share of self-produced electric power in Germany presented a share of 44% in comparison to the 56% share externally purchased electricity. Thus, steel manufacturers can reduce the dependency of external sources and operate more efficiently (VDEh, 2013). The calculation was carried out by means of an input-output consideration of the process gases for each process step, depending of the plant setup and the existence of the process steps on-site. An energy balance was applied in order to determine a possible surplus of gases which is, in case of the installation of an on-site power plant, used for electricity production in ps_6. Therefore, average amounts of energy ($\left[\frac{MJ}{t\ intermediate\ product\ ps_x}\right]$) per gas output at the origin of creation, and gas input at the origin of reuse (see gas flows in Figure 2-10) were applied according to the amount of actual intermediate products ($PV_{ps_x,i,l}$) produced in the reference year.

$$ipg_{ps_1,i,l} = \begin{cases} \dfrac{ipg_{COG} + ipg_{BF\ Gas} + ipg_{BOF\ Gas}}{1000} \times PV_{ps_1,i,l} & , PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} > 0 \wedge BOGR_l = 1 \\ \dfrac{ipg_{COG} + ipg_{BF\ Gas}}{1000} \times PV_{ps_1,i,l} & , PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} > 0 \wedge BOGR_l = 0 \\ \dfrac{ipg_{COG}}{1000} \times PV_{ps_1,i,l} & , PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} = 0 \wedge BOGR_l = 0 \\ 0 & , PV_{ps_1,i,l} = 0 \end{cases} \quad (4\text{-}31)$$

$$ipg_{ps_2,i,l} = \begin{cases} \dfrac{ipg_{COG} + ipg_{BF\ Gas}}{1000} \times PV_{ps_2,i,l} & , PV_{ps_2,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i} > 0 \\ \dfrac{ipg_{COG}}{1000} \times PV_{ps_2,i,l} & , PV_{ps_2,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} < 0 \\ 0 & , PV_{ps_2,i,l} = 0 \end{cases} \quad (4\text{-}32)$$

$$ipg_{ps_3,i,l} = \begin{cases} \dfrac{ipg_{COG} + ipg_{BF\ Gas} + ipg_{BOF\ Gas}}{1000} \times PV_{ps_3,i,l} & , PV_{ps_3,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge BOGR_l = 1 \\ \dfrac{ipg_{COG} + ipg_{BF\ Gas}}{1000} \times PV_{ps_3,i,l} & , PV_{ps_3,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge BOGR_l = 0 \\ \dfrac{ipg_{BF\ Gas}}{1000} \times PV_{ps_3,i,l} & , PV_{ps_3,i,l} > 0 \wedge PV_{ps_1,i,l} = 0 \wedge BOGR_l = 0 \\ 0 & , PV_{ps_3,i,l} = 0 \end{cases} \quad (4\text{-}33)$$

$$ipg_{ps_4,i,l} = \begin{cases} \dfrac{ipg_{COG} + ipg_{BF\,Gas}}{1000} \times PV_{ps_4,i,l} & ,PV_{ps_4,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} > 0 \\ \dfrac{ipg_{COG}}{1000} \times PV_{ps_4,i,l} & ,PV_{ps_4,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} < 0 \\ 0 & ,PV_{ps_4,i,l} = 0 \end{cases} \tag{4-34}$$

$$ipg_{ps_5,i,l} = \begin{cases} \dfrac{ipg_{COG} + ipg_{BF\,Gas} + ipg_{BOF\,Gas}}{1000} \times PV_{ps_5,i,l} & ,PV_{ps_5,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} > 0 \wedge BOGR_l = 1 \\ \dfrac{ipg_{COG} + ipg_{BF\,Gas}}{1000} \times PV_{ps_5,i,l} & ,PV_{ps_5,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} > 0 \wedge BOGR_l = 0 \\ \dfrac{ipg_{COG}}{1000} \times PV_{ps_5,i,l} & ,PV_{ps_5,i,l} > 0 \wedge PV_{ps_1,i,l} > 0 \wedge PV_{ps_3,i,l} = 0 \wedge BOGR_l = 0 \\ 0 & ,PV_{ps_5,i,l} = 0 \end{cases} \tag{4-35}$$

These values were derived from the NLP model and represent a calculated average of eight German production plants. The calculation is in turn originally based on minimum and maximum values of the Best Available Techniques documents (European Commission, 2013) for Europe (see Appendix B, Table B-3). A replacement of this data and thus a refinement of the model is possible if plant-specific primary data is available.

4.3.5.3 Step 3: Electricity production in connected power plants

In this step, an estimation of electricity production, which is based on the previously created energy balance and a calculated surplus of process gases, was carried out (see Step 2). This also includes the consideration of secondary fuels which are added during the process in the power plant.

Due to the scarce data regarding power plants, no explicit amounts of secondary fuels could be determined. Furthermore, it was assumed that the electricity consumption remains constant over the years and that variations in a power plant specific energy balance are compensated by the addition of externally purchased natural gas.

Subsequently, the plant-specific factor of electricity production per t crude steel was calculated in an intermediate step. Therefore, the site-specific power plant output $(ppo_{ps_6,i,l})$ in MW per calendar year was incorporated with an utilization rate of 50% (see Table 4-9):

$$power_{ps_6,i,l} = \frac{\left(ppo_{ps_6,i,l} \times 3600 \times 24 \times 365 \times 50\%\right) \div 1000}{pv_{ps_3,l}} \tag{4-36}$$

In order to derive power plant-specific average factors for additional secondary fuel, in this case natural gas, the ratio of an average factor for additional secondary fuels $(sff = 1{,}68GJ)$ per t crude steel (Breun, 2016) in relation to a calculated average factor of electricity production per t crude steel in Germany $(aepg = 1{,}28GJ)$ was applied on the previously calculated factor of electricity production:

$$ipg_{NG_l} = \frac{sff}{aepg} \times power_{ps_6,i,l} \tag{4-37}$$

The model uses the amount of pig iron produced in the blast furnace (ps_4) as reference value for the amount of required secondary fuels in the power plant. This simplification was assumed due to the high amount of surplus gases from the blast furnace, which are generally crucial for the operation of a power plant.

Thus, the electricity production ($elect_{ps_6,i,l}$) could be estimated by the utilization of an average electrical efficiency of 40% (ee_{ps_6}):

$$elect_{ps_6,i,l} = \left(\sum_{\tilde{\iota}=1}^{\tilde{n}} opg_{ps_1,ps_3,ps_4,\tilde{\iota},l} - \sum_{\tilde{\iota}=1}^{\tilde{n}} ipg_{ps_1,ps_2,ps_3,ps_4,ps_5,\tilde{\iota},l}\right) + ipg_{NG_l} \times \sum_{\tilde{\iota}=1}^{\tilde{n}} pv_{ps_3,\tilde{\iota},l} \times ee_{ps_6} \times \frac{cap_{ps_6,i}}{\sum_{\tilde{\iota}=1}^{\tilde{n}} cap_{ps_6,\tilde{\iota},l}} \quad (4\text{-}38)$$

The value for electrical efficiency, which depends on the type of generator and the calorific value of the gas used, was obtained from the BAT document (European Commission, 2013). With locally produced electricity, the dependence on external electricity supply can be reduced and furthermore, additional electricity and heat can be sold to external parties. The estimated amount of produced electricity ($elect_{ps_6,i,l}$) is also used to calculate emission factors (see Step 7) which are then applied in the credit procedure. By putting the electricity amount (see Eq. (4-38)) in relation to the production volume of pig iron from the blast furnace ($PV_{ps_5,l}$), the local electricity factor $elect_{ps_{3,l}}^{local}$ and the average electricity factor $elect_{ps_3}^{\text{Ø}}$ ($\left[\frac{GJ}{t\ intermediate\ product\ ps_3}\right]$) for the 22 examined plants were determined. In two cases, no power plant is installed and thus a surplus of gases is assumed to be flared. This leads to additional CO_2 emissions without the possibility of energy recuperation.

4.3.5.4 Step 4: Carbon balance for process step specific carbon emissions

According to the energy balancing conducted in Step 2, a carbon balance was calculated in order to subsequently quantify the amount of carbon emissions from the power plant ($emiss_{f_6}$).

$$emiss_{ps_6,i,l} = \left(\begin{matrix}\left(\sum_{\tilde{\iota}=1}^{\tilde{n}} opg_{ps_1,ps_3,ps_4,\tilde{\iota},l} - \sum_{\tilde{\iota}=1}^{\tilde{n}} ipg_{ps_1,ps_2,ps_3,ps_4,ps_5,\tilde{\iota},l}\right) \\ +ipg_{NG_l} \times \sum_{\tilde{\iota}=1}^{\tilde{n}} pv_{ps_3,\tilde{\iota},l} \times \frac{cc_{NG}}{1000}\end{matrix}\right) \Big/ cc_{CO_2} \times \frac{cap_{ps_6,i,l}}{\sum_{\tilde{\iota}=1}^{\tilde{n}} cap_{ps_6,\tilde{\iota},l}} \quad (4\text{-}39)$$

Therefore, the process gases were initially examined for its carbon content per energy (Pfeifer et al., 2009): coke oven gas 0.010 $\left[\frac{kg\ C}{MJ}\right]$, blast furnace gas 0.071 $\left[\frac{kg\ C}{MJ}\right]$, basic oxygen furnace gas 0.051 $\left[\frac{kg\ C}{MJ}\right]$, natural gas 0.020 $\left[\frac{kg\ C}{MJ}\right]$. The quantification of the carbon balance is based on a combination of the previously calculated average amounts of energy per gas output as well as gas input at the different process steps, and a scaling to the actual amount of the according intermediate product produced on-site. Due to the additional utilization of secondary fuels for electricity production process in the power plant, the carbon content of natural gas (cc_{NG}) and the amount of produced pig iron as reference value needed to be included in the calculation. Finally, in order to estimate the carbon emissions of the power plant, an average factor for the carbon content of carbon dioxide (cc_{CO_2}) of 0.3 $\left[\frac{kg\ C}{kg\ CO_2}\right]$ was consulted.

4.3.5.5 Step 5: Allocation of reported carbon emissions to calculated carbon emissions

In the technology-driven bottom-up approach, the energy-related CO_2e emissions of the connected power plants of specific production sites (incl. secondary energy input) were estimated in Step 1 to Step 4. Within Step 5, the actually reported CO_2 emissions on site level ($emiss_{ps_x,i,l}^{reported}$) are top-down integrated. They constitute the basis for a following definition of local process-related emission factors on a process step-level, which then enables the final emission adjustment for intercompany trading (see Appendix B, Table B-4). Taking a look at the reported site-specific CO_2 emissions, usually a non-conformity of CO_2 emission quantification becomes evident. Due to a missing standardization of the level of detail for the publication of plant-specific CO_2 emissions, the granularity of data varies highly. There is a significant discrepancy recognizable within the publications, ranging between a single CO_2 emission value for the overall plant and seven single values for separate process steps. Thus, in order to enable an assignability to the according process steps, an intermediate calculation is necessary.

Therefore, the overall structure of the production plant was examined by the information obtained from the PLANTFACTS data base (VDEh, 2014a) with respect to local process steps on site and number of facilities per process step, similar to Step 1 (see Table 4-9). In an intermediate step, theoretical emissions for each process step ($emiss_{ps_x,i,l}^{theor}$) were calculated. This calculation is based on the production volumes defined in Step 1 and the usage average emission factors (see Appendix B, Table B-5) derived from the BAT document (European Commission, 2013):

$$emiss_{ps_x,i,l}^{theor} = efact_{ps_x} \times PV_{ps_x,i,l} \tag{4-40}$$

The reported emissions (European Environment Agency, 2012) can now be physically allocated accordingly to the distribution of theoretical emissions for single process steps on a production site ($\tilde{x}$ serves as an auxiliary variable and corresponds to x):

$$emiss_{ps_x,i,l}^{pv} = emiss_{ps_x,i,l}^{reported} \times \frac{emiss_{ps_x,i,l}^{theor}}{\sum_{\tilde{x}=1}^{6} emiss_{ps_{\tilde{x}},i,l}^{theor}} \tag{4-41}$$

Thus, it is ensured that the calculated overall emissions correspond to the published emissions and that a plausible distribution on process step level is performed. For the power plant level, the same normalization was applied referring to the CO_2e emissions from the production of electricity, calculated in Step 4.

4.3.5.6 Step 6: Simulation of fully integrated steel mills to create a comparability

In terms of European emission reporting obligation, integrated iron and steel mills are defined as facilities which are located next to each other and functionally connected for the production of pig iron and further processing to crude steel. Preprocess steps for input materials such as coke and sinter are not yet separately considered in the reporting scheme (BMJV, 2013).

Thus, all required process steps for the production of crude steel are not necessarily carried out on-site. Furthermore, it is not assured that the amount of intermediate products produced on-site meets the necessary input amount for the down-stream production process. Thus, a trading of intermediate products between production sites exist. Consequently, the reported CO_2 emissions per site can report too low (external procurement) or too high emission values (external sales).

In order to define the emissions for purchased or sold products, all 22 plants were modelled as fully integrated sites. This means that all substantial intermediate products are simulated to be produced on site. Therefore, the production volume of the basic oxygen furnace ($PV_{ps_4,i,l} = PV_{ps_4,i,l}^{theor}$) was used as reference value to define the production volumes for the three upstream process steps. By means of material conversion rates (see Step 1) the production volumes for the process steps ps_1, ps_2 and ps_3 were simulated backwards. The theoretical production volumes per process step ($PV_{ps_x,i,l}^{theor}$) such as for the blast furnace (ps_3), which is oriented by the following downstream process step of the basic oxygen furnace (ps_4), are calculated as follows:

$$PV_{ps_1,i,l}^{theor} = \begin{cases} \left(\sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_3,\tilde{\imath},l}^{theor} \times mcr_{ps_1,ps_3} + \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_2,\tilde{\imath},l}^{theor} \times mcr_{ps_1,ps_2}\right) \times \frac{CAP_{ps_2,i,l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_2,\tilde{\imath},l}} & , CAP_{ps_1,i,l} > 0 \\ \sum_{\tilde{\imath}=1}^{\tilde{n}} \frac{\left(\sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_3,\tilde{\imath},l}^{theor} \times mcr_{ps_1,ps_3} + \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_2,\tilde{\imath},l}^{theor} \times mcr_{ps_1,ps_2}\right)}{n} & , CAP_{ps_1,i,l} = 0 \end{cases} \tag{4-42}$$

$$PV_{ps_2,i,l}^{theor} = \begin{cases} \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_3,\tilde{\imath},l}^{theor} \times mcr_{ps_2,ps_3} \times \frac{CAP_{ps_2,\tilde{\imath},l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_2,i,l}} & , CAP_{ps_2,i,l} > 0 \\ \sum_{\tilde{\imath}=1}^{\tilde{n}} \frac{PV_{ps_3,\tilde{\imath},l}^{theor} \times mcr_{ps_2,ps_3}}{n} & , CAP_{ps_2,i,l} = 0 \end{cases} \tag{4-43}$$

$$PV_{ps_3,i,l}^{theor} = \begin{cases} \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_4,\tilde{\imath},l}^{theor} \times mcr_{ps_3,ps_4} \times \frac{CAP_{ps_3,i,l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_3,\tilde{\imath},l}} & , CAP_{ps_3,i,l} > 0 \\ \frac{\sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_4,\tilde{\imath},l}^{theor} \times mcr_{ps_3,ps_4}}{n} & , CAP_{ps_3,i,l} = 0 \end{cases} \tag{4-44}$$

$$PV_{ps_4,i,l}^{theor} = PV_{ps_4,i,l} \tag{4-45}$$

$$PV_{ps_5,i,l}^{theor} = \begin{cases} \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_4,\tilde{\imath},l}^{theor} \times mcr_{ps_4,ps_5} \times \frac{CAP_{ps_5,i,l}}{\sum_{\tilde{\imath}=1}^{\tilde{n}} CAP_{ps_5,\tilde{\imath},l}} & , CAP_{ps_5,i,l} > 0 \\ \sum_{\tilde{\imath}=1}^{\tilde{n}} \frac{PV_{ps_4,\tilde{\imath},l}^{theor} \times mcr_{ps_4,ps_5}}{4} & , CAP_{ps_5,i,l} = 0 \end{cases} \tag{4-46}$$

The downstream process in the rolling plant (ps_5) equals the amount of production in the basic oxygen furnace (conversion rate of 1). This step creates the basis for a balancing of these differences in production volumes and resulting CO_2e emissions by means of a following credit procedure (see Step 7).

4.3.5.7 Step 7: Credit procedure to integrate trading of intermediate products

In order to estimate additional production volumes, which can be positive or negative, the allocated actual production volumes ($PV_{ps_x,i,l}$) on a process step level (see Step 1) were set in relation with the theoretical volumes ($PV_{ps_x,i,l}^{theor}$):

$$APV_{ps_x,i,l} = PV_{ps_x,i,l} - PV_{ps_x,i,l}^{theor} \tag{4-47}$$

A negative $APV_{ps_x,i,l}$ illustrates that the actual production volume does not meet the theoretical production volume. In consequence, this leads to a purchase of intermediate products in order to meet the actually produced amount of crude steel in the basic oxygen furnace. Correspondingly, the same applies for a positive additional production volume. The additional production volume is later included in the emission adjustment in Step 8.

However, not only the traded production volume is included but also energy amounts derived from the traded intermediate products have to be considered. Hence, according to Step 3, the amount of additional production volume from the blast furnace was referred to as a reference value. For purchased pig iron, an average electricity factor $elect_{ps_3}^{\emptyset}$ ($\left[\frac{GJ}{t\ intermediate\ product\ ps_3}\right]$) was applied (see Step 3) as the explicit origin of supply could not be predetermined in the model. In the opposite case, the local estimated electricity factor $elect_{ps_3,i,l}^{local}$ ($\left[\frac{GJ}{t\ intermediate\ product\ ps_3}\right]$) was utilized:

$$APV_{ps_6,i,l} = \begin{cases} \sum_{\tilde{\imath}=1}^{\tilde{n}} APV_{ps_3,\tilde{\imath},l} \times elect_{ps_3,i,l}^{local} & , APV_{ps_6,i,l} > 0 \\ \sum_{\tilde{\imath}=1}^{\tilde{n}} APV_{ps_3,\tilde{\imath},l} \times elect_{ps_3}^{\emptyset} & , APV_{ps_6,i,l} < 0 \\ 0 & , APV_{ps_6,i,l} = 0 \end{cases} \quad (4\text{-}48)$$

4.3.5.8 Step 8: Emission adjustment to combine the reported and calculated emissions

Based on the previous calculation steps, the plant-specific estimation of CO_2e emissions, referred to the functional unit, can be computed. Besides the amount of electricity produced in the power plant, the trading of intermediate products has a direct influence on the CO_2e balance of the examined process steps and thus on the overall emissions of a production site.

Therefore, the emissions resulting from the trading were defined ($emiss_{ps_x,i,l}^{apv}$) on a process step level by means of emission factors:

$$emiss_{ps_x,i,l}^{apv} = \begin{cases} APV_{ps_x,i,l} \times efact_{ps_x,i,l}^{local} & , APV_{ps_x,i,l} > 0 \\ APV_{ps_x,i,l} \times efact_{ps_x,i} & , APV_{ps_x,i,l} < 0 \\ 0 & , APV_{ps_x,i,l} = 0 \end{cases} \tag{4-49}$$

On the one hand, purchased products, which could not be traced back to the specific origin of production, were consequently adjusted via an average industry factor $efact_{ps_x}$ (European Commission, 2013). On the other hand, resulting from Step 5, a local factor for sold products was applied. Therefore, the reported emissions which were allocated to the single process steps were put in relation to the actual production volumes:

$$efact_{ps_x,i,l}^{local} = \frac{emiss_{ps_x,i,l}^{pv}}{PV_{ps_x,i,l}} \tag{4-50}$$

A particular focus was again set on the power plant as a sink for the management of internal energy flows from process gases, which were created in different production steps. Hence, for the credit procedure of the power plant (see Eq. (4-51)), the overall amount of produced electricity was credited at first, by means of an average emission factor $efact_{ps_6}^{electmix}$ (see Appendix B, Table B-6) depending on the country where the manufacturer is located. This step plays a crucial role, as the energy mixes and thus the emission factors vary strongly between countries due to the different sources for electricity production. For example in Germany, the energy mix of 2012 is comprised of approximately 77% electricity produced in power plants which rely on fossil or nuclear fuels (gas, brown coal, hard coal and nuclear energy) in comparison to only 23% electricity from renewable sources, such as wind power, photovoltaics and biomass (UBA, 2016).

Then, corresponding to the previous calculation, a distinction between the traded products and its emission factor had to be made:

$$emiss_{ps_6,i,l}^{apv} = \begin{cases} elect_{ps_6,i,l} \times efact_{ps_6}^{electmix} + APV_{ps_6,i,l} \\ \quad \times \left(efact_{ps_6,l}^{reported} - efact_{ps_6}^{electmix}\right) & , APV_{ps_6,i,l} > 0 \\ elect_{ps_6,i,l} \times efact_{ps_6}^{electmix} + APV_{ps_6,i,l} \\ \quad \times \left(efact_{ps_6}^{cc} - efact_{ps_6}^{electmix}\right) & , APV_{ps_6,i,l} < 0 \\ 0 & , APV_{ps_6,i,l} = 0 \end{cases} \tag{4-51}$$

In order to adjust the externally sourced products, an average factor $efact_{ps_6}^{cc}$ of all 22 investigated plants was calculated from the carbon balance in Step 4 in relation to the locally produced amount of electricity. In contrast, sold products were adjusted by a plant-specific emission factor $efact_{ps_6,l}^{reported}$. This factor was derived from the CO_2e emissions which were allocated to the power plant in combination with the locally produced electricity.

To reach the targeted comparability among the examined production sites, the reported site-specific CO_2 emissions and the extended adjusted emissions which result from the intermediate trading were summed up respectively adjusted:

$$\sum_{i=1}^{n} emiss_{ps_x,i,l}^{adjusted} = \sum_{i=1}^{n} emiss_{ps_x,i,l}^{pv} + \sum_{i=1}^{n} emiss_{ps_x,i,l}^{apv} \tag{4-52}$$

The values were conclusively standardized to the amount of crude steel in order to meet the primarily defined functional unit of one t crude steel.

Finally, in order to complete the defined cradle-to-gate system boundaries (see section 4.3.3), the activities and according emissions of the upstream raw material supply chain were incorporated. As site-specific information in this regard could not be obtained due to the restricted access to primary data, industry average CO_2e emission values, which were derived from the ecoinvent database (Ecoinvent, 2007-2013) according to the CML2001 method for the impact category GWP100 (CML, 2020), were integrated depending on the necessary theoretical production volumes (see Step 6):

$$emiss_{ps_x,i,l}^{urmsc} = efact_{ps_x}^{urmsc} \times 1000 \times \sum_{\tilde{\imath}=1}^{\tilde{n}} PV_{ps_x,\tilde{\imath},l}^{theor} \quad (4\text{-}53)$$

Due to the missing data availability regarding the exact energy balance for single process steps, average input for electricity and natural gas was used for all process steps in the production plant. As electricity plays a major role and represents one of the top three triggers for CO_2e emissions in the upstream supply chain, the carbon footprint for the electricity input at the different process steps was adjusted on a regional – country – basis. On country level, the country specific data for conversion rates of the energy mixes to CO_2e are available (see section 4.3.4 and Appendix B, Table B-6).

In comparison to the production steps of the integrated site and the according production volumes, for the power plant (ps_6) the entire amount of produced electricity was consulted, taking the average electrical efficiency (ee_{ps_6}) into account:

$$emiss_{ps_6,l}^{urmsc} = efact_{ps_6}^{urmsc} \times 1000 \times \frac{\sum_{i=1}^{n} elect_{ps_6,i,l}}{ee_{ps_6}} \quad (4\text{-}54)$$

The secondary fuel natural gas has already been used in several steps of the calculation. As illustrated in Eq. (4-51), the overall amount of electricity, which includes the addition of natural gas in the power plant, has been credited and then adjusted by the amount of products traded. However, the actual CO_2e emissions for the externally purchased natural gas for the power plant (ipg_{NG}) have not been included yet.

These are calculated with average values ($efact_{ps_6}^{urmsc,NG}$) from the ecoinvent database (Ecoinvent, 2007-2013), scaled to the power plant-specific average factors for additional secondary fuel (see Step 3), and the theoretical production volume of the blast furnace at the considered plant:

$$emiss_{ps_6,l}^{urmsc,NG} = efact_{ps_6}^{urmsc,NG} \times ipg_{NG_l} \times \sum_{i=1}^{n} PV_{ps_3,i,l}^{theor} \quad (4\text{-}55)$$

4.4 Transfer of sub-model B to another material commodity[17]

In line with the overarching research objective and the structure of the integrated combined model (see Figure 4-1) as well as in reference to the requirements for sub-model B (see section 4.3.1), which aims at creating transparency of environmental performance on a site-specific level, a transfer of the developed standardized approach to another material commodity, such as aluminum was conducted.

The site-specific performance assessment model for aluminum - ECCO_2 aluminum (Evaluation tool to compare CO_2 emissions of the aluminum industry), follows the modular and sequential approach developed, which is based on the combination of a bottom-up and top-down calculation (see Figure 4-13). Specific characteristics of the production process for aluminum are integrated according to the developed procedure. The model is also based exclusively on the usage of publicly available data and is programmed in Microsoft Visual Basic and Excel to enable a user-friendly handling and regular updates of input data for practitioners (see section 4.1).

[17] Parts of this section were previously published in Schiessl et al. (2020a).

4.4.1 Definition of scope and functional unit

As carbon emissions represent the largest share of all GHG emissions in the non-ferrous metal industry, 97.22%, the scope in this study was accordingly defined on CO_2 emissions (UBA, 2019a). This includes process-related emissions, which are directly created during the aluminum production process at the site (Scope 1), and indirect, energy-related emissions (Scope 2), which are released during the electricity production that is hence consumed in the manufacturing process. Additionally, perfluorocarbons (PFC), which are formed during the anode effect in the electrolysis are also incorporated into the scope of the model. During this reaction very potent and stable greenhouse gases CF_4 (tetrafluoromethane) and C_2F_6 (hexafluoroethane), which are covered in the Kyoto protocol and included in the assessment, are formed in an approximate ratio of 10:1 (Ecofys, ISI, Öko-Institut, 2009; European Commission, 2014). The powerfulness of PFCs in terms of environmental impact is clearly evident considering the GWP with a 100-year time horizon for CF_4 of 7,390 t CO_2e/t raw aluminum and for C_2F_6 of 12,200 t CO_2e/t raw aluminum (IPCC, 2007).

Finally, all greenhouse gases resulting from upstream supply chain activities (Scope 3) were also considered. Resulting from the consultation of the same automotive expert group as for the development of the steel model, the geographic focus was laid on the four primary aluminum sites in Germany (see Figure 4-12).

In order to carry out a normalization of the LCI dataset (Roy et al., 2009), the functional unit was determined as one t of raw aluminum. This is a crucial performance measure in LCA which enables a comparability among aluminum producers (Bieda et al., 2015; International Standards Organisation, 2006b; Kndungu and Molavi, 2014), as raw aluminum represents the output product of the examined aluminum plants.

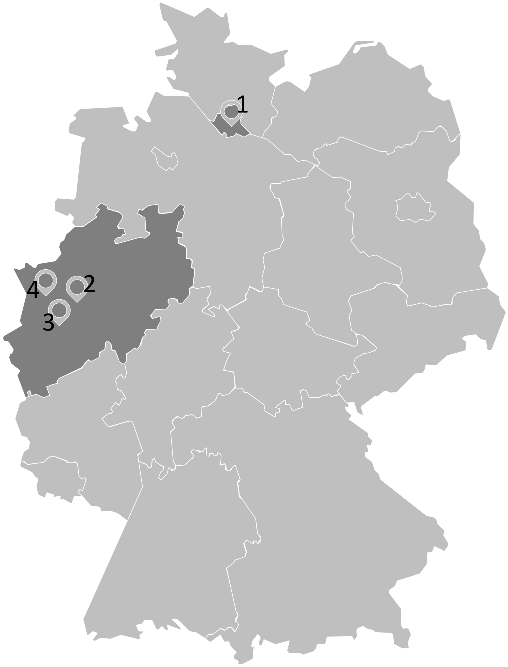


Figure 4-12: Geographic location of the considered primary aluminum plants in Germany

4.4.2 System boundaries

In combination with the functional unit, the system boundaries were set to enable a comparability among the results per site (see Figure 2-12) and to fit complementarily to the steel assessment (see section 4.3.3). It comprises all onsite operations for the production of primary aluminum within the gate-to-gate boundaries 'Production Plant'. The system under study is furthermore extended to a cradle-to-gate consideration of the 'Upstream supply chain SC' by means of industrial average emission data for upstream input material, which is based on ecoinvent data (Ecoinvent, 2007-2013) relying on the CML2001 method for the impact category GWP100 (CML, 2020), due to a non-availability of site-specific information.

The process flow diagram of the aluminum production, illustrated in Figure 2-12, summarizes all assessed process steps, emissions and external supplies which impact the site-specific CO_2e emissions in this study.

4.4.3 Data collection

A comprehensive data gathering process was conducted in the life cycle inventory phase (International Standards Organisation, 2006a), which is the basis for an assessment of the environmental impact on a site-specific level.

As the access to primary data is very restricted in the aluminum industry, the focus was laid on the collection of regularly updated and publicly available data sources (reference year of 2012[18]). This enables a continuous extension of the time horizon under study. In comparison to the data collection process carried out for the assessment of steel manufacture sites, the availability of public data is even more constricted in the aluminum industry and thus the data gathering was more effortful.

Similar to the regulations valid for the steel industry, each primary aluminum producing plant is required to apply for and receive permission for operation according to Industrial Emissions Directive 2010/75/EU (European Commission, 2010). Accordingly, the BAT reference document for the non-ferrous metal industry applies (European Commission, 2014, 2017). In this study, the BAT reference document, which was co-developed by the European Aluminium Association and its industrial members (European Aluminium, 2019; European Commission, 2017), the Environmental Profile Report (European Aluminium, 2013) and the publicly available site-specific data (see Table 4-11) serve as basis for the bottom-up, technology-driven assessment (see section 4.4.4).

[18] The reference year 2012 was chosen with regard to the data availability and the harmonization and comparison with the steel model (see section 4.3.4).

The obligation to report emissions to the European parliament and the council according to EC regulation No 166/2006 (European Commission, 2006) also requires member states to report the release of air pollutants from the aluminum producing industry. More specifically, the electrolytic production of non-ferrous crude metals and the production of graphite anodes (see section 2.4.1) are included, which represent the fundamentals for the top-down incorporation of the reported site-specific emissions (see section 4.4.4). Additional information about the data used is provided in Appendix B.

Table 4-11: Data sources applied (ECCO$_2$ aluminum)

Data Scope	Type of data	Source
Plant specific data	Capacities	Federal activity reports (BGR, 2012) International area reports - Minerals Yearbook (U.S. Geological Survey, 2013, 2015) Company specific reports
	Production Volumes	Company specific reports
	Emissions	European Pollution and Transfer Register E-PRTR (European Environment Agency, 2012)
General technical parameter	Production Process	Best Available Techniques BAT (European Commission, 2014, 2017) Environmental Profile Reports (European Aluminium, 2013) Life cycle inventory data (World Aluminium, 2013)
Country specific data	Electricity Mix	German Environment Agency (UBA, 2019a) European Environment Agency (European Environment Agency, 2018)
Carbon Footprint	Input material aluminum manufacturing	ecoinvent Data Base (Ecoinvent, 2007-2013)

4.4.4 Model development for aluminum

Some of the examined production sites do not have all necessary production steps for the required intermediate products located on-site. Others produce more than the locally required amounts. Hence, there exists a trading, purchase and sale of intermediate products between aluminum production sites. In a consequence, the related CO_2e emissions are currently reported at the location of origin where the intermediate products are manufactured. In order to enable a comparability among manufacturing sites and a subsequent normalization to the defined functional unit (t raw aluminum) in the developed model, these traded emissions are allocated by means of a credit procedure to the site where the intermediate products are finally processed to raw aluminum.

The modelling and assessment approach consists of seven calculation steps (see Figure 4-13[19]). In the first three Steps (S1-S3), a combination of a bottom-up technological calculation of site-specific material flows and a top-down integration with the reported process-related CO_2 emissions per site is conducted. Moreover, in Step 3 (S3) all plants are modelled as fully integrated plants and the emissions resulting from trading of intermediate products are adjusted respectively. In Step 4 (S4), the electricity consumption and its energy-related emissions in process steps located on-site are calculated, while adjustments for traded products are made according to the previous steps. In Step 5 (S5) and Step 6 (S6), PFC emissions resulting from the anode effect (section 2.4.1) as well as upstream supply chain emissions are included. Then, in Step 7 (S7), all types of previously calculated emissions are consolidated to comparable, overall site-specific values. Due to the high dependency of the developed model on the purpose of this study and the availability of data, in the following the model approach and the utilization of elementary structural data are described in a combined way.

[19] The single steps (S1-7) correspond to section 4.4.4 and will be further explained in the text.

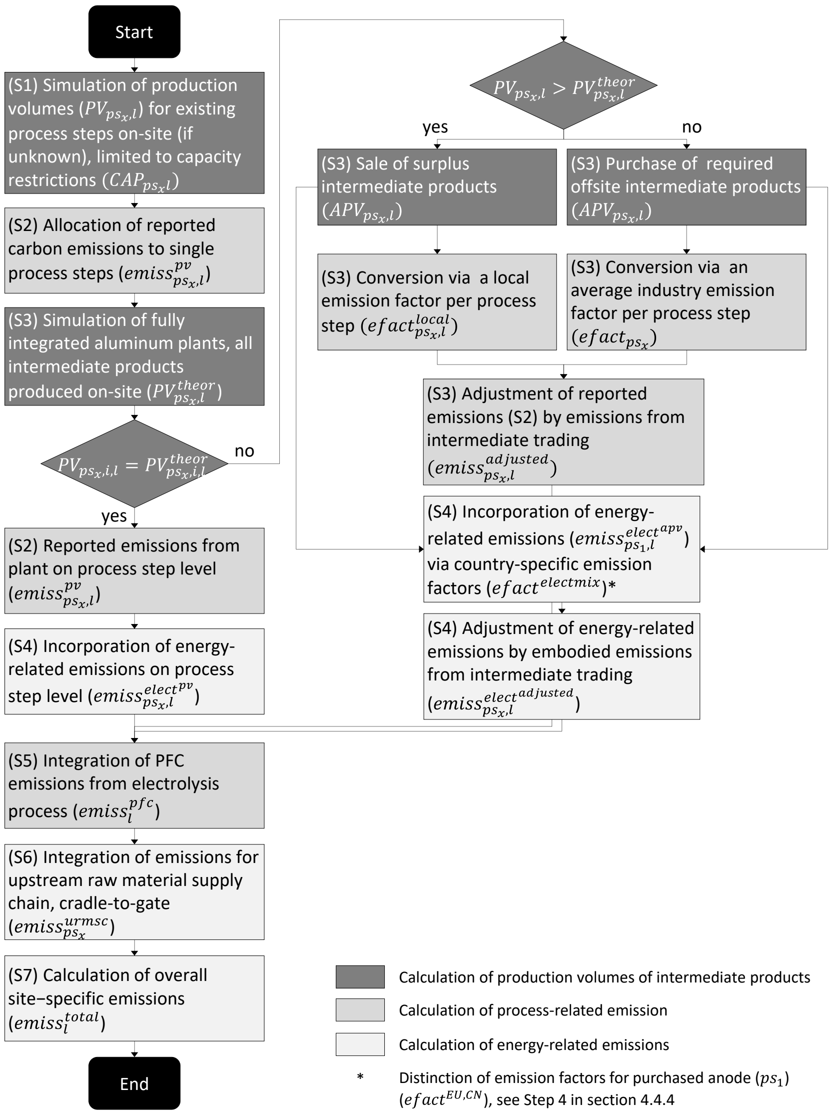


Figure 4-13: Flow chart of the site-specific CO_2e approach for predefined calculation steps

4.4.4.1 Step 1: Plant set-up to scale reported production volumes to process steps

Initially, the plant set-up is examined at the investigated production locations (l) according to the available process steps (ps_x) on-site (see Figure 2-12). It serves as basis for a later determination of the trading volumes of intermediate products (section 4.4.4.3) and to derive site-specific, process-related emission factors.

In order to determine if a production process is located at the examined production site, the capacities for single process steps ($CAP_{ps_x,l}$) were used (see Appendix B, Table B-7). In the aluminum industry, no reporting standards for the production volumes on process step level ($PV_{ps_x,l}$) exist. Whenever the actual production volume of an upstream or downstream process onsite ($CAP_{ps_x,l} > 0$) is not published (see Appendix B, Table B-8), average material conversion rates (mcr_{ps_x,ps_x}) are consulted to estimate the production volumes, while capacity restrictions (maximum capacities per process step) are taken into account. The material conversion rates (see Appendix B, Table B-9) are aggregated European average values (in $\left[\frac{t\ ps_x}{t\ ps_x}\right]$), which were derived in an survey among European aluminum manufacturers (reference year 2010) by European Aluminium (2013).

As basis for the estimation, the production volume of raw aluminum ($PV_{ps_3,l}$) was determined as reference value (see Figure 2-12 and section 4.4.3) and the production volumes for the process steps ps_1 and ps_2 were simulated backwards. In contrast, for the downstream process in ps_4 a forward calculation was carried out:

$$PV_{ps_2,l} = \begin{cases} mcr_{ps_2,ps_3} \times PV_{ps_3,l} & , CAP_{ps_3,l} > 0 \\ 0 & , CAP_{ps_3,l} = 0 \end{cases} \quad (4\text{-}56)$$

$$PV_{ps_1,l} = \begin{cases} mcr_{ps_1,ps_2} \times PV_{ps_2,l} & , CAP_{ps_1,l} > 0 \\ 0 & , CAP_{ps_1,l} = 0 \end{cases} \quad (4\text{-}57)$$

$$PV_{ps_4,l} = \begin{cases} \frac{PV_{ps_3,l}}{mcr_{ps_3,ps_4}} & ,CAP_{ps_4,l} > 0 \\ 0 & ,CAP_{ps_4,l} = 0 \end{cases} \quad (4\text{-}58)$$

Due to small material losses during rolling processes (ps_4), more input of the intermediate product raw aluminum (ps_3) is needed for one t of aluminum product (material conversion rate > 1), which requires an adjustment of the calculation (see Eq. (4-58)).

At this stage, due to non-availability of site-specific data, company or site-specific efficiency measures were not included. They are incorporated in the integration of top-down reported CO_2 emissions per production site in the following Step 2, and are further discussed in the conclusion (section 6).

4.4.4.2 Step 2: Allocation of reported carbon emissions to calculated carbon emissions

Relying on the previously examined plant set-up (Step 1), the actually reported site-specific CO_2 emissions of aluminum manufacturers ($emiss_l^{reported}$) are integrated into the model (see Appendix B, Table B-10).

The reported site-specific CO_2 emissions often comprise several emission-relevant on-site activities summarized to one overall CO_2 emission value (European Environment Agency, 2012). Thus, for an assignability to the according process steps, an intermediate calculation is necessary. For this, theoretical emissions for each process step ps and each location l ($emiss_{ps_x,l}^{theor}$) are calculated by means of industry average emission factors ($efact_{ps_x}$) (see Appendix B, Table B-11) and the actual production volumes ($PV_{ps_x,l}$) defined in Step 1:

$$emiss_{ps_x,l}^{theor} = efact_{ps_x} \times PV_{ps_x,l} \quad (4\text{-}59)$$

Consequently, the reported emissions can be physically allocated and distributed to the respective process steps on-site ($\tilde{x}$ serves as an auxiliary variable and corresponds to x):

$$emiss_{ps_x,l}^{pv} = emiss_l^{reported} \times \frac{emiss_{ps_x,l}^{theor}}{\sum_{\tilde{x}=1}^{4} emiss_{ps_{\tilde{x}},l}^{theor}} \quad (4\text{-}60)$$

This ensures that the allocated emissions ($emiss_{ps_x,l}^{pv}$) correspond to the reported emissions ($emiss_l^{reported}$) and that a plausible distribution across the process steps is performed.

In order to determine local, site-specific emission factors, consequently, the allocated emissions ($emiss_{ps_x,l}^{pv}$) were set in relation with the actual reported production volumes:

$$efact_{ps_x,l}^{local} = \frac{emiss_{ps_x,l}^{pv}}{PV_{ps_x,l}} \quad (4\text{-}61)$$

4.4.4.3 Step 3: Emission adjustment to combine the reported and calculated emissions

In order to create a comparability among aluminum plants and to determine the trading of intermediate products between plants in an auxiliary calculation, all examined plants are simulated as fully integrated. As not all obligatory process steps for the production of raw aluminum have to be carried out on-site ($CAP_{ps_x,l} = 0$), all necessary intermediate products are simulated to be produced onsite (fully integrated plant). This is necessary as the reported site-specific CO_2 emissions which only cover on-site activities (see Step 2) can thus report too low or too high emission values if intermediate products are produced offsite and procured, or manufactured on-site and then sold offsite.

Similar to the auxiliary calculation in Step 1, theoretical production volumes of upstream or downstream process steps on-site are derived via average material conversion rates. At this stage, capacity constraints are deliberately neglected and the production volume of raw aluminum is again consulted as a reference value ($PV_{ps_3,l}^{theor} = PV_{ps_3,l}$). The theoretical production volumes for the process steps ps_1 and ps_2 were simulated backwards, whereas for ps_4 a forward calculation was carried out (see Step 1):

$$PV_{ps_1,l}^{theor} = mcr_{ps_1,ps_2} \times PV_{ps_2,l} \quad (4\text{-}62)$$

$$PV_{ps_2,l}^{theor} = mcr_{ps_2,ps_3} \times PV_{ps_2,l} \quad (4\text{-}63)$$

$$PV_{ps_3,l}^{theor} = PV_{ps_3,l} \quad (4\text{-}64)$$

$$PV_{ps_4,l}^{theor} = \frac{PV_{ps_3,l}}{mcr_{ps_3,ps_4}} \quad (4\text{-}65)$$

Based on Step 1, the allocated actual production volumes per location ($PV_{ps_x,l}$) and the previously estimated, theoretical volumes ($PV_{ps_x,l}^{theor}$) are consequently put into relation in order to define additional production volumes (surpluses or shortages):

$$APV_{ps_x,l} = PV_{ps_x,l} - PV_{ps_x,l}^{theor} \quad (4\text{-}66)$$

In case the location's production volume is lower than the required theoretical production volume (negative $APV_{ps_x,l}$), a purchase of intermediate products from another site is assumed. Vice versa if the volume of the actual production on-site exceeds the necessary amount for the following process step, it indicates an offsite sale (positive $APV_{ps_x,l}$).

The embodied emissions, which come along with the trading of intermediate products ($emiss_{ps_x,l}^{apv}$), were defined by emission factors $efact_{ps_x}$. As for purchased products the origin of production cannot be traced back, average European factors were applied ($efact_{ps_x}$, see Appendix B, Table B-11). In contrast, for sold products the derived local emission factors ($efact_{ps_x,l}^{local}$) were consulted (see Step 2):

$$emiss_{ps_x,l}^{apv} = \begin{cases} APV_{ps_x,l} \times efact_{ps_x,l}^{local} & , APV_{ps_x,l} > 0 \\ APV_{ps_x,l} \times efact_{ps_x} & , APV_{ps_x,l} < 0 \\ 0 & , APV_{ps_x,l} = 0 \end{cases} \quad (4\text{-}67)$$

To create a comparability among aluminum production sites, the allocated and reported CO_2 emissions (see Step 2) are adjusted by the emissions resulting from traded intermediate products (additional production volumes):

$$emiss_{ps_x,l}^{adjusted} = emiss_{ps_x,l}^{pv} + emiss_{ps_x,l}^{apv} \quad (4\text{-}68)$$

With regard to the defined functional unit of kg CO_2e/t raw aluminum (see section 4.4.1), the values were conclusively normalized to the amount of raw aluminum produced onsite ($PV_{ps_3,l}$).

4.4.4.4 Step 4: Electricity consumption for produced and traded products

The production process of primary aluminum is highly energy intensive and particularly requires electricity (see section 2.4.1). As no site-specific information on the electricity consumption is available, a calculation on a national basis was carried out. Therefore, at first the amount of electricity according to the actual production volumes of intermediate products ($PV_{ps_x,l}$) is calculated by means of average input factors (see Appendix B, Table B-12) for the energy amount required per process step ($ip_{ps_x,l}^{elect}$):

$$elect_{ps_x,l}^{pv} = PV_{ps_x,l} \times ip_{ps_x,l}^{elect} \quad (4\text{-}69)$$

It is assumed that the production sites rely on the electricity provided by national power grids. Thus, the country-specific energy mix and country-specific conversion rates of the energy mix to CO_2e ($efact^{electmix}$) can be assumed, only depending on the location of the manufacturing plant. For Germany, this accounts to 0.573 kg CO_2e/kWh (UBA, 2019b) via the following equation:

$$emiss_{ps_x,l}^{elect^{pv}} = elect_{ps_x,l}^{pv} \times efact^{electmix} \quad (4\text{-}70)$$

Similar to Step 3, the emissions related to the traded intermediate products ($APV_{ps_x,l}$) are determined for each location l for process steps ps_2 to ps_4(equation (7)). It is assumed that trading is conducted exclusively within country borders and thus the same emission factor ($efact^{electmix}$) applies to all traded products.

In terms of trading of the intermediate product anode, a distinction is made between sold ($APV_{ps_x,l} > 0$) and purchased additional production volume ($APV_{ps_x,l} < 0$):

$$emiss_{ps_1,l}^{elect^{apv}} = \begin{cases} APV_{ps_1,l} \times ip_{ps_1,l}^{elect} \times efact^{electmix} & , APV_{ps_1,l} > 0 \\ APV_{ps_1,l} \times ip_{ps_1,l}^{elect} \times efact^{EU,CN} & , APV_{ps_1,l} < 0 \\ 0 & , APV_{ps_1,l} = 0 \end{cases} \quad (4\text{-}71)$$

For sold anode, the country specific emission factor ($efact^{electmix}$) is consulted. In contrast, for purchased anode the mean value of the European and Chinese emission factor for electricity production ($efact^{EU,CN}$) derived from Ecoinvent (2007-2013) is assumed with 0.818 kg CO_2e/kWh (EU: 0.488 kg CO_2e/kWh, CN: 1.148 kg CO_2e/kWh). This assumption is based on the fact that no exact country of origin is published for *anode* products. But, according to Norsk Hydro ASA (2012) and TRIMET Aluminium SE (2013), the examined sites rely primarily on anodes sourced from Europe and China.

Similar to the emission adjustment for the process-related emissions in Step 3, the energy-related, embodied emissions from the local on-site electricity consumption are combined with the embodied emissions caused from electricity used to produce the traded intermediate products:

$$emiss_{ps_x,l}^{elect^{adjusted}} = emiss_{ps_x,l}^{elect^{pv}} + emiss_{ps_x,l}^{elect^{apv}} \quad (4\text{-}72)$$

A normalization to the functional unit is conducted, similar to Step 3.

4.4.4.5 Step 5: PFC emissions from electrolysis process

Besides the process- and energy related emissions (CO_2 and other GHG emissions described in CO_2e), which were considered in the calculation so far, perfluorocarbon emissions (CF_4 and C_2F_6) are incorporated in the assessment (see section 4.4.1). PFC emissions are part of the European reporting obligation for non-ferrous metal producing plants, E-PRTR (European Environment Agency, 2012). Facilities are required to report the total annual amount of perfluorocarbon emissions without a further breakdown into the type or exact composition (see Appendix B, Table B-10). Hence, the reported PFC emissions per production site ($emiss_l^{reported^{pfc}}$) were first converted into their GWP (expressed in CO_2e) by means of a characterization coefficient (emission factor ($efact_{Ø}^{pfc}$)). Then, a normalization to the functional unit was conducted:

$$emiss_l^{pfc} = \frac{emiss_l^{reported^{pfc}} \times 1000 \times efact_{Ø}^{pfc}}{PV_{ps_3,l}} \quad (4\text{-}73)$$

As the exact composition of different PFC molecules per site is not available, an average ratio for Centre Worked Prebake - Point centre feed anodes (PFPB) is applied in combination with the GWP of CF_4 and C_2F_6 (World Aluminium, 2016):

$$efact_{Ø}^{pfc} = \left(\frac{9}{10} \times 7{,}390\right) + \left(\frac{1}{10} \times 12{,}200\right) \quad (4\text{-}74)$$

4.4.4.6 Step 6: Upstream cradle-to-gate supply chain emissions

In order to fully assess the defined scope and the system boundaries (cradle-to-gate) (see sections 4.4.1 and 4.4.2), finally emissions from the upstream raw material supply chain were integrated. As respective site-specific information is not publically available, industry average values from the ecoinvent database (Ecoinvent, 2007-2013) were consulted.

Due to the site-specific consideration of the emissions from the anode production ($emiss_{ps_1,l}^{adjusted}$), the emissions for electricity consumption for all process steps ($emiss_{ps_x,l}^{elect^{adjusted}}$) and the reported PFC emissions ($emiss_l^{reported^{pfc}}$), these values have accordingly been excluded from the industry averages. As all examined manufacturers are located in the same country, consequently the same value of 2,814 kg CO_2e/t raw aluminum (Ecoinvent, 2007-2013) for upstream raw material supply chain activities ($emiss_l^{urmsc}$) applies.

4.4.4.7 Step 7: Overall site-specific emissions (adjusted)

Finally, the total amount of site-specific emissions per production location can be derived by the addition of the previously calculated, different types of emissions (process-related emissions $emiss_{ps_x,l}^{adjusted}$ and energy-related emissions $emiss_{ps_x,l}^{elect^{adjusted}}$, PFC emissions $emiss_l^{pfc}$ and upstream supply chain emissions $emiss_l^{urmsc}$):

$$emiss_l^{total} = \sum_{x=1}^{4} emiss_{ps_x,l}^{adjusted} + \sum_{x=1}^{4} emiss_{ps_x,l}^{elect^{adjusted}} + emiss_l^{pfc} + emiss_l^{urmsc} \quad (4\text{-}75)$$

With this value, the environmental performance of different aluminum manufacturing sites provides the basis for a possible integration into supplier selection decisions (see section 5).

5 Application of the integrated CO_2e assessment and decision support model[20]

In this section, the developed integrated CO_2e assessment and decision support model is exemplary applied in an automotive case study. Initially the application results of the environmental performance assessment for the examined material commodities are presented, validated and discussed in section 5.1, 5.2 and 5.3. Moreover, the estimated site-specific results are applied in section 5.4 to derive implications for emission mitigation targets. In section 5.5, the developed sub-models are coupled and the combined techno-economic approach is applied in a decision-making case study for the supplier selection of a chosen sample part. By means of sensitivity analysis, in section 5.6 the model is tested for robustness. In section 5.7, scenario simulations for the criteria integration in order to support the formulation of a new criteria while incorporating both an environmental as well as an economic perspective are presented.

5.1 Site-specific performance results for steel

According to the defined geographical scope of this study (see section 4.3.2), the developed attributional model was applied on a selection of 22 production locations of integrated steel plants in EU-15 countries.

The production sites, which vary in levels of process steps, have a maximum of four facilities (i) per process step (x) at location (l) $(ps_{x,i,l}, x \in \{1;6\}$,

[20] Parts of this section have been previously published in Schiessl et al. (2020a) and Schiessl et al. (2020b).

$i \in \{1;4\}, l \in \{1;22\}$). The results of the site-specific performance estimation for the selected European sample of primary steel manufacturers are shown in Figure 5-1.

The illustrated differences among the steel mills under study confirm the initially described need for a site-specific assessment of suppliers CO_2e performance, when CO_2e shall be used for making supplier selection decisions. In reference to the defined requirements of the model and the focus on an estimation of the overall performance per site and not on a detailed facility level (see section 4.3.1), the results for fully integrated steel mills in kg CO_2e/t crude steel (see section 4.3.5) range from the so called 'Best-in-Class' (BiC) supplier with 1,879 kg CO_2e/t crude steel to the least efficient 'Worst-in-Class' (WiC) supplier with a performance of 2,990 kg CO_2e/t crude steel. Hence, the overall performance range represents a deviation of 58% from the BiC to the WiC steel production site which includes both, country specific and in particular site-specific differences in production efficiency. The estimated results show an average performance value of 2,352 kg CO_2e/t crude steel among the investigated European steel plants. An analysis on a national level, for example of all eight German integrated steel mills which are included in the European sample illustrated above, shows a lower average environmental performance value of 2,174 kg CO_2e/t crude steel. An environmental performance for the BiC supplier of 1,879 kg CO_2e/t crude steel and the WiC supplier of 2,497 kg CO_2e/t crude steel moreover reveals a lower performance range of 33% compared to the European market of selected manufacturers.

The single values for production steps can show discrepancies, which is due to the top-down integration of the reported CO_2e emissions and the consequently conducted allocation to the single process steps. This aspect can however be neglected, as all reported CO_2 emissions were incorporated in the model and as described above, the overall value per production plant (see Figure 5-1) is oriented to the main production volumes and the according emissions. An analysis of the results revealed that these differences can be traced back to several reasons. One significant reason is the varying level of production depth and hence that not all considered production sites present fully integrated steel plants. This means that some necessary process steps are not located at site and thus the according intermediate products need to be externally sourced (see section 1.1). In comparison to fully integrated plants, this can for example negatively affect the reuse of process gas flows and the internal energy management, as the process steps are not as efficiently linked as possible. This goes hand in hand with existing variations in capacity utilization rates, which additionally reinforce this argument. Moreover, company internal process know-how on efficiency measures plays a crucial role. This also counts for company internal, process step specific adjustments of technological installations. The geographic location of the manufacturing plant on a country level can also lead to variations in results, as the avoidance of external electricity generation is credited in the model by means of country specific energy mixes (see section 4.3.5).

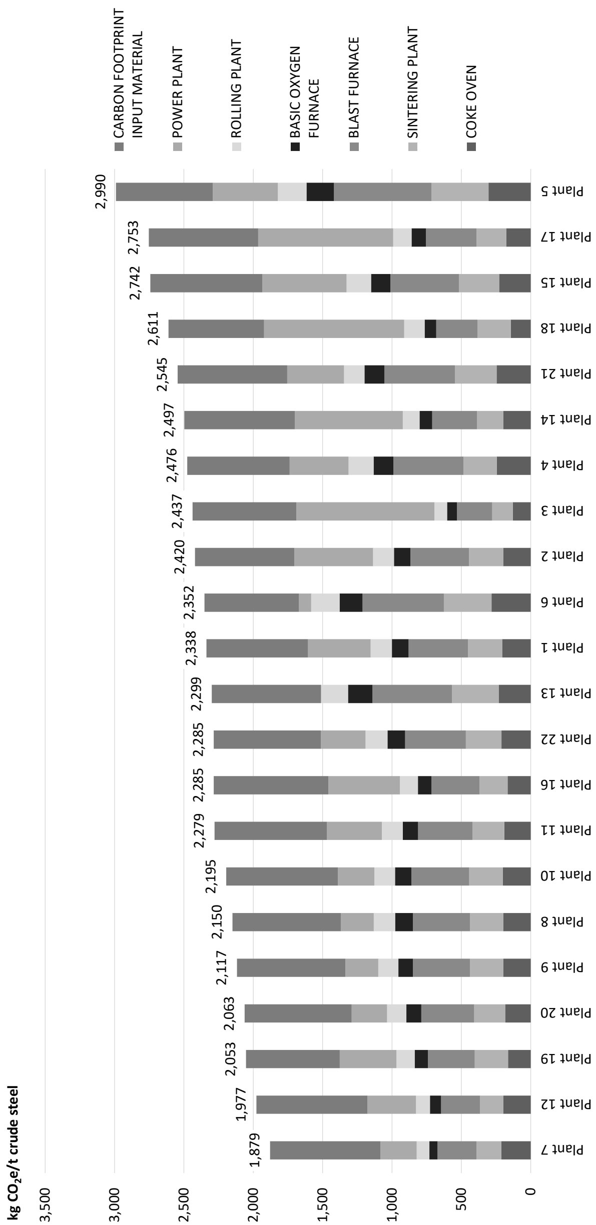


Figure 5-1: Results of the 22 integrated steel mills in EU-15 after the emission adjustment

5.2 Site-specific performance results for aluminum

The developed model, which was transferred to the material commodity aluminum (see section 4.4), was, according to the defined scope (see section 4.4.1), consecutively applied on all electrolysis-based, primary aluminum manufacturing sites in Germany (four sites) ($ps_{x,l}, x \in \{1; 4\}, l \in \{1;\ 4\}$).

The estimated results for the production sites under study (overall amounts per production site) range from the most efficient 'Best-in-Class' (BiC) plant 13,689 kg CO_2e/t raw aluminum to the least efficient 'Worst-in-Class' (WiC) plant 14,946 kg CO_2e/t raw aluminum. As shown in Figure 5-2, there is only slight scattering of results of approximately 9%. On average, there are 14,111 kg CO_2e/t raw aluminum emitted among the examined primary aluminum plants.

Despite the relatively low percentage deviation between the BiC and WiC site, the absolute difference of 1,275 kg CO_2e/t raw aluminum (see Figure 5-2) supports the initially described need for a CO_2 performance assessment of suppliers on a site level (see section 4.2.4), when it is intended to use CO_2e as basis for supplier selection decision making.

The deviations of the estimated, absolute environmental performances of the examined manufacturing sites can mainly be traced back to company internal process know-how and process step specific efficiency measures respectively advanced technological installations. However, due to the top-down integration approach of the reported CO_2 emissions, which is oriented to the main production volumes, already implemented company-specific process expertise is incorporated in the model. The applied allocation procedure on process step level (see Step 2) can lead to slight discrepancies in terms of the single values per process step.

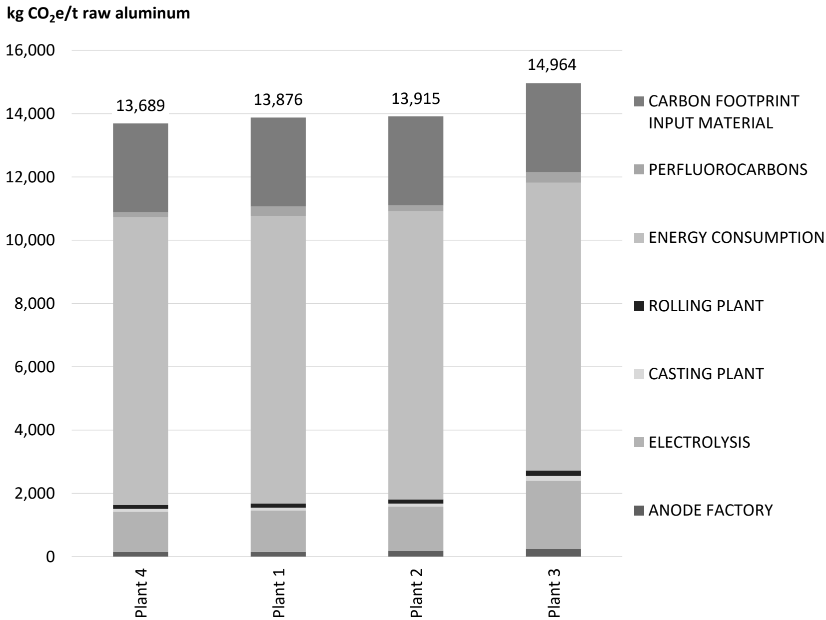


Figure 5-2: Results of the examined, German primary aluminum plants after the emission adjustment

5.3 Validation of the site-specific performance results

5.3.1 Validation of results for steel manufacturing

Over a period of two years the developed model and the estimated results were analyzed and validated in personal interviews with experts from one steel manufacturer from the German-speaking region. This comprised an in-depth analysis of each step of the calculation, the described assumptions as well as the logic for creating a comparability by simulating fully integrated sites (each process step on-site). The detailed model and specifically the modelling of intermediate product trading at various process steps was confirmed while no company internal know-how was disclosed. The results per site were additionally compared to primary data of two other European steel manufacturers, which are included in the examined sample of 22 EU-15 manufacturers. Due to existing non-disclosure agreements, only percent variances of the overall site value (kg CO_2e/t crude steel) can be published. These values however illustrate an auspicious deviation of max. 5% per site.

Moreover, the estimated average site value of 2,352 kg CO_2e/t crude steel (22 European steel manufacturers) was compared to an European industry average value of 2,408 kg CO_2e/t crude steel derived from the ecoinvent database (Ecoinvent, 2007-2013). The estimated average value goes coherently with the consulted ecoinvent average value and shows only a slight deviation of 2.3% (56 kg CO_2e/t crude steel).

Finally, the estimated overall site values of the eight German steel manufacturers included in the European sample were compared to the results from the NLP model developed by Breun (2016). As basis for the comparison, the NLP model (see sections 3.2.4 and 4.3.1) was updated with data from 2012 in order to align the reference years. This study focused on the same eight integrated steel sites in Germany however in gate-to-gate consideration without the carbon footprint of upstream supply chain activities (w/o CF). Therefore, the estimated values from the $ECCO_2$ steel model are also illustrated from an equal gate-to-gate perspective (see Figure 5-3). The results of Breun (2016) show a deviation of 34% between the most efficient BiC supplier and the least efficient WiC supplier. In comparison, the results from the developed $ECCO_2$ steel approach for the same eight manufacturers, without considering the carbon footprint of the upstream supply chain, illustrate a very close deviation of 36% between the BiC and WiC supplier. A comparison among the single values per considered manufacturing sites revealed a mean deviation of only 4%.

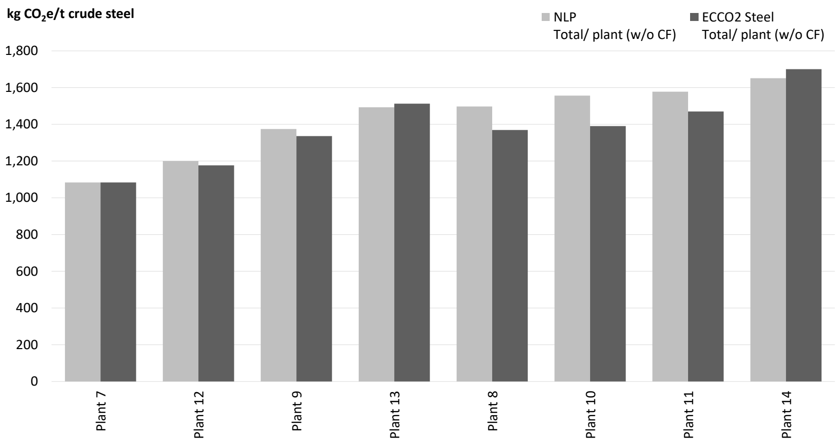


Figure 5-3: Comparison of site-specific results for eight German steel manufacturers from the NLP and $ECCO_2$ steel model

5.3.2 Validation of results for aluminum manufacturing

The calculation procedure of the developed model including the created comparability (simulation of all intermediate products being produced on site), as well as the described assumptions were continuously analyzed and validated with experts from one manufacturer from the German-speaking region in in-depth interviews over a period of two years. The detailed modelling approach was confirmed but no internal know-how was revealed. Only percentage variances of the absolute values which show a very promising deviation of max. 6% can be published because of a non-disclosure agreement.

In addition, the estimated average value was compared to the European average value of 12,121 kg CO_2e/t raw aluminum derived from the ecoinvent database (Ecoinvent, 2007-2013), relying on an electricity generation emission intensity of 0.353 kg CO_2e/kWh for the reference year 2012 (European Environment Agency, 2018). The significant difference of 1,990 kg CO_2e/t raw aluminum furthermore points out the crucial role of electricity (especially for the electrolytic reduction process) and the according underlying energy mix depending on the country of location. Due to the defined scope of the study, the model makes use of the emission intensity for the German energy mix in 2012 of 0.573 kg CO_2e/kWh (UBA, 2019b), illustrating a deviation of 62% (0.220 kg CO_2e/kWh). Moreover, the total amount for PFC emissions of 1,860 kg CO_2e/t raw aluminum deposited in the database exceeds the incorporated, reported and only normalized PFC emissions, on average by 1,559 kg CO_2e/t raw aluminum. This can be considered as indication for the efficient process control and conduction of the examined production sites.

A manual manipulation of the ecoinvent data, applying the Germany emission intensity and the average PFC emissions from the developed model, results in an adjusted, average value of 13,921 kg CO_2e/t raw aluminum. Thus, only a slight deviation of 1.37% (190 kg CO_2e/t raw aluminum) in comparison to the average, estimated value of 14,111 kg CO_2e/t raw aluminum becomes apparent.

5.4 Implications for emission mitigation targets

In an exemplary application, the results obtained from the developed site-specific, attributional approach for steel (see section 5.1) were used to derive consequences for the overall amount of GHG emissions in Europe. Therefore, the estimated environmental impacts of the selected raw materials, in this case also considered as products, are used similarly to a consequential LCA approach, which estimates the effects of the production and usage of a product on global environmental burdens(Ekvall, 2020).

At first, the average material composition of the VW GOLF VII (see Figure 2-8) with a share of 912 kg steel (62.9% of the entire vehicle weight) is consulted in combination with all new registered 15.136 Mio passenger cars in Europe in 2017 (European Commission, 2019a) as basis for the calculation. Hence, a projection of the new vehicle registrations and the material share, with the estimated average environmental impact of 2,353 kg CO_2e/t crude steel derived from the examined steel manufacturers in Europe (see section 5.1), presents a share of ~1% of the overall European GHG emissions (4.629 Mt CO_2e, (European Environment Agency, 2019d)). Thus, based on the same material parameters as above, a comparative calculation by means of the environmental impact of the derived BiC and WiC steel supplier (see Figure 5-1) reveals a possible annual reduction potential of 15.34 Mt CO_2e with respect to all new European registrations in 2017 (see Figure 5-4).

The same sample car (see Figure 2-8), with a share of 119 kg aluminum (8.2% of the entire vehicle weight), is again consulted to derive consequences for overall European GHG emissions. In combination with the estimated average amount of 14,111 kg CO_2e/t raw aluminum, a projection on all new registered passenger cars in Europe in 2017 illustrates a share of 0.6% of the entire GHG emissions in Europe. An application of the same parameters in combination with the BiC and WiC aluminum manufacturers reveals a possible reduction potential of 2.3 Mt CO_2e in reference to new vehicle registrations in 2017 (see Figure 5-5).

The performed approximations not only confirm the necessity of a site-specific consideration but also point out the general need to foster technological improvements of steel manufacturers to reduce environmental impact.

It however represents only an individual perspective, as currently not all customers can possibly source the material, in this case primary steel, from the revealed BiC European supplier due to capacity restrictions. Nevertheless, a rising demand from several customers for 'greener' produced steel will urge raw material manufacturers respectively suppliers to rethink existing production processes in order to maintain and even increase competitive advantages as well as market share. In consequence, it will additionally lead to a movement of the entire steel producing market and will trigger the improvement of internal process efficiencies and the according reduction of the carbon footprint of steel products.

Moreover, in case of pursuing a general carbon neutrality of a product, as illustrated by the example of the Volkswagen ID project (Volkswagen AG, 2019) mentioned in section 1.1, even the most efficient, BiC supplier will be obliged and motivated to further improve existing or develop new production technologies, and to further maximize efficiency in production processes.

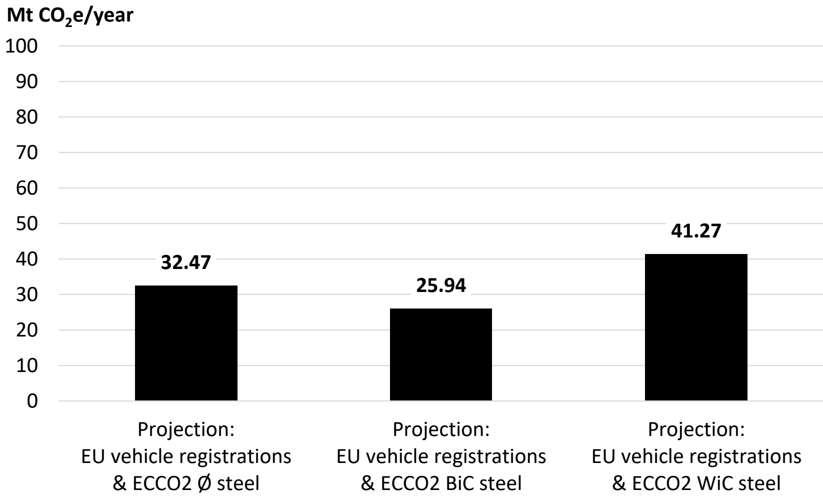


Figure 5-4: Consequential approximations on a European scale - steel

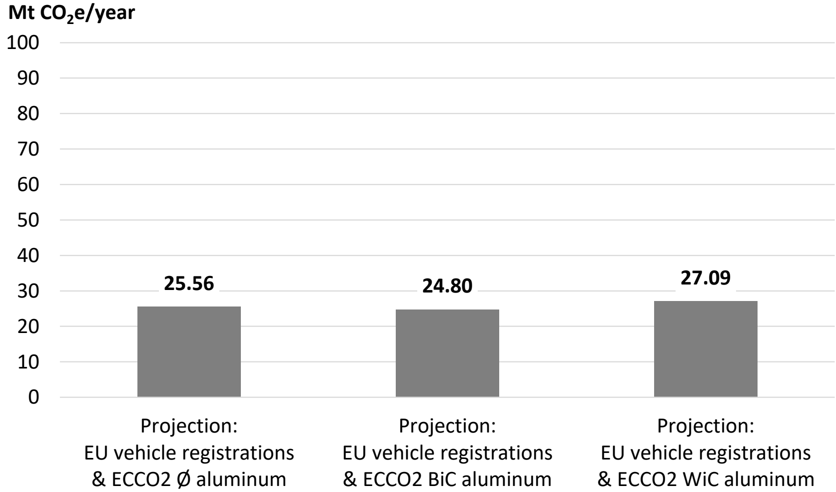


Figure 5-5: Consequential approximations on a European scale - aluminum

Besides the previously described approximations based on an individual consideration of steel and aluminum, the estimated site-specific results allow for a combined modelling of for example a vehicle consisting of a specific material composition from an environmental perspective.[21] Therefore, the material composition presented in Figure 2-8 of the VW GOLF VII is used in combination with the site-specific environmental performance results for a projection based on the European vehicle registrations from 2017. In addition to the general breakdown by single types of raw material, a differentiation

[21] The developed standardized approach for site-specific environmental performance assessment has furthermore been transferred to the secondary production of steel and aluminum and applied in a case study on selected German manufacturing sites. Due to the simplified production processes of the secondary materials in comparison to the complex only the results of the calculation are presented in Appendix B, Figure B-1 and Figure B-2. The results used for plastics, polyamide 6 (PA6), rely on a model of Müller et al. (2020), which was also developed in the course of the research project of the Karlsruher Institute of Technology (KIT) in cooperation with industrial partners from the automotive industry (see section 1.2), and are presented in Appendix B, Figure B-3.

depending on the production processes for the material types and the according environmental impact needs to be taken into account. Therefore, an industry mix for material usage is consulted showing a ratio of 80/20% for primary and secondary steel (Acosta Fernández and Bringezu, 2007) and of 68/32% for primary and secondary aluminum (Helms, 2011). For plastics 100% polyamide 6 (PA6) was exemplarily assumed. The results illustrated in Figure 5-6 show a significant difference of 18.51 Mt CO_2e between the environmental impact of the sample vehicle depending on the BiC and WiC suppliers for each material.

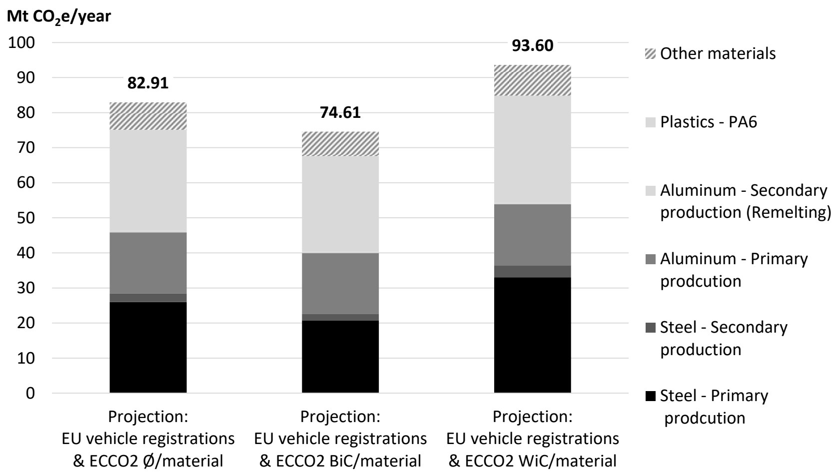


Figure 5-6: Consequential approximations on a European scale - material composition

The estimated environmental performance results also allow to simulate changes in material compositions and replacements of one type of material with another (for example primary and secondary steel) in order to reveal additional environmental impact reduction potentials. For example a 50% replacement of primary steel with secondary, recycled steel will lead to a total value of 4,058 kg CO_2e/car, based on the average environmental performances, 2,353 kg CO_2e/t for primary and 879 kg CO_2e/t for secondary steel. It illustrates a potential to reduce the carbon footprint by 537 kg CO_2e respectively 12%. A projection on a European scale by means of all new passenger car registrations in 2017 will lead to a possibility to reduce the European carbon footprint by 8.13 Mt CO_2e in comparison to the previously described and applied industry mix for material usage (see Figure 5-6).

Moreover, in relation to automotive life cycle phases (see section 2.2.2), the results of the developed approach for the assessment of the manufacturing phase allow to make approximations regarding the vehicle use phase

Taking the material share of steel of the VW Golf example (62.9% or 912 kg), a conversion into environmental impact based on the least and most efficient primary steel supplier (see Figure 5-1) results in a range of 1,714 to 2,727 kg CO_2e/vehicle and thus illustrates a possibility to save up to approximately 1,000 kg CO_2e per car. Setting the environmental impact of 1,000 kg CO_2e in relation to exemplary average emissions from the vehicle use phase of 113 g CO_2/km (Volkswagen AG, 2012) while considering a vehicle lifespan of 150,000 km (Weymar and Finkbeiner, 2016), the saving in the manufacturing phase equals roughly 9,000 km CO_2e emissions in the use-phase.

5.5 Combination of sub-models to an integrated techno-economic model

At this stage, the developed sub-models are coupled by integrating the results derived from the site-specific performance assessment into the decision support model to form a techno-economic model. So far, an introduction of CO_2e as new decision criteria in supplier selections was not possible as only average performance values from data-bases, which do not allow for a site-specific consideration and comparison among alternative suppliers, were available.

By means of the developed site-specific CO_2e approach this hurdle can be now be overcome.

In a first step, the site-specific performance results for the EU-15 primary steel manufacturers are exclusively considered (see Figure 5-1). Therefore, the selected sample part and the according selection criteria as well as supplier performance data described in section 4.2.3.4 are consulted, and combined with site-specific environmental performance data from the sample of European primary steel manufacturers for the new criteria 'CO_2e component manufacturing' (C51). The procedure corresponds to the exemplary application of the decision support model in section 4.2.4 (see Figure 4-8, Case 1 and 2) and serves to furthermore demonstrate the relevance of a site-specific level of performance assessment and the impact on supplier decisions to be made. Hence, the sample part with a total weight of 18.36kg is again assumed to be produced exclusively from steel, however due to the consideration of the site-specific values per t crude steel the CO_2e performance now varies.

Consequently, for supplier 1, a total CO_2e performance of 50.53 kg CO_2e/part (by 2,753 kg CO_2e/t crude steel), for supplier 2 of 43.17 kg CO_2e/part (by 2,352 kg CO_2e/t crude steel), for supplier 3 of 37.68 kg CO_2e/part (by 2,053 kg CO_2e/t crude steel), for supplier 4 of 43.17 kg CO_2e/part (by 2,352 kg CO_2e/t crude steel) and for supplier 5 of 42.92 kg CO_2e/part (by 2,338 kg CO_2e/t crude steel) is calculated (see Figure 5-7, Case 3).

In combination with the performance on the other economic selection criteria, a ranking of alternative suppliers is derived for Case 3 (see Figure 5-7). The calculation of suppliers' total performance score based on integration of supplier specific performance data in combination with the investigated criteria weight of 2.67% for criteria C51 leads to a new supplier ranking of S3 → S1 → S2 →S5 → S4. More details on the calculated ranking are presented in Table 5-1.

In this case 3, the environmental performance data for supplier 1 and supplier 3 show a deviation of 34.10%. This difference in environmental performance in terms of criteria C51 leads to a changed alternative recommendation, preferring supplier 3 over supplier 1.

Thus, the originally revealed necessity of site-specific CO_2e performance evaluation as basis for the integration of CO_2e as supplier selection criteria is considered to be confirmed.

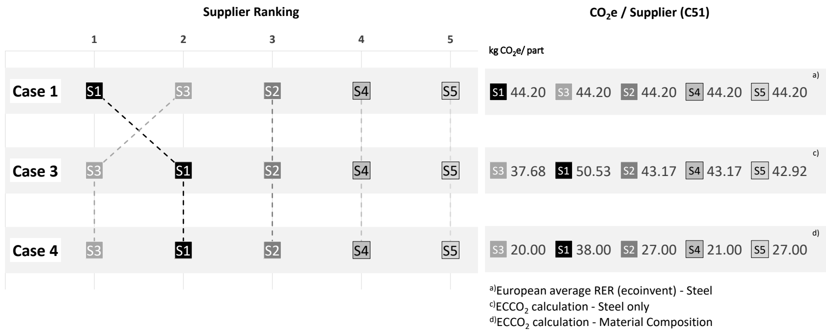


Figure 5-7: Influence of CO_2e (C51) on supplier ranking (Part 2)

Table 5-1: Evaluation and ranking of alternatives (Case 3) based on $ECCO_2$ calculation - steel

Supplier	Distance (PIS)	Distance (NIS)	Proximity Index (relative closeness)	Ranking
	ds^+	ds^-	$P_i = \frac{ds^-}{ds^+ + ds^-}$	
S1	0.0312643	0.0937531	0.7499205	2
S2	0.0702395	0.0605765	0.4630662	3
S3	0.0310927	0.0937687	0.7509823	1
S4	0.0892722	0.0371559	0.2938895	5
S5	0.0980000	0.0433874	0.3068689	4

After the general confirmation of the functionality of the model by means of Case 1, Case 2 and Case 3, a more complex material composition of the sample part, which represents a real-life case of a part sourced by a German OEM from a Tier-1 supplier, was applied in the further course of this research. Therefore, Case 4 was chosen to demonstrate the possibility of the developed model to simultaneously include different materials in the decision-making process in combination with site-specific CO_2e performance data. The material composition of the selected sample part comprises a variety of different components made by primary and secondary steel as well as aluminum, plastics (Polyamide 6) and a small share of additional materials. As described in section 4.2.3.4, due to confidentiality no further information on the exact material breakdown could be published, however an indication is given in Appendix A, Figure A-4. The calculation of environmental performance data in case 4 (see Table 5-2) is based on the application of the derived site-specific evaluation results (see Figure 5-1, Figure 5-2[22] and Appendix B, Figure B-1, Figure B-2 and Figure B-3) on the actual material compositions of the selected real life case part. The results show CO_2e performance data for supplier 1 of 38 kg CO_2e/part, for supplier 2 of 27 kg CO_2e/part, for supplier 3 of 20 kg CO_2e/part, for supplier 4 of 21 kg CO_2e/part and for supplier 5 of 27 kg CO_2e/part (see Table 5-2).

[22] The values used for aluminum are based on the average result from the four examined German aluminum sites and were adjusted with the emission factors for the electricity mix depending on the country of origin of according aluminum suppliers. Due to confidentiality reasons the location of the supplier could not be disclosed.

Table 5-2: Material composition (Case 4) calculated with combined LCA - $ECCO_2$ approach

	CO_2e Raw material production*	Primary steel		Secondary steel		Primary aluminum		Secondary aluminum		Plastics PA-6		Rest**	
	Sum/ part	$ECCO_2$ (kg CO_{2e}/kg)	CO_2e/part (kg CO_2e)	$ECCO_2$ (kg CO_{2e}/kg)	CO_2e/part (kg CO_2e)	$ECCO_2$ (kg CO_{2e}/kg)	CO_2e/part (kg CO_2e)	$ECCO_2$ (kg CO_{2e}/kg)	CO_2e/part (kg CO_2e)	$ECCO_2$ (kg CO_{2e}/kg)	CO_2e/part (kg CO_2e)	GaBi7 2017 (kg CO_2e/kg)	CO_2e/part (kg CO_2e)
Supplier 1	38 kg CO_2e/part	2.753	0.461	0.793	9.727	10.695	20.808	1.601	4.672	6.354	1.557	0.746	0.607
Supplier 2	27 kg CO_2e/part	2.352	0.394	0.793	9.727	6.642	8.723	1.601	5.685	6.354	1.557	0.746	0.607
Supplier 3	20 kg CO_2e/part	2.053	0.344	0.793	9.727	5.785	0.281	1.601	7.709	6.354	1.557	0.746	0.607
Supplier 4	21 kg CO_2e/part	2.352	0.394	0.793	9.727	6.642	0.969	1.601	7.554	6.354	1.557	0.746	0.607
Supplier 5	27 kg CO_2e/part	2.338	0.391	0.793	9.727	8.247	8.023	1.601	6.230	6.354	1.557	0.746	0.607

*due to confidentiality no further breakdown of the percent share of material could be published

**operating supplies: lubricants, cleaners, etc.

The different CO_2e performance data per part of the five considered supplier alternatives can on the one hand be attributed to the site-specific efficiencies in production processes of the analyzed raw material suppliers. On the other hand, it can be traced back to slight variations in the material composition of the raw material used by the different suppliers. For example, the amount of primary aluminum used has a strong impact on the overall environmental performance data of a supplier, as primary aluminum has a very high CO_2e performance score per t compared to steel, due to the strong dependency on electricity and thus the country specific energy mix. The focus was again laid on the CO_2e emission from raw materials used in the selected part and emissions for further downstream processing and logistics were excluded.

The implementation of the calculated environmental performance data (see Table 5-2) in the decision support sub-model result in a changed preference ranking: S3 → S1 → S2 →S5 → S4 (see Figure 5-7, Case 4 and Table 5-3).

Table 5-3: Evaluation and ranking of alternatives (Case 4) based on $ECCO_2$ calculation - material composition

Supplier	Distance (PIS)	Distance (NIS)	Proximity Index (relative closeness)	Ranking
	ds^+	ds^-	$P_i = \frac{ds^-}{ds^+ + ds^-}$	
S1	0.0320442	0.0937531	0.7452714	2
S2	0.0702899	0.0607331	0.4635298	3
S3	0.0310927	0.0940316	0.7515055	1
S4	0.0892606	0.0378358	0.2976939	5
S5	0.0980372	0.0436025	0.3078408	4

The results are again based on the consolidated criteria weights derived from the expert group from the non-consumable purchasing division and the overall supplier performance data according to the other selection criteria (see Table 4-4).

In comparison to the established preference ranking of Case 1 (see Figure 5-7), in case 4, supplier 3 illustrates the most preferable alternative with a P_i of 0.7515055 (see Table 5-3). In terms of the newly integrated criteria C51, the performance data of supplier 3 and the previously first ranked supplier 1 deviate by 18 kg CO_2e/part respectively 90.00%. This results in a total reduction of the environmental impact of 18,000 t CO_2e considering the entire project duration, respectively total amount of parts sourced. Additionally, not only environmental effects can be disclosed, but also implications on the economic aspect of a decision situation can be derived. The consequent selection of supplier 3 entails only slightly higher project cost of 0.210 Mio € in comparison to supplier 1 while inducing a significant reduction potential of the environmental impact. Further implications from an economic perspective are emphasized on in section 5.7.

By means of Case 4, the general necessity for as well as functionality of the combined techno-economic model developed in section 4 (see Figure 4-1) is finally confirmed and the possibility to draw first conclusions from an economic as well as environmental perspective is illustrated.

5.6 Sensitivity analysis

In order to analyze and determine the uncertainty of the model output in correlation to the input factors, a thorough sensitivity analysis was conducted. Thus, the stability of the results from the pairwise comparison is analyzed and the robustness of the sub-model for decision support tested, which is essential for multi-criteria models used for supplier selections but has not been focused on in scientific literature so far (see section 3.1.5). It is especially important when the results partially rely on expert assessments, as it is the case in this research contribution with the criteria weights derived by pairwise comparisons (Perçin, 2009). It thus enables decision makers to identify the most critical pairwise comparisons and to consequently make adjustments in the considered set of selection criteria, if necessary. The following conduction of sensitivity analysis relies on the consolidated criteria weights (AIJ) derived from the selected sample of 25 purchasing experts (see Table 4-4) in combination with the real-life case study part (see Table 4-6) including the supplier specific CO_2e performance scores in Case 4 (see Figure 5-7).

Initially a numerical, one-at-a-time (OAT) analysis (see section 4.2.2.3) was performed and the criteria weights were constantly changed in steps of plus/minus five percent up to plus/minus twenty five percent (Δ_{SS}: +0,05; +0,10; +0,15; +0,20; +0,25; -0,05; -0,10; -0,15; -0,20; -0,25). The step weight procedure is applied on the derived criteria weights assuring that the adjusted weights are not less than zero. Furthermore, the condition that the total sum of weights for the manipulated and the proportionally adjusted criteria needs to be one, is still valid. After each manipulation of weights, the ranking and possible changes are analyzed (Fox et al., 2015; Leonelli, 2012).

Illustrated in Table 5-4 the results show an overall robustness for all criteria of 95% regarding the first-ranked supplier (Top 1), 94% regarding the first- and second-ranked supplier (Top 2) and 91% regarding the first three suppliers in the rankings (Top 3).

Table 5-4: Robustness per criteria resulting from one-at-a-time (OAT) analysis

Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
Sub-criteria	C11 Parts cost	C12 Industrialization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development/ industrialization time	C32 Infrastructure and supply	C41 Development experience	C42 Investment in innovation	C51 CO_2e component manufacturing	Overall Robustness
TOP 1	100.00%	100.00%	100.00%	100.00%	100.00%	57.14%	100.00%	100.00%	100.00%	95.24%
TOP 2	100.00%	100.00%	100.00%	100.00%	100.00%	57.14%	100.00%	100.00%	90.00%	94.13%
TOP 3	100.00%	100.00%	100.00%	100.00%	100.00%	52.38%	100.00%	72.22%	93.33%	90.88%

It shows the relative insensitivity of the proposed decision-making model, including CO_2e as new criteria, to criteria weighting. In addition, an examination of the single criteria identifies 'Infrastructure and supply' (C32) as sub-criteria of the local criteria 'Flexibility' (see Table 4-4) as the most critical criteria. The robustness of criteria C32 is 57% regarding the first-ranked supplier, 57% regarding the first- and second-ranked supplier and 52% regarding the first three suppliers in the rankings (see Table 5-4). The individual examination of rank changes resulting from the OAT analysis (see Figure 5-8) may lead to a re-evaluation of the criteria set by the decision maker, especially if this most critical criteria is still necessary for the decision situation. A possible course of action for the re-evaluation is explained in Fox et al. (2015). It involves a re-consultation of the purchasing experts and the confirmation of necessity of the according criteria. Hence, the derived pairwise comparisons were critically reviewed in order to ensure that the decision maker's preferences are in accordance with the calculated results (see Table 4-4), and then the results were finally re-presented to the purchasing experts. It generally illustrates that a strong emphasis needs to be laid upon the data gathering process and the accuracy of the calculation process, in case the most critical decision criteria shall remain in the decision-making process (Fox et al., 2015).

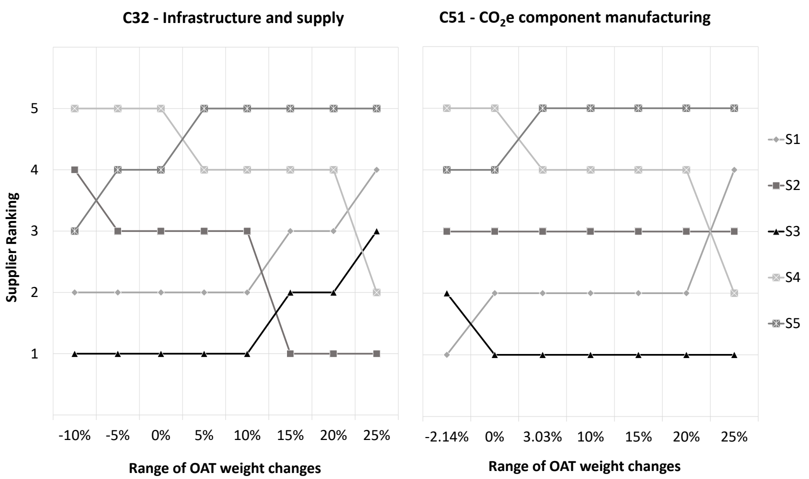


Figure 5-8: Effects of the sensitivity analyses under different criteria weights (OAT)

Given the goal of this study to integrate CO_2e from the manufacturing phase (C51) as decision criteria into supplier selection decisions, in the course sensitivity analysis also a special focus was laid upon this new criteria and the one-at-a-time step weight procedure was applied. The analysis shows a robustness of 100% regarding the first-ranked supplier, 90% regarding the first- and second-ranked suppliers and 93% regarding the first three suppliers in the rankings (see Table 5-4). A more in-depth examination moreover reveals that a reduction of C51 of only 2.14%, resulting in a weight of 0.53%, already has a strong impact on the alternatives respectively supplier rankings (see Figure 5-8). It specifically leads to a switch of the top two ranked suppliers. Hence, the criteria C51 represents the Absolut-Top (AT) critical criteria, which means that the smallest change of this criteria weight has a direct effect on the top ranked or best alternative (Triantaphyllou and Sánchez, 1997). Moreover, C51 also represents the Absolut-Any (AA) critical criteria, meaning that the smallest change among all criteria leads to any change in the ranking. An increase of 3.03% leading to a weight of 5.70% for C51 already triggers a switch of the fourth-and fifth-ranked suppliers (see Figure 5-8). Equally to the proposed and applied treatment of criterion C32, the integration of C51 demands for an even stronger emphasis on data collection and precision for the decision makers. The initially conducted expert interviews revealed that CO_2e is basically not of importance for the current decision-making process. The results of the sensitivity analysis highlight even more that not only the introduction of CO_2e as new criteria is important, but also that the integration in form of weighting assignment requires a thorough procedure.

Additionally to the analysis of the criteria weights, the supplier performances were analyzed accordingly. However, exclusively the performances of all five suppliers (see Table 4-6 and Table 5-2) regarding the new decision criteria 'CO_2e component manufacturing' were examined in order to investigate the Absolut Any or Absolut Top performances. The analysis of C51 revealed that the environmental performance of supplier 1 is the most sensitive to affecting the final ranking of suppliers (see Table 5-2).

It shows that a reduction of 40.4% of the environmental performance of supplier 1, resulting in a performance of 22.65 kg CO_2e/part, leads to a replacement of supplier 2 as best ranked supplier, considering all criteria and according performance scores. Additionally, this reduction also represents the smallest manipulation with an effect on any change in the order of supplier ranking. This furthermore strengthens the importance of integrating C51 as decision criteria, and to emphasize on a close collaboration with the suppliers to induce environmental efficiency measures in order to generally reduce CO_2e emissions in manufacturing processes.

In addition to the conducted OAT weight changes, another sensitivity analysis method, proposed and applied by Hanine et al. (2016), Gumus (2009) and Mousavi et al. (2013), was conducted to further test and verify the robustness of the model (see section 4.2.2.3). Therefore, the criteria weights are switched and each criteria weight is exchanged with another criteria weight. Consequently, eight new additional conditions, which lead to eight additional cases, are included in the investigation. Moreover, the equal weight criteria, which represents an equal distribution of all criteria, is added (Hanine et al., 2016; Mousavi et al., 2013). This leads to an overall amount of ten cases for the consideration within the sensitivity analysis, including the original main case with the consolidated criteria weights (AIJ) from the expert interviews (see Table 4-4). The proximity index (relative closeness) and the resulting order of ranking is displayed in Table 5-5 and Figure 5-9.

The results of the criteria weight exchanges equally show a 100% robustness for the first-ranked supplier (Top 1) and the first- and second-ranked supplier (Top 2). The robustness for the first three suppliers in the ranking (Top 3) only shows a slight deviation and results in a robustness of 97%. This can be traced back to the switch of the criteria weights for C11 'Parts cost' (20.89%) and C42 'Investment in innovation' (7.15%) which causes a change in ranking for supplier between supplier 2 and supplier 5. Hence, the additional application of sensitivity analysis by means of criteria weight exchanges furthermore confirms the robustness of the developed decision support model.

Table 5-5: Results of the sensitivity analysis by means of criteria weight exchange (closeness coefficient and supplier ranking)

Conditions	Alternative supplier					Ranking
	S1	S2	S3	S4	S5	
Case 1 (main)	0.745271424	0.463529796	0.751505526	0.297693883	0.307840811	S3-S1-S2-S5-S4
Case 2	0.828430741	0.404438335	0.832762287	0.220670577	0.217357229	S3-S1-S2-S4-S5
Case 3	0.744946837	0.460639076	0.751141913	0.305393564	0.310410618	S3-S1-S2-S5-S4
Case 4	0.759785998	0.46658972	0.765745106	0.278907405	0.293256309	S3-S1-S2-S5-S4
Case 5	0.805937889	0.457233784	0.810884143	0.224079016	0.243118859	S3-S1-S2-S5-S4
Case 6	0.658966075	0.568194935	0.662070458	0.380907195	0.266230362	S3-S1-S2-S4-S5
Case 7	0.758999288	0.433417221	0.764969656	0.280022074	0.294016937	S3-S1-S2-S5-S4
Case 8	0.805956313	0.327901034	0.81051725	0.203251381	0.559819765	S3-S1-S5-S2-S4
Case 9	0.576531505	0.490199583	0.783218904	0.434586182	0.362824757	S3-S1-S2-S4-S5
Equal	0.730804063	0.413343448	0.813995957	0.279816968	0.389029227	S3-S1-S2-S5-S4

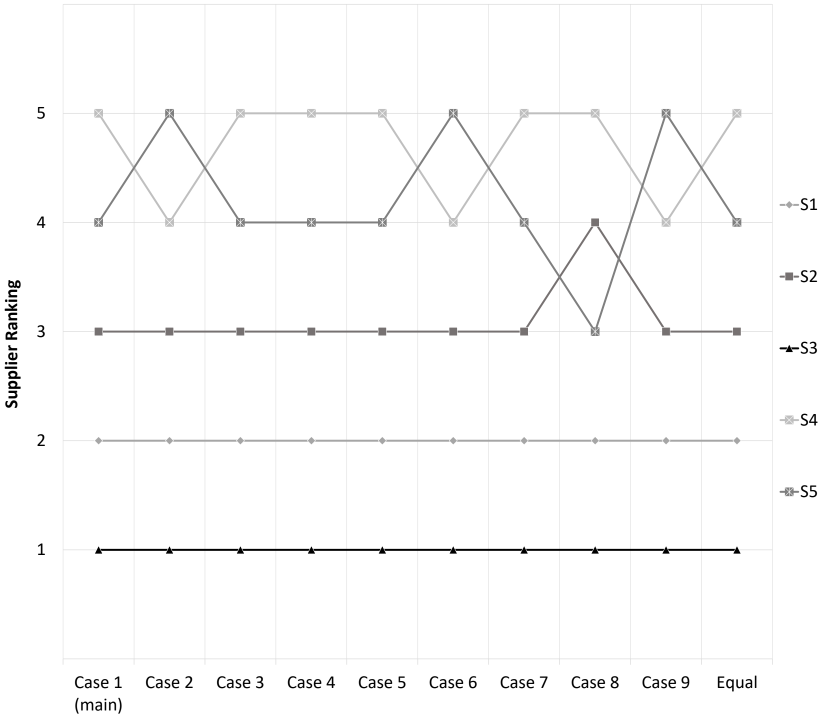


Figure 5-9: Graphical results of the sensitivity analysis under different criteria weights (exchange)

Finally, the rank reversal issue, as described in section 4.2.2.3, was tested. Consequently, another sixth alternative respectively supplier was added to the initial set of five suppliers and the effects on the order of ranking were examined. Therefore, the last ranked supplier and the according supplier performance for all criteria was consulted.

Similarly, one alternative was then deleted and the ranking was verified and compared to the original order of ranking (Fox et al., 2015). The results, illustrated in Figure 5-10, show no changes in the ranking of suppliers and furthermore confirm the general robustness of the developed model.

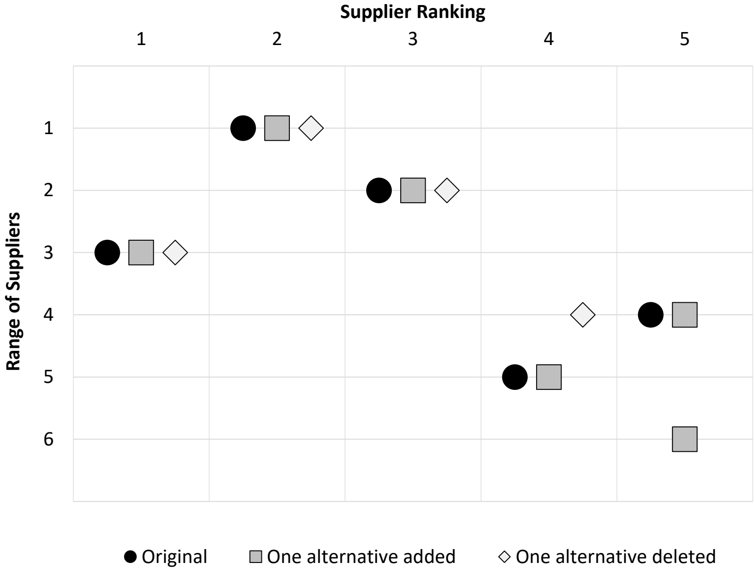


Figure 5-10: Analysis of rank reversal phenomenon

5.7 Scenario simulations for criteria integration

The previously developed techno-economic approach is completed with the application of what-if scenario analysis in order to enable the formulation of CO_2e as decision criteria. The focus lies on simultaneously modelling environmental as well as economic implications as basis for the definition of the new criteria C51. One way of scenario simulation, the integration of the new criteria C51 as additional selection criteria, is illustrated in section 5.7.1.

This procedure also allows for the derivation of a monetary value for CO_2e from a decision maker perspective. Another is presented in section 5.7.2, which focuses on a consideration of the environmental performance from a monetary perspective and a consequent, direct integration into the main criteria ‘cost’ (C1).

5.7.1 Integration of CO_2e as additional selection criteria

In order to support the criteria formulation of a new criteria, a simulation based on the concept of sensitivity analysis (OAT) was deployed and is illustrated in the following. A framework of the developed procedure, which follows the general model structure (see Figure 4-1), is presented in Figure 5-11. It can be considered as final step of the approach to support the formulation of a new decision criteria from a customer perspective. Based on the created transparency in terms of environmental performance on a site-specific level, now environmental as well as economic aspects can be incorporated in the criteria formulation process. As illustrated in section 5.5, the consideration of the site-specific performance data (see Figure 5-7, Case 4) leads to a change of the most preferable supplier alternative despite the relatively low criteria weight of 2.67% for C51 (see Table 4-4). This is however case specific and depends on the selected sample part as well as the according environmental performances of the selected suppliers.

In case the introduction of the new criteria does not directly trigger a change of ranking, due to for example an even lower importance of the new criteria or because of the environmental performances of the suppliers under study, the step weight procedure (see section 4.2.2.3 and 5.6) can be consulted.

In order to support the formulation process of a new selection criteria, supplier selection decisions can be investigated to reveal the critical criteria weight which has an effect on the decision-making process. Similar to the first consideration of the estimated site-specific performances in a supplier selection decision described in section 5.5, not only environmental but also economic effects can be examined and analyzed (before and after the weight manipulation). The simulations should be carried out in collaboration with purchasing experts and the results should be verified by them in order to assure a practical feasibility. Finally, an effective criteria weight can be defined against the background of the objective to reduce the carbon footprint of a product. In this research contribution only a single part was investigated and due to the case specific conditions, the proposed simulation procedure was not further applied in a case study.

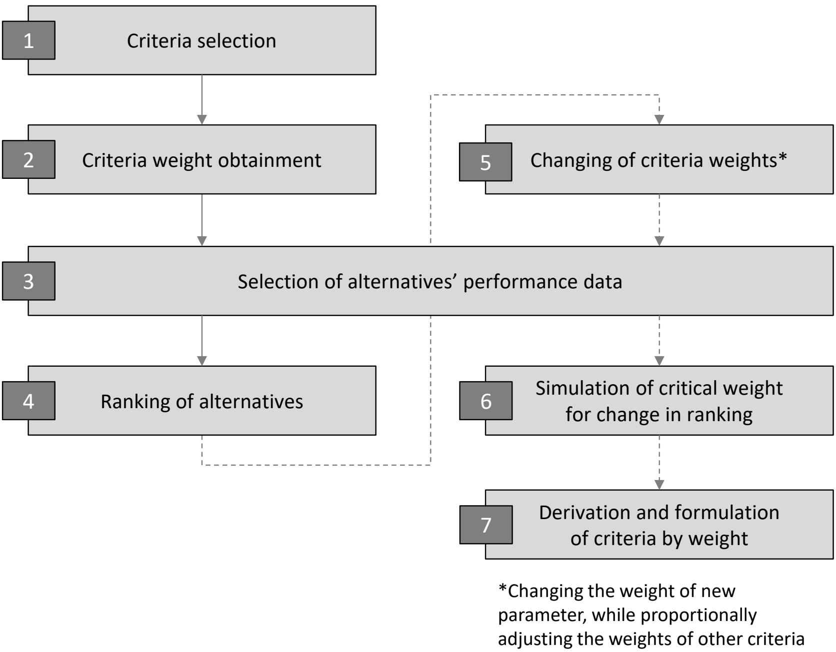


Figure 5-11: Framework for the extension of the range of selection criteria

The proactive procedure to integrated CO_2e as additional criteria into an existing set of selection criteria can also be used as basis to derive a certain value for CO_2e from the perspective of the. Therefore, the previously presented course of action only requires a slight extension. However, in contrast to the examination of a single part only, a more wide-spread application on a variety of parts is recommended. In order to show the general principles of the suggested approach and further possible applications, only for an illustrative purpose a fictitious case was selected (see Figure 5-12).

Thus, a weighting according to the volume of products to be purchased is included in the simulation. For the simulation approach, again the step-weight procedure is consulted and the weight for the new criteria continuously manipulated until a critical change in ranking is examined. Consequently, the monetary differences of the preferred supplier before and after the simulation for each single supplier selection decisions, which is in this case called award decision (AD), are put into relation to the according environmental performance differences. Finally, the according sums of all supplementary cost and CO_2e reductions for all ADs considered are put into relation in order to derive a ratio and thus a monetary value in € per ton CO_2e from a company-wide perspective. This example (see Figure 5-12) assumes the fictitious result of five ADs. It includes the earlier analyzed supplier selection decision of a real-life sample power train part (AD 1). Resulting from the comparison of the supplementary project cost and the emission reduction potential per AD the following ratios (€/t CO_2e) are derived: AD1 11.67 €/t CO_2e, 200 €/t CO_2e, 100 €/t CO_2e, 69.77 €/t CO_2e and 84.21 €/t CO_2e. The overall ratio of all supplementary cost (AD1-5: 13.31 Mio €) and the according sum of CO_2e reduction potential (167.00 t CO_2e) reveals in the fictitious sample application a value of 79.9 €/t CO_2e (AD1-5). Building on this, the customer specific monetary value can be used for new strategic alignments and as such for future decisions to be made, which are illustrated in the following section 5.7.2.

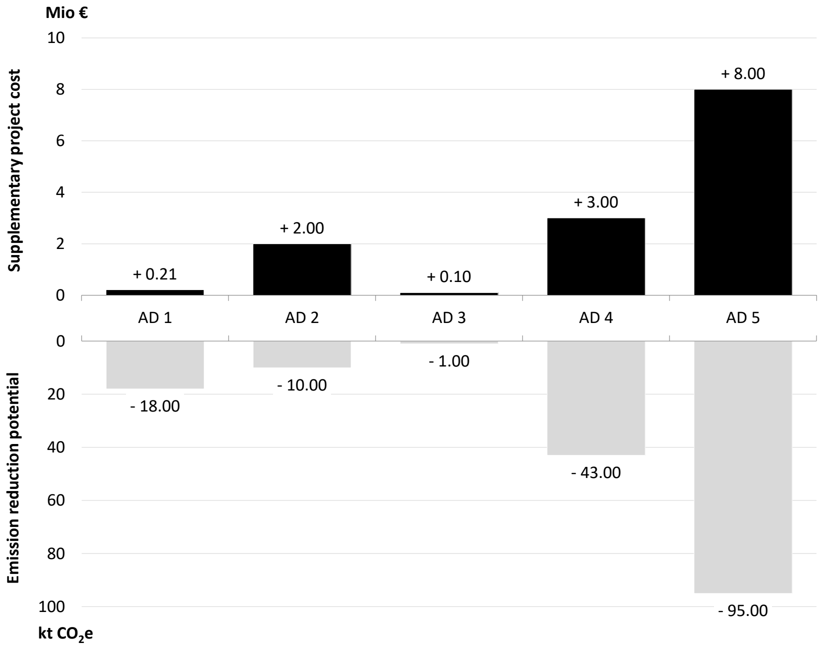


Figure 5-12: Sample application of scenario simulation to derive monetary value for CO_2e

Due to the proactive nature of the presented procedure, it is up to the decision maker which simulated criteria weight to choose. Thus, the amount of CO_2e to be reduced respectively how much a company is willing to spend for sustainability improvements can be defined to an individual optimum. In reverse order, the ratio of the sum of supplementary cost and the sum of CO_2e reduction potentials can be calculated and the environmental saving per monetary unit (€) can be defined from a company specific perspective as in this case 0.013 t CO_2e/€. An application of the presented procedure on a cross-industrial level, both on a national and international scale, in order to derive a generally valid carbon price and to challenge the effectiveness of existing cost approaches (see section 5.7.2.1) could present a future field of research and is further discussed in section 6.3.

5.7.2 Integration of CO_2e in cost as selection criteria

"Even if most investigated companies have some sort of supply chain related environmental policy, in most cases 'the environmental criteria are paid lip service in the selection process, it is the money that decides'" (Nawrocka, 2008, p. 356).

Thus, in addition to the illustrated procedure of integration CO_2e from the manufacturing phase as additional selection criteria, the estimated CO_2e performances could be directly incorporated into the existing cost criteria (see Figure 5-13).

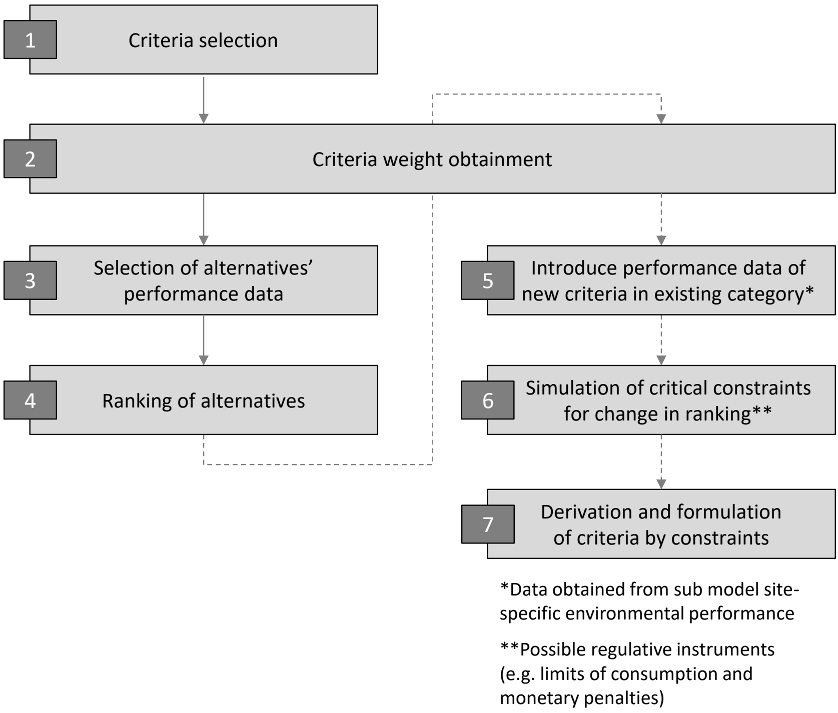


Figure 5-13: Framework for including a new criteria in an existing selection criteria category

Based on the conducted expert interviews, this would be, from a corporate perspective, the most preferable solution in order to establish a consistent and effective application of the CO_2e criteria in decision-making processes.

As the European Commission (EPSC, 2016) has started first discussions on possibly regulating CO_2e from the manufacturing phase in the future, a simulation was carried out assuming a CO_2e limit in combination with a monetary penalty for the exceeding of the limit, similar to the principle of regulating CO_2 emissions in the use-phase (see section 2.2.3 and Figure 2-6).

The objective pursued was to investigate how these assumptions might affect current supplier selection decisions. The currently separate criteria weight for CO_2e (C51) was proportionally distributed among the other criteria accordingly to the OAT sensitivity procedure (Alinezhad and Amini, 2011; Fox et al., 2015), described in section 4.2.2.3. This assumption was justified with the initially investigated zero importance of CO_2e from manufacturing during the expert interviews (see section 4.2.3.3). The adjusted criteria weights without the CO_2e criteria, which are in this research called proportionally adjusted, are presented in Table 4-4. The initial application of these weights results in the following supplier ranking: S1 → S3 → S2 →S5 → S4.

A penalty of 80.00 €/t CO_2e corresponding to the cost approach from the German Federal Environment Agency for CO_2 relation to climate damage (UBA, 2019c) was assumed (see Table 5-6). Now the performance score of the currently preferred supplier S1, 38 kg CO_2e/part, was used as basis for simulating possible CO_2e reduction targets. This procedure follows the principles of sensitivity analysis for investigating the most critical measure of performance (Triantaphyllou and Sánchez, 1997). The simulation analysis shows that the setting of a CO_2e limit per part of 20.60 kg CO_2e/part, which represents a reduction of 45.80% of the performance of the currently preferred supplier 1, leads to a first change of the supplier ranking: S3 → S1 → S2 → S5 → S4. As the environmental performance of S3 lies below the introduced limit, no monetary penalties had to be considered.

In order to better demonstrate the idea of the simulation procedure, a limit of 17.10 kg CO_2e/part, representing a reduction of 55.00% of the supplier performance of S1, was used for the subsequent simulation. Before the integration of the CO_2e performance into the cost criteria with the assumed penalty and limit, the overall project cost (1 Mio parts, see Table 4-6) of the selected supplier S1 would be 280.00 Mio €. This corresponds to emitting 38,000 t CO_2e over the project duration. Supplier S3 would be ranked second with overall project cost of 280.21 Mio € while emitting only 20,000 t CO_2e. After the introduction of the CO_2e criteria the ranking changes and supplier S3 would become the best ranked alternative by 280.44 Mio €, by a remaining CO_2e performance (see Figure 5-14). The project cost are calculated as the sum of the original project cost plus a penalty for emission exceedance of 0.232 Mio € $\left((38.000 \text{ t } CO_2\text{e} - 17.100 \text{ t } CO_2\text{e}) \times 80.00 \text{ €/t } CO_2\text{e}\right)$. Supplier S1 would now be ranked second due to overall project cost of 281.67 Mio € resulting from its higher emission of CO_2e and an according penalty of 1.672 Mio € $\left((20.000 \text{ t } CO_2\text{e} - 17.100 \text{ t } CO_2\text{e}) \times 80.00 \text{ €/t } CO_2\text{e}\right)$. Even though supplier S3 would initially represent slightly higher project cost of 0.210 Mio € and would also have to pay a penalty of 0.232 Mio €, its selection would result in a reduction of 18,000 t CO_2e, and an avoidance of 1.230 Mio € $(281.67 \text{ Mio €} - 280.44 \text{ Mio €})$ additional cost.

The illustrated example shall serve to demonstrate how a variety of future scenarios (economic and environmental) can be modelled in order to formulate the specification of a new selection criteria, as in this case CO_2e, and to derive sustainable supplier selection strategies. As recommended in the previous sections of scenario simulations, an application on a broader scope of parts is recommended in order to derive even more universal conclusions and is discussed in section 6.

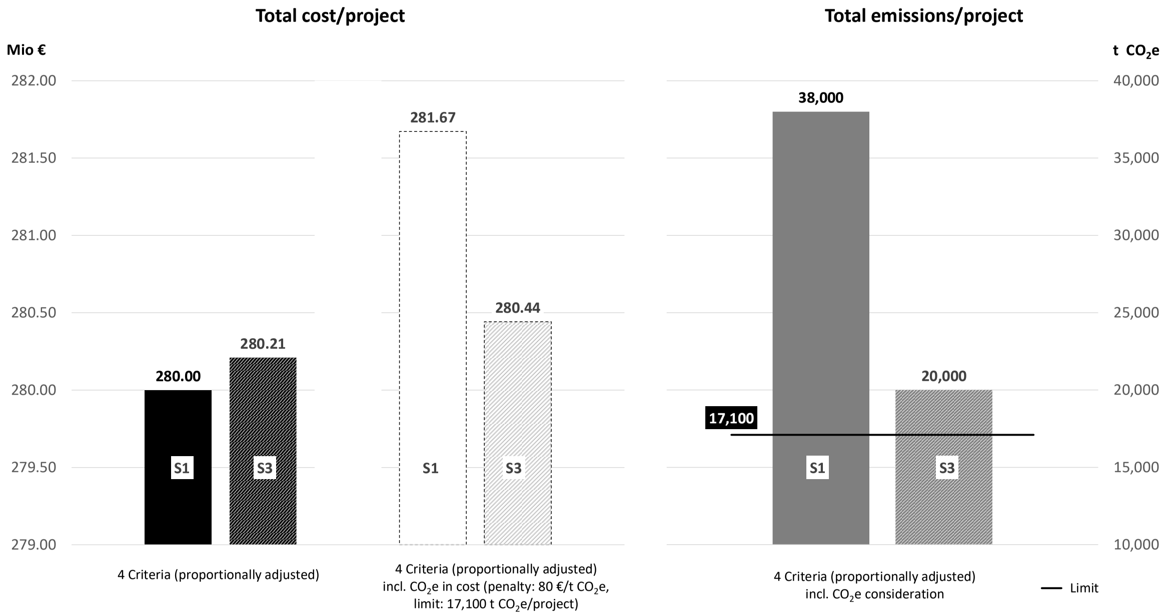


Figure 5-14: Illustration of results of a simulation of environmental and economic effects

5.7.2.1 Existing carbon cost approaches

In terms of environmental cost respectively carbon cost, there exists a wide range of cost characteristics which can be applied and used for the presented approach. Table 5-6 illustrates a selection of cost approaches which already find application in several industrial sectors on a national or international level. Besides the consulted average carbon cost rate of 80.00 €/t CO_2e, the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety also provides a range of estimates for sensitivity analysis from 40.00 to 120.00 $€_{2010}$/t CO_2 for a short term consideration based on the reference year 2010 (UBA, 2019c). In 2019, the cost estimates for the consideration of climate-related damage were updated to 180.00 $€_{2016}$/t CO_2 based on the reference year 2016 (UBA, 2019c).

A sample application including the minimum and maximum cost rate (see Table 5-6) provided by UBA (2019c) on the use case consulted for the model application (see section 4.2.3.3 and 4.2.3.4), combined with a range of adjusted carbon limits, can be found in Appendix B, Table B-13.

Another carbon price is provided by the European trading scheme for carbon dioxide which comprises a variety of energy intensive industrial sectors, among others the energy providers, commercial aviation and metal producers, and the following gases: CO_2, N_2O and PFC (UBA, 2018b). Therefore, carbon caps are defined which will be continuously decreased. Within these upper limits a trade of emission certificates is allowed and performed at selected stock exchanges (EEX, 2020). In order to further reduce greenhouse gas emissions, in 2019 the federal government of Germany introduced the national emissions trading system (nEHS) to extend the carbon pricing on the traffic and building sector by 2021 (The Federal Government, 2019). It starts with a politically determined fixed price of 25.00 €/t CO_2 for certificates, and finds application in companies which provide heating and fuels. The carbon price will successively be increased up to a price corridor of 55.00 - 65.00 €/t CO_2 valid in 2026.

In addition, national governments and according ministries individually introduced taxation schemes for the usage of passenger vehicles (Central Customs Authority, 2017). For example in Germany, motor vehicle tax does not only focus on cubic capacity taxation but also incorporates a taxation of 2 € per g CO_2/km for the exceedance of the CO_2 limit of 95 g CO_2/km since 2014. Taking into account the entire lifespan of 150,000 km and 17 years (ICCT, 2018a; Weymar and Finkbeiner, 2016), and an according average usage of 8,824 km/y, a conversion with the defined tax of 2 € per g CO_2/km results in an absolute value of 0.002 €/g CO_2 or 266.67 €/t CO_2 (see Table 5-6). According to the existing regulations in the automotive industry and the implemented fleet targets (see section 2.2.3 and Figure 2-6), a similar conversion of the introduced penalty of 95 € per g CO_2/km for exceedance (European Commission, 2009, 2019b) illustrates an actual carbon price of 633.33 €/t CO_2 based on the same vehicle lifespan consideration (Weymar and Finkbeiner, 2016).

Thus, a great variety of cost approaches and carbon prices is available for the conduction of the developed proactive approach. The huge differences among prices is also part of the concluding discussion in section 6.

Table 5-6: Selection of different environmental cost approaches for CO_2

Category	Cost of CO_2 in €/t CO_2	Reference Date /Year	Description	Source
Climate damage cost rate	40.00/80.00/120.00	2010	low/mid/high	German Environment Agency (UBA, 2014)
	180.00 205.00 240.00	2016 2030 2050	-	German Environment Agency (UBA, 2019c)
European trading scheme (ETS) for European Emissions Allowances (EUA)	20.24	25.04.2020	-	European Energy Exchange AG (EEX, 2020) (UBA, 2018b)
National emissions trading system (nEHS)	25.00 55.00 55.00 - 65.00	from 2021 2025 2026	-	The Federal Government (The Federal Government, 2019)
Exceedance of CO_2 limit (German motor vehicle taxation scheme)	226.67	since 2014	For exceeding the limit of 95g/km; part of the taxation scheme besides cubic capacity taxation $\left(2\frac{€}{g}\ per\ \frac{g\ CO_2}{km} \times 100{,}000\ \frac{g}{t}\right)^{*} \Big/ \left(\frac{17y}{150{,}000\,{}^{km}/_{17y}}\right)^{**}$	* Central Customs Authority (Central Customs Authority, 2017) ** International Council on Clean Transportation (ICCT, 2018a) Automtive study (Weymar and Finkbeiner, 2016)
Exceedance of CO_2 limit (European emission performance standards for new passenger cars)	633.33	from 2019	$\left(95\frac{€}{g}\ per\ \frac{g\ CO_2}{km} \times 100{,}000\frac{g}{t}\right)/(150{,}000km)^{**}$	European Commission (European Commission, 2009, 2019b)

5.7.2.2 Definition of carbon limits

In combination with the previously illustrated cost approaches, several existing emission regulation approaches could be used as basis for the proactive definition of carbon reduction targets relating to the defined environmental goals. One approach which could be proactively used, also for a more widespread application on the entire product portfolio of a company, is the European regulations on vehicle usage in form of fleet targets for vehicle manufacturers (European Commission 2009).

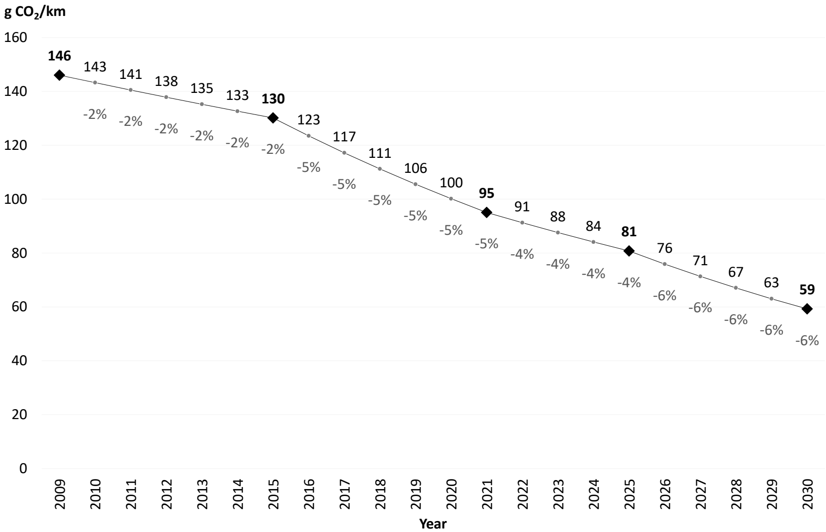


Figure 5-15: Calculated yearly breakdown of European CO_2 emission performance targets for vehicle manufacturers (based on European Commission (1998); European Commission (2000b); European Commission (2009); European Commission (2019b); ICCT (2011); ICCT (2018b); ICCT (2019))

Based on the development history of existing EU regulations on vehicle fleet consumption described in section 2.2.3, carbon limits in reference to the created emissions during the manufacturing phase of passenger vehicles could be derived. Similar to the defined targets for the vehicle use phase (see Figure 2-6), which are initially based on a voluntary self-disclosure (European Commission, 2000a, 2000b) and then constantly reduced, the same procedure and efficiency targets for CO_2 reduction could be used for an proactive approach in the manufacturing phase. For the over the course of time adjusted limits, a linear reduction on a yearly basis could be assumed (see Figure 5-15). Also, company specific intermediate targets could be defined for the years until the next officially set target is reached.

Another possible approach for setting CO_2 reduction targets in line with the overall goal of limiting global warming to 2°C/1.5°C is the Sectoral Decarbonization Approach (SDA) presented by the Science Based Targets Initiative (2015). The recommended approach, which was developed by a consortium of the carbon disclosure project (CDP), the United Nations Global Compact, the World Resources Institute (WRI), and the World Wide Fund for Nature (WWF), provides companies with a method to define and set emission targets in line with to the two degrees goal (Science Based Targets Initiative, 2015).

In the SDA, a defined global 2°C carbon budget is further allocated to different sectors (see Figure 5-16) and includes a consideration of a growth factor in relation to the growth of the economy and population (Science Based Targets Initiative, 2015). It allows companies within an according sector to derive reduction respectively science-based targets for scope 1, 2 and 3 emissions, based on its relative share of the overall activity of the sector as well as a carbon intensity (absolute CO_2 emissions/production volume) relative to the base year intensity of the sector. The method assumes a converging of a company's intensity with the sectoral intensity in 2050. Hence, the defined intensity pathway allows for a deduction of absolute carbon budgets in reference to the defined target period.

The illustrated approach could be consulted as basis for the derivation of hypothetic carbon limits or respectively targets, which can then be used in the recommended scenario simulations in order to support the reduction of emissions from the manufacturing phase.

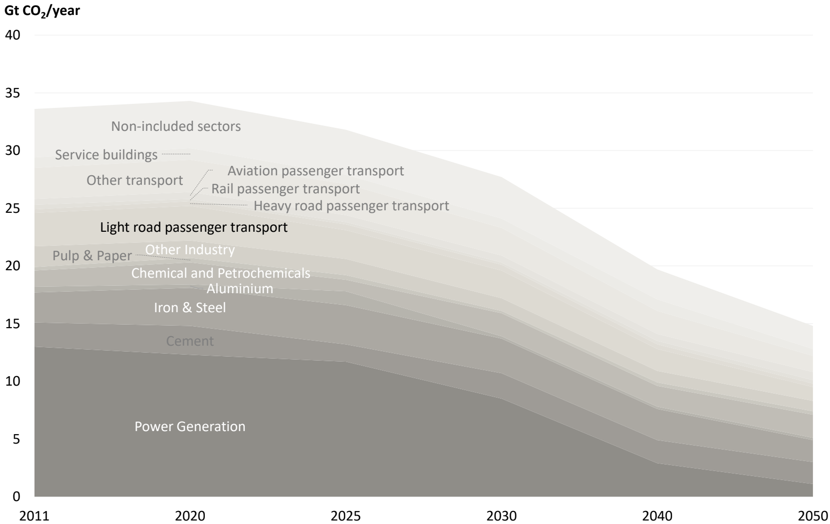


Figure 5-16: Sectoral breakdown of absolute CO_2 emissions budget, 2011–2050 (Science Based Targets Initiative, 2015)

Therefore, the material composition of a product, as for example the reference vehicle defined for this case of application (see section 2.2.4 and Figure 2-8) needs to be analyzed for the singular material groups in accordance to the defined sectors in the SDA approach. In combination with the entire amount of vehicles produced and under consideration of the estimated carbon emissions resulting from the sub-model for environmental performance assessment, the absolute emissions for the base year can be defined, and a carbon intensity derived.

Hence, an activity for the target year can be derived, based on the assumed development of the amount of vehicles planned for future production, which can accordingly be broken down to the material groups. Consequently, in reference to the material sectors of the SDA and by application of the SDA approach, CO_2 reduction targets for the material groups can be derived and used to define component or vehicle targets. In Table 5-7 and Table 5-8 a sample application on the previously selected reference vehicle (VW Golf VII) based on the according steel content of 912 kg (see Figure 2-8) in combination with the results of the site-specific assessment approach is presented to illustrate the principle of the recommended procedure. The same approach could be applied on different materials and sectors in order to reproduce the material composition of an entire vehicle or a component, and thus to derive consolidated reduction targets based on the single calculations.

Table 5-7: General principle of application incl. source information

	Material share (%)	Steel/vehicle (kg)	Number of vehicles (#)	Purchased material/company (kg)	Emission factor (t CO_2/t crude steel)	Emission/vehicle (t CO_2)	Emissions/company (t CO_2)
Data	(Industry Average)	(VW Golf VII)	(Sales Volkswagen, EU)	(Calculation)	($ECCO_2$ Steel, Ø)	(Calculation)	(Calculation)
Source	(Acosta Fernández and Bringezu, 2007)	(Lieberwirth and Krampitz, 2015) (Schmid and Zur-Lage, 2014)	(Volkswagen AG, 2020)	-	(Schiessl et al., 2020)	-	-
Primary Steel	80%	729.6			2.352	1,716.02	
Secondary Steel	20%	182.4			0.8792	160.37	
Base Year 2019			4,006,102	3,653,565,024		1,876.39	7,516,990,823
Target Year 2024			4,486,834	4,091,992,827			

*assumption: 12% decrease in sales volume

Table 5-8: Results of the SDA target setting approach (based on Science Based Targets Initiative (2019))

	Base year (2019)	Target year (2024)	% Reduction
Company | Scope 1 emissions (t CO_2)	7,516,990,823	6,003,325,236	20.1%
Company | Scope 1 emission intensity (t CO_2/t)	2.1	1.50	28.7%

Despite the recommendation of the SDA to focus on intensity targets for the examination of Scope 3 upstream supply chain emissions, a consideration of absolute values and short-term targets, including regular adjustments according to changes in the activity rate of the sector, can illustrate a promising opportunity. It can serve to make a first proactive step to sensitize internal purchasing experts and suppliers to possible mandatory targets in the near future.

6 Conclusions, discussions and outlook

In this section a summary and conclusion of the findings of the research contribution are presented. The developed approach and the implemented model are also critically discussed and model limitations are illustrated. Finally, an outlook on potential future areas of further developments of the model and on future fields of application is given.

6.1 Summary and conclusions

In this research contribution, the research questions of how a new criteria such as CO_2e can be integrated in existing decision-making processes, and how a therefore necessary transparency can be created, are answered.

The objective of this research is the development and implementation of a model which enables the creation of transparency and comparability among raw material manufacturers respectively suppliers, and facilitates decision support for making supplier selection decisions. For that purpose, an integrated CO_2e assessment and decision support model for supplier selections is developed, implemented and applied on a real-world case study in order to illustrate its practical applicability. The developed model enables the assessment and comparison of CO_2e emissions of raw material manufacturers on a site-specific level, the integration in decision-making processes for supplier selections and the consequent simulation of different future scenarios in order to assist decision makers with the formulation of the new criteria to improve sustainable efficiencies of products while considering the economic effects.

In order to achieve the objective of this research contribution and to answer the derived research questions, at first, in section 2, the background and framework conditions of sustainability in supply chains are explained. It shows the challenges and opportunities of sustainability in supply chain management for corporations with a focus on environmental respectively green purchasing. In reference to the case study application of the developed model, the current situation of environmental sustainability in the automotive industry is also presented. It becomes obvious that currently no focus is placed on the environmental impact of the manufacturing of products, for example the vehicle manufacturing phase, and that an according supply chain transparency is currently lacking. As the raw material production of metal is one key emitter of global GHG emissions and has a major impact on for example the management and mitigation of emissions of the production of passenger cars, framework information of the metal industry and according production processes are described. These represent the basis for the development of the environmental performance assessment model (submodel B).

In section 3, existing methods and models on decision support with respect to supplier selection processes, including their application in the single phases of supplier selection, are reviewed and analyzed in order to reveal their strengths and weaknesses. Emphasis is placed on the criteria formulation phase and methods used in this context. Moreover, existing studies are reviewed for sustainable decision criteria applied, which serves as basis for a later selection of appropriate set of decision criteria for the case study application of the model. This examination thus partially answers the research subquestion of which economic and ecologic factors are relevant for sustainable supplier selections (1). As supplier selections are made based on a simultaneous consideration of multiple criteria, a multi-criteria decision analysis approach (MCDA) appears suitable for the formulation and integration of new environmental performance criteria in supplier selection decisions. In an equal way, literature is reviewed on methods and approaches for the assessment of environmental performances for raw material manufacturing sites, which also enable a comparability among production sites. The focus is on the concept of life cycle analysis, which comprehensively takes environmental effects of the whole life cycle of a product or process into account and serves for example for product evaluation and decision making and on in-depths methods applied for the assessment material and energy flows. Section 3 concludes with the identification of the research gaps respectively the need for research, which shall, in accordance with the defined research objective, be closed.

In section 4, initially the model structure of the integrated CO_2e assessment and decision support model for supplier selection consisting of two sub-models is described and, based on the identified research gaps, the concepts of the sub-models as well as the selection of the therefore used methods are justified. The sub-model for decision support (sub-model A), serves as framework model into which the results of sub-model for environmental performance assessment are integrated. The sub-model is based on a combination of the AHP and TOPSIS method and serves to derive criteria weights and finally rank suppliers according to their performance on the selected criteria. The combination of these methods enables, in reference to the identified research gaps, the consideration of expert opinion which is crucial for supplier selection decision making, and allows for the usage of quantitative real-world supplier performance data. Moreover, it creates the basis for the simulation of what-if scenarios in order to support the formulation and thus integration of a new criteria such as CO_2e into existing decision-making processes from an environmental as well as economic perspective, which is illustrated during the model application in section 5. Based on a selected set of criteria resulting from the literature research, an expert consultation respectively application of the AHP procedure with purchasing experts from three divisions reveals a significantly low criteria weight and thus minor importance of CO_2e from the manufacturing phase as decision criteria in current supplier selection processes. Thus, the research sub-question of which economic and ecologic factors are relevant for the evaluation of sustainable supplier performances (1) can be considered as answered. This furthermore confirms the need for research on a specific and quantifiable environmental performance criteria revealed during the literature review in section 3. As no regulations regarding the quantification and mitigation of GHG emissions in the manufacturing phase of for example vehicle production are set in place, the derived importance of the newly considered environmental criteria – CO_2e is substantially driven by the investigated corporation, the selected expert sample and generally the business field of operation (see section 6.2).

The sub-model for environmental performance assessment (sub-model B) consequently serves to create site-specific transparency of environmental performance of raw material manufacturers in the metal industry and thus a quantitative performance measure for CO_2e. In a systematic and modular LCA based approach, which can be classified into the category of attributional LCA approaches, a technology-driven bottom-up calculation of site-specific material and energy flows is combined with the integration of site-specific top-down information on environmental impact (CO_2). By this means, the model also assures that company specific process improvement measures, which outline the core competences of the suppliers and might vary not only between companies but also between production sites, are included. The developed methodology, which is initially developed for the assessment of steel manufacturing sites and shall serve as standardized procedure for the assessment of different material commodity production sites, is consequently transferred to assess aluminum production sites. In reference to the derived need for research and the identified hurdles of comparability and widespread application, the developed model closes this gap by the consideration of intermediate product trading between different production sites and technical restrictions. In this context, the availability of data and model complexity illustrates a particular hurdle which is overcome by the design of the model, which makes exclusive use of publicly available data sources which are updated on a regular basis and is thus independent of restricted company internal primary data.

In section 5, the developed integrated CO_2e assessment and decision support model for supplier selection is exemplary applied in an automotive case study. Due to the structure of the developed model, consisting of two sub-models, initially the sub-model for environmental performance assessment is applied on a selected sample of steel and aluminum manufacturers. Consecutively, the estimated results of the environmental performance of the examined raw material suppliers, are integrated into the sub-model for decision support, which represents the coupling point of the two sub-models and thus the merger to an integrated techno-economic model. The developed sub-model for environmental performance assessment is applied in two case studies in the metal industry. The analysis of the 22 European steel and four German aluminum manufacturing sites show considerable differences of the environmental performance of among the raw material production sites. In case of the steel manufacturing sites under study, the results illustrate deviations of up to 58% respectively 1,111 kg CO_2e/t crude steel between the most efficient ‘Best-in-Class’ (BiC) and the least efficient ’Worst-in-Class‘ (WiC) site. Among the aluminum production sites, a range of approximately 9% shows a low percentage deviation between the BiC and WiC sites however represents an absolute difference of 1,275 kg CO_2e/t raw aluminum. The application cases, and the in-depth validation of result with industry experts from steel and aluminum manufacturers as well as a comparison with industry average values from an LCA database show that the model provides plausible and reasonable site-specific total amounts of kg CO_2e/t material. It illustrates that the developed sub-model creates realistic results, based on the exclusive use of public available data sources and thus overcomes the identified hurdle of restricted availability of primary data.

This furthermore confirms the reliability of the suggested calculation procedure which assures that company-specific as well as site-specific internal process know-how is considered, despite an unavailability of explicit data, while the model complexity in terms of process depth is limited to a required minimum. This enables a practical applicability of the developed sub-model (including regular data-updates and manual integration of varying primary data) and allows for an application of the results to derive consequences on a more global scale, for example on the overall amount of CO_2e emissions in Europe. Thus, the research sub-question (4) of which method is suitable to estimate material and energy flows of products in order to evaluate and compare the environmental performance of suppliers from a life cycle perspective, is answered.

The developed integrated CO_2e assessment and decision support model for supplier selection, including the results of the site-specific performance, is applied in an automotive case study on the supplier selection of a sample power train part, which is purchased in the non-consumable division of the selected OEM. Initially the AHP/TOPSIS based model with the selected set of criteria, the derived criteria weights and the collected supplier performance data on these criteria is applied in combination with industry average data from an LCA database (equal performance value for all suppliers and sites). This served to illustrate how current supplier selection decision including environmental aspects can be made, and as benchmark case for the analysis of the effects, when site-specific environmental performance results are considered in supplier selection processes. An exemplary application of the model including the estimated environmental performance results for steel sites shows that, despite the derived low criteria weighting for 'CO_2e Component manufacturing' (C51) of 2.67%, the consideration of site-specific performance score leads to a change in the ranking of the most preferable supplier. The model application at this stage thus practically confirms the originally revealed necessity for site-specific performance values as basis for the integration of CO_2e as criteria for supplier selection. Additionally, a more complex material composition of the sample part (real-life case) consisting of different materials is applied to demonstrate the possibility of the model to include different materials in the decision-making process in combination with site-specific CO_2e performances, and thus to enable a more wide-spread practical application. As decision making in a multi-criteria environment based on expert opinions is associated with a certain level of subjectivity, sensitivity analyses are performed to examine the robustness and stability of the developed model.

Hence, the first part of the main research question of how new decision factors, such as CO_2e generated during the production process of vendor parts, can be measured and integrated in well-established supplier selection processes, besides existing decision criteria as well as the according research subquestion of which level of transparency, respectively level of data about CO_2-emission regarding upstream supply chain activities is relevant for an integration into supplier selection decisions (3) are considered to be answered.

In order to support the formulation of CO_2e as decision criteria, two scenario simulations are developed and applied on the selected sample part with the real-life material composition. As the integration of a new additional criteria depends not only on the supplier performance score but also on the according criteria weighting, the consideration of the suppliers environmental performance scores (CO_2e) in the developed approach does not necessarily lead to a change in supplier rankings and more specifically a change of the most preferred supplier. Therefore, the developed model allows for a manipulation of the new criteria weight and an according proportional adjustment of the remaining criteria based on the concept of the numerical incremental, one-at-a-time (OAT) sensitivity analysis. The model thus allows to reveal the critical criteria weight which has an effect on the supplier ranking in a decision-making process and enables, based on this information, the efficient formulation of a new selection criteria. Due to the consideration of cost criteria in the chosen set of selection criteria, which still represent the most important criteria in supplier selection decision making, the developed model enables the simultaneous analysis of economic environmental effects (before and after the weight manipulation). In reference to the developed scenario simulation procedure, the model also facilitates the derivation of a certain monetary value for CO_2e from the perspective of the decision maker by putting the monetary differences of the preferred supplier before and after the simulation for each single award decision into relation to the according environmental performance differences. This enables decision makers to design new strategic alignments which can be used for future supplier selection decisions in order to reduce carbon emissions. The developed model also enables scenario simulations to directly integrate the CO_2e performances into the existing cost criteria. Inspired by the concept of CO_2 emission regulations in the use-phase of passenger vehicles, the developed model allows for the assumption of different CO_2e limits in combination with a monetary penalty for the exceeding of the limits, in order to investigate how these assumptions might affect current supplier selection decisions and thus to support an efficient formulation of a new criteria such as CO_2e from the manufacturing phase of a product.

An exemplary application on the chosen automotive case study shows that the selection of more environmentally efficient suppliers is not compulsory connected with significantly higher project cost, and thus that the consideration of environmental performances in supplier selections can enable the development of new sustainable supplier selection strategies. In addition, two possible approaches for the definition of environmental limits are provided as well as a selection of diverse environmental cost definitions for CO_2 respectively CO_2e are illustrated. Thus the second part of the main research question of how new decision factors, such as CO_2e generated during the production process of vendor parts, can be measured and integrated in well-established supplier selection processes, besides existing decision criteria and the according sub-question of which decision support method or combination of different methods is suitable to formulate and integrate a new criteria (2), are answered.

6.2 Discussion and critical appraisal

The combination of the AHP and TOPSIS method used in sub-model for decision support provides the advantage to integrate expert opinion for criteria weighting while using supplier performance data for supplier ranking, in order to support the supplier selection decision-making process. Thus, the disadvantage of subjectivity when using AHP pairwise comparisons for supplier performance evaluation is decreased. However, there is still a certain level of subjectivity among the derived criteria weights. Moreover, the possibility exists that the derived results of the AHP method might not reflect the decision makers opinion and would therefore lead to a re-evaluation of the pairwise comparisons or to an exclusion of the according evaluation. Therefore, a template is created in Microsoft Excel and used for the AHP interviews, which automatically highlights ordinal and cardinal inconsistencies of each pairwise comparison as well as the consistency ratio of the entire evaluation of all criteria. Thus, the accuracy and robustness of the results can be efficiently increased, the computational effort be limited to a necessary minimum and the acceptance of the results by the experts be increased. During the expert consultation, it has become apparent that CO_2e from the manufacturing phase does not play a role in current decision making. However, due to the principle of the AHP method to set two criteria in relation by means of pairwise comparisons, which prevents a zero weight evaluation, a criteria weight greater than zero is assigned to the new decision criteria. The results of the sensitivity analysis, based on the selected case of application, show that the developed model is relatively robust and insensitive to criteria weighting. The most sensitive criteria has not been removed due to its importance in the selected case study. However, an adjusted selection of criteria would have resulted in an even higher model robustness. This furthermore illustrates the dependency of the results on the criteria selection and according supplier performance cases. In this context, the number of criteria also plays an important role. In supplier selection cases, which require the consideration of a higher number of selection criteria, the application of the AHP method would lead to a higher complexity for the evaluation among experts as well as for the processing of data, and could lead to less robust results. This could make the application of AHP unsuitable and would require a different multi-criteria decision analysis method. Finally, the selection of methods (individually used or in combination) could lead to the rank reversal phenomenon, if an additional alternative respectively supplier is added to or removed from the sample. In case of the selected sample part used in the supplier selection case study the rank reversal phenomenon has not occurred. However, an application on various parts could lead to adjustments respectively improvements of the model, and could further contribute to the robustness of results.

The combination of the bottom-up calculation of technical process flows and the top-down integration of site-specific environmental impact information (reported CO_2) in order to create a quantitative, site-specific transparency of environmental performance of raw material manufacturers, provides the advantage to incorporate company specific efficiency measures respectively internal process know-how without the need for restricted company specific primary data. Thus, the high time expenditure for data gathering and research is efficiently reduced. Moreover, the disadvantage of unequal respectively differently defined system boundaries, which prevent a comparability among production sites and a more wide-spread application, is overcome by the simulation of fully integrated plants (all substantial intermediate products are assumed to be produced on site) and an according consideration of intermediate product trading between production sites by means of a credit procedure for purchased or sold products. Due to the restricted access to primary data some assumptions have been necessary respectively average data has been consulted during the model development. For example, the production efficiency of each facility for one process step is assumed to be equal as no further site-specific information is available. Moreover, the approach assumes the production volume of the blast furnace as reference value and basis for the calculation of upstream process steps, even though some production sites could produce more intermediate products for market sales than needed for the on-site pig iron production, such as for example coke. In this context, average material conversion rates are used for the calculation due to an unavailability of more specific data of the production sites under study. This reference value is also used for the calculation of the amount of required secondary fuels in the power plant. It constitutes a simplification which is assumed due to high amount of surplus gases produced in the blast furnace and its according importance for power plant operations. In reference to the integrated aspect of intermediate product trading (purchase and sale), the model assumes trading activities only among raw material manufacturing sites in the according industry segment. In order to complete the defined cradle-to-gate system boundaries, the carbon footprint for upstream input materials, for example for the mining of iron ore, is included by means of average data from an industry data base. This is owed to the restricted information about the source of supply and the generally restricted data availability. Based on the defined scope of the model and the target to create a comparability among raw material manufacturing sites, the alloying process is neglected as the composition of the alloys highly depend on customer-specific requirements and have no direct influence on the site-specific energy management system of a production plant. The developed model however allows for a replacement of these assumptions with, and an easy integration of site-specific primary information if available, which could hence lead to an even higher accuracy of results.

Some of these limitations constitute a promising field of future research and illustrate a further need for methodological and content-related research, which are described in the following.

6.3 Outlook on future research

Future research can be dedicated to further enhance the accuracy as well as robustness of the model and the results, to extend the scope of consideration and the fields of application of the developed model. In the field of multi-criteria decision making, the application of other criteria evaluation methods, such as integrated weighting methods, could be promising in order to decrease subjectivity in the process of deriving criteria weights, and to enable the consideration of a larger quantity of criteria without increasing the complexity for the evaluation and the effort for data processing. Moreover, alternative supplier ranking as well as sensitivity methods such as probabilistic simulations, or mathematical models, could be consulted to investigate reproducibility of results and to verify the robustness of the model. As the developed model makes use of case specific selection criteria, the selection and application of other supplier selection criteria could be interesting to further examine effects on sensitivity of the new CO_2e criteria and the resulting impacts on supplier selection decisions.

With regard to the site-specific environmental performance evaluation, the presented approach primarily concentrates on the estimation of CO_2 emissions in the focus system ‘Production Plant’. An extension of the scope by integrating indirect greenhouse gases emitted in the production process, such as CO, NO_X/NO_2, can be promising in order to even further increase GHG emission accuracy of the site-specific results. Moreover, the investigation and creation of a site-specific upstream supply chain transparency of the input material for the raw material production is an interesting area for future research and an opportunity to increase the GHG emission accuracy over the whole supply chain. In order to generate a higher supply chain transparency, future studies could extend the cradle-to-gate system boundaries and examine emissions for further processing of the produced raw material, and for transport emissions, for example to the Tier-1 and from the Tier-1 supplier to an OEM. In this context, a future extension of the focus system towards inter-industrial trading of by-products respectively residues, such as slags, dust, sulphur or sulphuric acid, ammonium sulphate, benzene, coke tar and coke pitch, and a resulting credit procedure for the avoidance of emissions could be of interest. For example the secondary product blast furnace slag has, in form of granulated blast furnace slag, a widespread application in various areas, such as in the cement industry. Furthermore, process gases generated during the steel production processes can be re-used as raw material for chemical production. From a geographic perspective, an extension of the European scope to an international level, for example to American and Chinese production sites, illustrates a promising field in order to create transparency for global supply chains and to identify eventual GHG emission shifting. Based on the currently ongoing technology shift from internal combustion engine vehicles (ICEV) towards battery electric vehicles (BEV), a transfer of the standardized site-specific performance assessment procedure to and an examination of different material commodity productions, for example lithium, which is used for the production of battery storages, appears to be a promising area of future research. The results of the case study application of the site-specific performance model could also be applied for supplier selection decisions in other industries such as for example the construction, packaging or engineering industry. Finally, an application extension of the estimated site-specific emissions, which are in this study applied to support supplier selection decisions, to supplier development and monitoring, could furthermore illustrate an interesting field for scientific research.

In addition to the illustrated fields for future research for the single sub-models, an application of the integrated CO_2e assessment and decision support model for supplier selections in other industrial fields, such as the construction or aviation industry can be interesting. Whereas in the case application of this study a single source supplier selection decision is examined, it would be interesting to test a model application in multiple sourcing decision-making case studies. In this context, the application of the model to a broader scope of selection decisions respectively parts from a company is promising in order to derive even more universal conclusions, and it can further support the proposed scenario simulations with the goal to derive of a robust monetary value for CO_2e from a purchaser perspective of an according corporation. Based on a more widespread application, a statistical analysis to examine a correlation between the price of a part and the environmental performance value for CO_2e emissions could be interesting for future research. Further emphasis on the illustrated scenario modelling on economic and environmental effects could illustrate a promising field for future research. Therefore, research on the definition of emission limits relating to the defined environmental goals could be extended and other cost rates could be applied and analyzed in the developed approach. Besides the application of the developed model in a corporate environment, an application on an economy-wide level can support legislation on future environmental regulations on emission mitigation for the manufacturing phase of a product in accordance with the global 2 respectively 1.5 degrees Celsius climate stabilization goal. Thus, for example universal, cross-industrial emission limits or penalties could be derived, and existing carbon prices be verified for effectiveness. In order to strive for carbon-neutrality throughout the manufacturing phase of a product, research on extending emission limitations, and on emission compensation initiatives respectively incentive schemes for undercutting of emission limits illustrates a promising field of future research.

Appendix

A: Sub-model A for decision support

Question		Answer
Name	-	Expert 12
Female or male?	(1 = female, 2 = male)	2
Age group?	(1 = under 30, 2 = 30 - 39, 3 = 40 - 49, 4 = 50 - 59, 5 = 60 years and older)	1
Years of prof. experience?	(1 = less than 1 year, 2 = 1 - 3 years, 3 = 3 - 5 years, 4 = 5 - 10 years, 5 = more than 10 years)	3
Purchasing division?	(1 = strategy, 2 = non-consumable materials, 3 = consumable materials)	2
Hierarchy level?	(1 = specialist buyer (SB), 2 = team leader (TL), 3 = department manager (DM), 4 = senior department manager (SDM), 5 = division manager (DIVM))	1

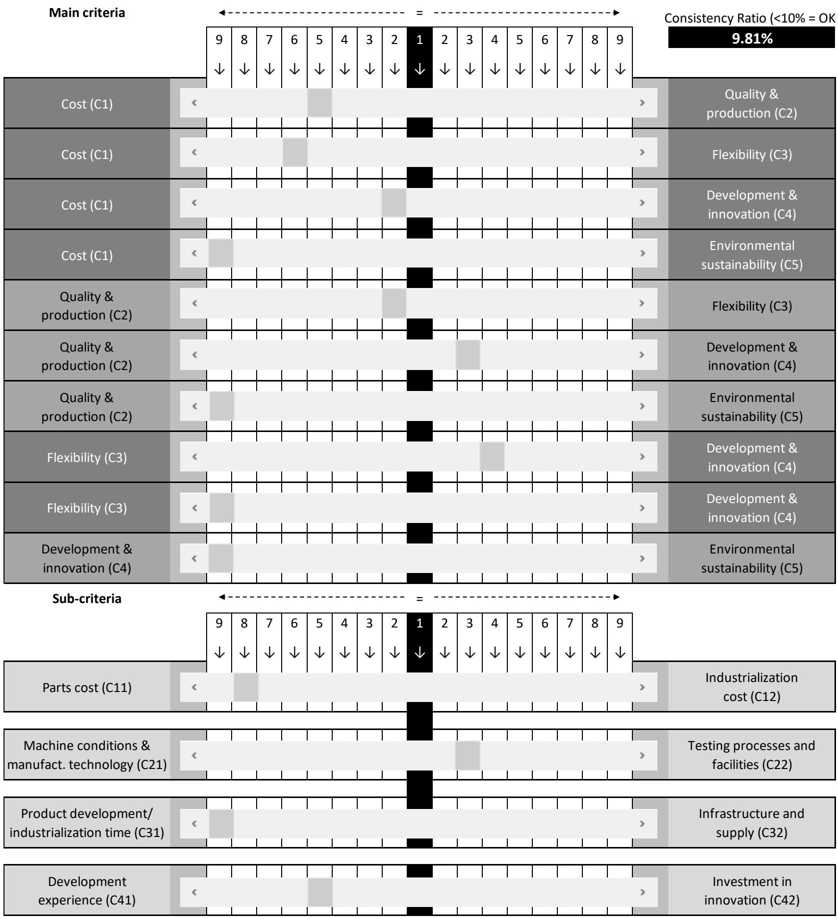


Figure A-1: Personalized AHP interview template

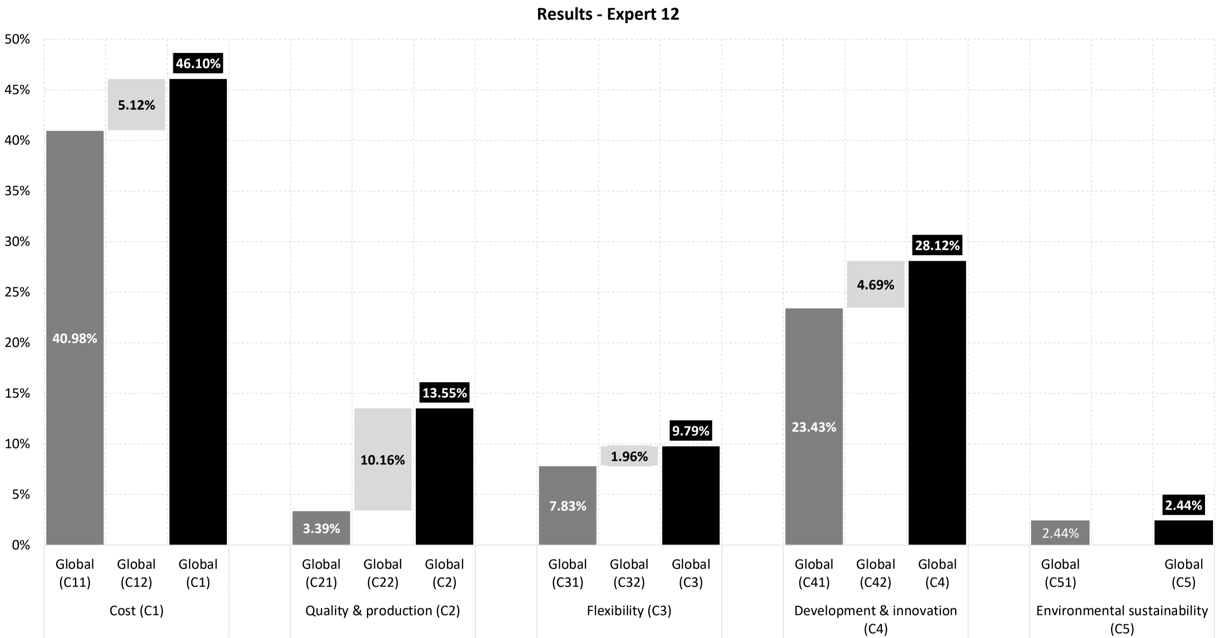


Figure A-2: Graphical and numerical presentation of AHP interview results (example)

Table A-1: AHP results - global criteria weights (priority rankings) for 41 purchasing experts

Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
Sub-criteria	C11 Parts cost	C12 Industri-alization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development/ industrialization time	C32 Infrastruc-ture and supply	C41 Development experience	C42 Investment in innovation	C51 CO_2e component manufacturing	Consistency Ratio (CR<10%)
Exp. 1	8.35%	25.05%	15.18%	3.79%	7.44%	22.32%	7.64%	7.64%	2.58%	4.54%
Exp. 2	44.16%	8.83%	15.81%	5.27%	1.93%	9.65%	10.41%	1.49%	2.44%	9.94%
Exp. 3	43.56%	6.22%	16.09%	3.22%	1.31%	7.84%	2.76%	16.55%	2.45%	9.44%
Exp. 4	38.73%	12.91%	11.96%	2.99%	3.09%	12.35%	11.58%	3.86%	2.53%	6.25%
Exp. 5	6.39%	19.18%	13.17%	4.39%	2.54%	7.61%	11.06%	33.19%	2.46%	9.02%
Exp. 6	24.23%	8.08%	29.87%	9.96%	8.50%	2.83%	10.57%	3.52%	2.44%	9.91%
Exp. 7	33.57%	6.71%	3.69%	14.74%	3.05%	9.14%	19.98%	6.66%	2.46%	9.06%
Exp. 8	33.19%	11.06%	8.10%	2.70%	5.61%	16.84%	15.02%	5.01%	2.47%	8.78%
Exp. 9	2.47%	7.41%	12.87%	38.62%	10.67%	3.56%	16.46%	5.49%	2.45%	9.64%
Exp. 10	5.20%	15.59%	33.87%	11.29%	1.92%	9.59%	16.74%	3.35%	2.46%	9.24%
Exp. 11	21.99%	21.99%	10.31%	10.31%	5.20%	5.20%	11.27%	11.27%	2.47%	8.81%
Exp. 12	40.98%	5.12%	3.39%	10.16%	7.83%	1.96%	23.43%	4.69%	2.44%	9.81%
Exp. 13	21.63%	21.63%	11.58%	11.58%	2.20%	15.43%	1.68%	11.75%	2.53%	6.40%
Exp. 14	18.24%	4.56%	26.44%	8.81%	4.38%	21.89%	9.85%	3.28%	2.53%	6.13%
Exp. 15	29.48%	4.91%	19.74%	19.74%	1.41%	8.46%	10.36%	3.45%	2.45%	9.55%
Exp. 16	8.33%	1.39%	37.59%	5.37%	25.51%	4.25%	12.09%	3.02%	2.44%	9.73%
Exp. 17	39.52%	9.88%	7.96%	15.93%	1.36%	8.18%	12.62%	2.10%	2.44%	9.81%
Exp. 18	16.27%	4.07%	9.80%	2.45%	10.54%	42.16%	2.45%	9.80%	2.48%	8.26%
Exp. 19	19.20%	6.40%	32.77%	10.92%	3.61%	14.43%	8.18%	2.04%	2.44%	9.72%
Exp. 20	1.98%	7.91%	17.16%	34.33%	9.49%	4.74%	16.46%	5.49%	2.45%	9.64%
Exp. 21	25.61%	4.27%	11.04%	3.68%	5.26%	36.81%	7.24%	3.62%	2.47%	8.51%
Exp. 22	35.49%	7.10%	3.40%	13.61%	1.99%	7.96%	4.67%	23.34%	2.45%	9.66%
Exp. 23	22.25%	3.18%	6.91%	41.48%	7.80%	1.95%	11.99%	2.00%	2.44%	9.99%
Exp. 24	21.50%	5.38%	8.73%	8.73%	11.64%	5.82%	17.79%	17.79%	2.62%	3.04%
Exp. 25	27.07%	9.02%	15.31%	5.10%	3.40%	17.01%	10.21%	10.21%	2.66%	1.31%
Exp. 26	36.17%	7.23%	3.59%	14.36%	7.76%	2.59%	19.39%	6.46%	2.45%	9.53%
Exp. 27	40.03%	5.72%	24.06%	3.44%	4.69%	4.69%	13.05%	1.86%	2.45%	9.49%
Exp. 28	34.58%	5.76%	4.68%	23.39%	5.29%	5.29%	14.83%	3.71%	2.47%	8.85%
Exp. 29	12.39%	12.39%	8.16%	32.63%	5.17%	5.17%	14.44%	7.22%	2.44%	9.75%
Exp. 30	3.94%	19.69%	3.60%	10.79%	6.55%	39.31%	11.95%	1.71%	2.47%	8.49%
Exp. 31	31.44%	10.48%	3.55%	14.20%	4.97%	19.88%	10.77%	2.15%	2.55%	5.31%
Exp. 32	38.62%	12.87%	7.41%	2.47%	10.67%	3.56%	18.29%	3.66%	2.45%	9.64%
Exp. 33	24.22%	8.07%	19.85%	9.92%	5.53%	16.60%	9.93%	3.31%	2.56%	5.23%
Exp. 34	40.08%	10.02%	10.47%	3.49%	3.37%	20.22%	7.43%	2.48%	2.44%	9.77%
Exp. 35	19.04%	4.76%	14.06%	14.06%	2.66%	7.99%	23.31%	11.65%	2.47%	8.81%
Exp. 36	26.74%	13.37%	8.73%	8.73%	6.25%	18.76%	9.93%	4.96%	2.52%	6.61%
Exp. 37	30.31%	7.58%	5.66%	16.99%	3.28%	9.84%	17.88%	5.96%	2.50%	7.56%
Exp. 38	7.83%	23.50%	18.46%	18.46%	3.45%	10.34%	3.85%	11.54%	2.57%	4.86%
Exp. 39	11.85%	2.96%	34.20%	6.84%	2.62%	21.00%	2.25%	15.76%	2.51%	7.03%
Exp. 40	13.52%	2.25%	37.36%	12.45%	4.14%	12.42%	7.65%	7.65%	2.54%	5.80%
Exp. 41	5.49%	16.46%	11.86%	2.37%	10.30%	41.19%	8.24%	1.65%	2.45%	9.64%

Table A-2: Consolidated global criteria weights by purchasing division (homogenous groups) and proportional adjustments

	Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
		C11	C12	C21	C22	C31	C32	C41	C42	C51	
Purchasing division	Sub-criteria	Parts cost	Industri-alization cost	Machine conditions and manufacturing technology	Testing processes and facilities	Product development/ industri-alization time	Infrastruc-ture and supply	Development experience	Investment in innovation	CO_2e component manufacturing	Consistency Ratio (CR<10%)
∑ Consumable material	Geometric mean (AIJ)	28.29%	9.28%	12.44%	12.93%	6.48%	9.00%	12.67%	6.30%	2.62%	2.82%
∑ Non-consumable material		20.89%	9.98%	16.33%	11.45%	5.68%	12.71%	13.14%	7.15%	2.67%	1.13%
∑ Strategy		26.30%	12.84%	12.97%	8.36%	4.40%	16.41%	10.97%	5.12%	2.63%	2.65%
∑ Consumable material	Porportional adjustment	29.05%	9.53%	12.77%	13.27%	6.66%	9.24%	13.01%	6.47%		
∑ Non-consumable material		21.46%	10.26%	16.77%	11.77%	5.84%	13.06%	13.50%	7.34%		
∑ Strategy		27.01%	13.19%	13.32%	8.58%	4.52%	16.85%	11.27%	5.26%		
∑ Consumable material	min	12.39%	2.25%	3.59%	2.47%	2.20%	1.95%	1.68%	1.86%	2.44%	
	max	40.03%	21.99%	37.36%	41.48%	10.67%	36.81%	19.39%	11.75%	2.54%	
∑ Non-consumable material	min	1.98%	1.39%	3.39%	2.37%	1.31%	1.96%	2.25%	1.49%	2.44%	
	max	44.16%	25.05%	37.59%	38.62%	25.51%	42.16%	23.43%	33.19%	2.66%	
∑ Strategy	min	7.83%	4.56%	3.55%	2.70%	3.09%	10.34%	3.85%	2.15%	2.47%	
	max	38.73%	23.50%	26.44%	18.46%	5.61%	21.89%	15.02%	11.54%	2.57%	

Table A-3: Consolidated global criteria weights by division (homogenous groups) as well as hierarchy level and proportional adjustments

		Main criteria	C1 Cost		C2 Quality & production		C3 Flexibility		C4 Development & innovation		C5 Environmental sustainability	
Purchasing division	Hierachy Levels	Sub-criteria	C11 Parts cost	C12 Industri-alization cost	C21 Machine conditions and manufacturing technology	C22 Testing processes and facilities	C31 Product development/ industri-alization time	C32 Infrastruc-ture and supply	C41 Development experience	C42 Investment in innovation	C51 CO_2e component manufacturing	Consistency Ratio (CR<10%)
Consumable material	∑ DIVM	Geometric mean (AIJ)	30.31%	7.58%	5.66%	16.99%	3.28%	9.84%	17.88%	5.96%	2.50%	7.56%
	∑ SDM		20.03%	8.18%	22.00%	12.70%	5.23%	9.05%	10.10%	10.10%	2.61%	3.35%
	∑ DM		22.01%	9.13%	8.81%	25.40%	7.55%	6.86%	13.10%	4.54%	2.59%	3.92%
	∑ TL		21.63%	21.63%	11.58%	11.58%	2.20%	15.43%	1.68%	11.75%	2.53%	6.40%
	∑ SB		37.66%	7.52%	11.62%	5.83%	8.33%	7.82%	14.76%	3.88%	2.59%	4.05%
	∑ DIVM	Porportional adjustment	31.08%	7.77%	5.81%	17.43%	3.36%	10.09%	18.34%	6.11%		
	∑ SDM		20.57%	8.40%	22.59%	13.04%	5.37%	9.29%	10.37%	10.37%		
	∑ DM		22.60%	9.38%	9.04%	26.08%	7.75%	7.04%	13.44%	4.66%		
	∑ TL		22.19%	22.19%	11.88%	11.88%	2.26%	15.83%	1.72%	12.05%		
	∑ SB		38.66%	7.72%	11.92%	5.99%	8.55%	8.03%	15.16%	3.98%		
Non-consumable material	∑ DIVM	Geometric mean (AIJ)	11.85%	2.96%	34.20%	6.84%	2.62%	21.00%	2.25%	15.76%	2.51%	7.03%
	∑ SDM		29.48%	4.91%	19.74%	19.74%	1.41%	8.46%	10.36%	3.45%	2.45%	9.55%
	∑ DM		17.97%	4.69%	24.53%	9.64%	11.50%	11.50%	12.71%	4.83%	2.65%	1.68%
	∑ TL		25.63%	10.56%	17.58%	4.72%	5.91%	15.39%	6.98%	10.59%	2.65%	1.74%
	∑ SB		19.29%	13.06%	11.63%	14.47%	5.03%	11.41%	16.50%	5.95%	2.66%	1.60%
	∑ DIVM	Porportional adjustment	12.16%	3.04%	35.08%	7.02%	2.69%	21.54%	2.31%	16.16%		
	∑ SDM		30.22%	5.04%	20.24%	20.24%	1.45%	8.67%	10.61%	3.54%		
	∑ DM		18.46%	4.81%	25.20%	9.90%	11.81%	11.81%	13.05%	4.96%		
	∑ TL		26.33%	10.85%	18.06%	4.84%	6.07%	15.81%	7.17%	10.87%		
	∑ SB		19.82%	13.41%	11.95%	14.87%	5.16%	11.73%	16.95%	6.11%		
Strategy	∑ DIVM	Geometric mean (AIJ)	7.83%	23.50%	18.46%	18.46%	3.45%	10.34%	3.85%	11.54%	2.57%	4.86%
	∑ SDM		18.24%	4.56%	26.44%	8.81%	4.38%	21.89%	9.85%	3.28%	2.53%	6.13%
	∑ DM		33.19%	11.06%	8.10%	2.70%	5.61%	16.84%	15.02%	5.01%	2.47%	8.78%
	∑ TL		31.44%	10.48%	3.55%	14.20%	4.97%	19.88%	10.77%	2.15%	2.55%	5.31%
	∑ SB		38.73%	12.91%	11.96%	2.99%	3.09%	12.35%	11.58%	3.86%	2.53%	6.25%
	∑ DIVM	Porportional adjustment	8.04%	24.12%	18.95%	18.95%	3.54%	10.61%	3.95%	11.84%		
	∑ SDM		18.72%	4.68%	27.13%	9.04%	4.49%	22.46%	10.11%	3.37%		
	∑ DM		34.03%	11.34%	8.31%	2.77%	5.75%	17.26%	15.40%	5.13%		
	∑ TL		32.26%	10.75%	3.64%	14.58%	5.10%	20.40%	11.05%	2.21%		
	∑ SB		39.74%	13.25%	12.27%	3.07%	3.17%	12.67%	11.88%	3.96%		

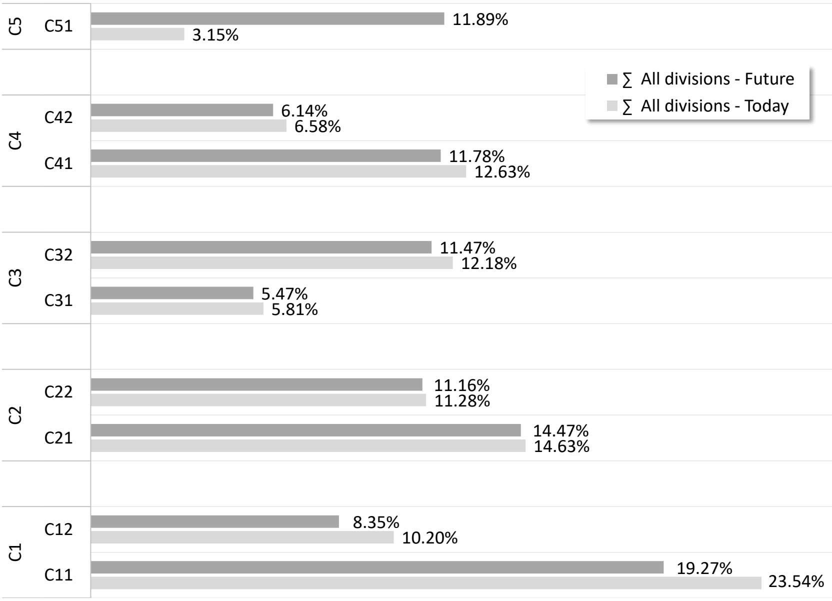


Figure A-3: Comparison of current criteria weights and according future estimations (entire expert sample)

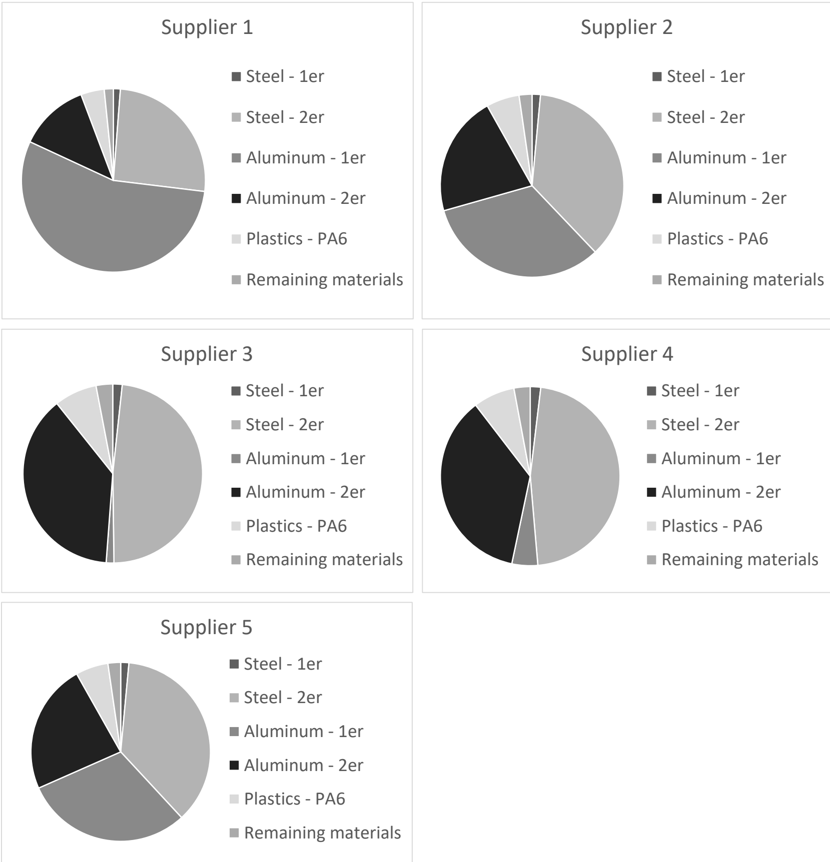


Figure A-4: Material composition per supplier (indication)

B: Sub-model B for environmental performance assessment

Table B-1: Material conversion rates (t/t) - steel (Breun, 2016; European Commission, 2013)

Description	Conversion rate	Notation
Coke → Sinter	0.05	mcr_{ps_1,ps_2}
Coke → Pig iron	0.30	mcr_{ps_1,ps_3}
Sinter → Pig iron	1.09	mcr_{ps_2,ps_3}
Pig iron → Crude steel	0.82	mcr_{ps_3,ps_4}
Crude steel → Rolled steel	1	mcr_{ps_4,ps_5}

Table B-2: Reported production volumes (t/a) - steel (ArcelorMittal, 2013; Ruukki, 2013; SSAB, 2013; TATA STEEL, 2013; VDEh, 2014b; Voestalpine, 2013; World Steel Association, 2013)

Production site	Blast Furnace	Basic Oxygen Furnace	Rolling Mill
1	4,340,000	5,330,000	4,700,000
2	1,370,000	1,475,841	1,475,841
3	4,343,000	4,786,000	4,743,000
4	1,893,384	2,299,000	2,299,000
5	5,990,000	6,370,000	3,595,000
6	3,888,000	3,941,000	3,637,000
7	11,419,000	11,559,000	8,876,559
8	0	1,145,000	512,000
9	0	2,058,944	354,949
10	4,273,000	4,588,000	3,340,000
11	4,620,000	5,200,000	595,775
12	2,944,494	3,200,000	3,199,000
13	3,799,997	2,272,000	1,359,936
14	1,500,000	1,800,000	1,500,000
15	6,651,550	8,076,500	8,076,500
16	5,435,551	6,600,000	4,950,000
17	3,972,000	4,276,000	3,851,000
18	1,587,016	1,927,000	0
19	1,242,893	879,000	532,000
20	3,133,660	3,000,000	2,250,000
21	1,822,750	2,213,235	0
22	1,695,703	3,100,000	2,325,000

(light grey)	Own assumption calculated with material conversion rates per according process step - see section 4.3.5 (Breun, 2016; European Commission, 2013)
(dark grey)	Own assumption calculated with installed capacity on site and a ratio of company- and country specific utilization rate as well as share of capacity (VDEh, 2014a; World Steel Association,

Table B-3: Average process gases (MJ/t) for reutilization on-site - steel (Breun, 2016; European Commission, 2013)

	coke oven gas (COG)	blast furnace gas (BF gas)	basic oxygen furnace gas (BOF gas)
Output	7,888	4,572	458
Input			
Coke oven	562	2,892	287
Sintering plant	31	29	
Blast furnace	361	1,599	130
Basic oygen furnace	446	18	
Rolling mill	735	186	37

Table B-4: Reported CO_2 emissions (t CO_2/a) - steel (European Environment Agency, 2012)

Production site	Reported emissions (CO_2)	COKE OVEN				SINTERING PLANT				BLAST FURNACE				BASIC OXYGEN FURNACE				ROLLING MILL			POWER PLANT		
		i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=1	i=2	i=3
1	8,440,000	x				x				x	x	x		x				x			x		
2	2,580,000					x				x	x			x				x			x		
3	3,430,000	x				x	x			x	x			x				x					
3	6,120,000																				x		
4	3,720,000	x								x	x			x				x			x		
5	11,900,000	x	x			x	x			x	x	x		x				x					
5	3,700,000																				x		
6	7,140,000	x				x				x	x			x				x					
6	258,000																				x		
6	299,000																					x	
7	467,000													x				x					
7	867,000														x				x				
7	2,550,000									x	x										x		
7	5,320,000					x	x	x				x	x										
7	1,930,000	x																					
7	2,920,000																					x	
7	2,540,000																						x
8	230,000													x				x					
9	262,424													x				x					
10	7,980,000	x				x				x	x	x		x				x			x		
11	4,790,000	x				x				x	x			x									
11	103,782																	x					
11	4,200,000																				x		
12	2,100,000					x				x	x			x				x					
12	2,254,675																				x		
13	705,000													x				x					
13	4,200,000					x	x			x	x												
13	871,000	x																					
13	1,050,000																				x		
14	1,270,000					x				x	x			x				x					
14	1,930,000																				x		
15	10,300,000	x	x			x	x			x	x	x		x	x			x	x				
15	7,480,000																				x		
16	5,980,000	x	x	x	x	x	x	x	x	x	x			x				x					
16	4,470,000																				x		
16	1,870,000																					x	
17	4,590,000	x	x	x		x	x			x	x			x	x			x	x				
17	6,170,000																				x		
18	1,010,000	x								x				x									
18	1,990,000																				x		
19	1,540,000	x								x	x			x				x			x		
20	5,120,000	x				x				x	x			x				x			x		
21	4,240,000	x	x			x				x				x							x		
22	3,760,000	x	x	x		x	x			x	x			x				x			x		

i = Number of facilities per process step
x = Process step included in reported emissions

Table B-5: Average emission factors (t CO_2/t) per intermediate products - steel (Breun, 2016; European Commission, 2013)

Process step	Emission factor
Coke oven (coke)	0.68
Sintering plant (sinter)	0.27
Blast furnace (pig iron)	0.50
Basic oygen furnace (crude steel)	0.12
Rolling mill (rolled steel)	0.15
Power plant (pig iron)	0.87

Table B-6: Average, country specific emission factors (t CO_2/GJ) for electricity production and the upstream raw material supply chain (kg CO_2/kg) - steel (Ecoinvent, 2007-2013; UBA, 2012)

	Austria	Belgium	Finland	France	Germany	Italy	Nether-lands	Spain	Sweden	United Kingdom
Electricity production (energy mix)	0.08619	0.09109	0.10668	0.02426	0.18433	0.17623	0.19053	0.14143	0.01065	0.16598
Upstream raw material supply chain input for										
Coke oven	0.55385	0.55492	0.55831	0.54039	0.57520	0.57344	0.57655	0.56587	0.53742	0.57121
Sintering plant	0.11623	0.11641	0.11697	0.11400	0.11976	0.11947	0.11999	0.11822	0.11351	0.11910
Blast furnace	0.11703	0.11703	0.11703	0.11703	0.11703	0.11703	0.11703	0.11703	0.11703	0.11703
Basic oygen furnace	0.10376	0.10415	0.10538	0.09887	0.11151	0.11088	0.11200	0.10813	0.09779	0.11007
Rolling mill	0.24888	0.25135	0.25921	0.21767	0.29834	0.29427	0.30147	0.27673	0.21081	0.28910
Power plant	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
Natural gas	0.01217	0.01217	0.01217	0.01217	0.01217	0.01217	0.01217	0.01217	0.01217	0.01217

Table B-7: Capacities (t/a) of the aluminum plants under study (BGR, 2012; Norsk Hydro ASA, 2012, 2013; TRIMET ALUMINIUM AG, 2012; TRIMET Aluminium SE, 2013; TRIMET SE, 2014; U.S. Geological Survey, 2013, 2015)

Prod. site	ANODE FACTORY	ELECTROLYSIS	CASTING PLANT*	ROLLING MILL
1	120,000	x	133,000	
2		x	175,000	
3	50,000	x	235,000	x
4	65,000	x	95,000	

x = Facility exists on site, no specific information available

* = Casting exclusively related to ingot casting (raw aluminum) of produced liquid aluminum from local smelter (assumption)

Table B-8: Reported production volume (t/a) - aluminum (BGR, 2012; Norsk Hydro ASA, 2012, 2013; TRIMET ALUMINIUM AG, 2012; TRIMET Aluminium SE, 2013; TRIMET SE, 2014; U.S. Geological Survey, 2013, 2015)

Prod. site	ANODE FACTORY	ELECTROLYSIS	CASTING PLANT*	ROLLING MILL
1	115,000	128,047**	125,659	
2		168,482**	165,341	
3	20,889*	50,950**	50,000	49,801**
4	65,000	96,805**	95,000	

* = Casting exclusively related to ingot casting (raw aluminum) of produced liquid aluminum from local smelter (assumption)

** = Calculated with material conversion rates (see Table B-9) according to Step 1 (see section 4.4.4)

Table B-9: Material conversion rates (t/t) - aluminum (European Aluminium, 2013)

Description	Conversion rate	Notation
Anode → Liquid aluminum	0.440	mcr_{ps_1,ps_2}
Liquid aluminum → Aluminum	1.019	mcr_{ps_2,ps_3}
Aluminum → Aluminum product	1.004	mcr_{ps_3,ps_4}

Table B-10: Reported emissions (t/a) - aluminum (European Environment Agency, 2012)

Prod. site	Reported Emissions (CO_2)	ANODE FACTORY	ELECTROLYSIS	CASTING PLANT*	ROLLING MILL	Reported PFC Emissions
1	217,000	x	x	x		4.67
2	247,000		x	x		3.97
3	136,000	x	x	x	x	2.13
4	152,000	x	x	x		1.77

x = Process step included in reported emissions

* = Casting exclusively related to ingot casting (raw aluminum) of produced liquid aluminum from local smelter (assumption)

Table B-11: Average emission factors (t CO_2/t) per intermediate products - aluminum (European Aluminium, 2013)

Process step	Emission factor
Anode factory (anode)	0.443*
Electrolysis (liquid aluminum)	1.574
Casting plant (aluminum)	0.113
Rolling mill (aluminum product)	0.128

*Carbon dioxide from non-fuel combustion sources (0.235) + from fuels (0.208) (World Aluminium, 2013)

Table B-12: Average input factors for energy consumption (kWh/t) - aluminum (European Aluminium, 2013)

Process step	Energy consumption
Anode factory (anode)	108
Electrolysis (liquid aluminum)	14,880
Casting plant (aluminum)	98
Rolling mill (aluminum product)	568

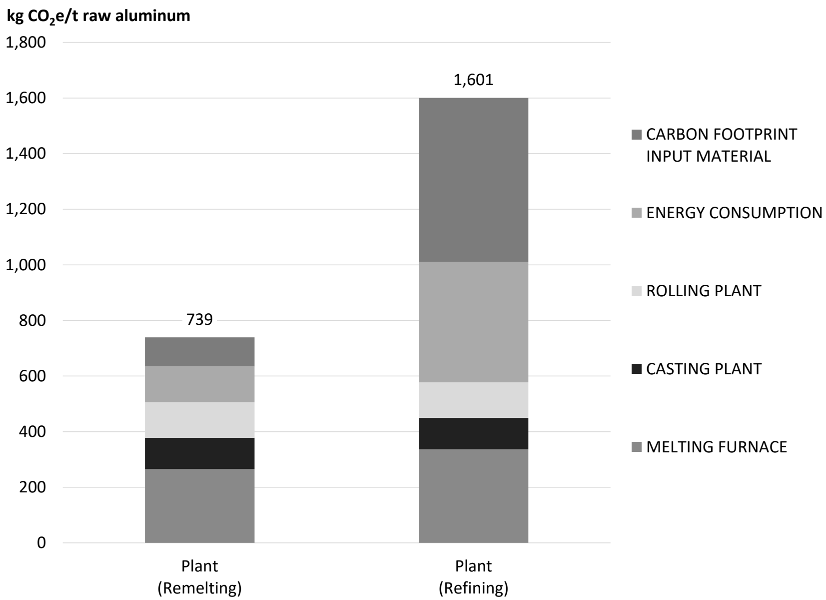


Figure B-1: Results for secondary aluminum plants in Germany

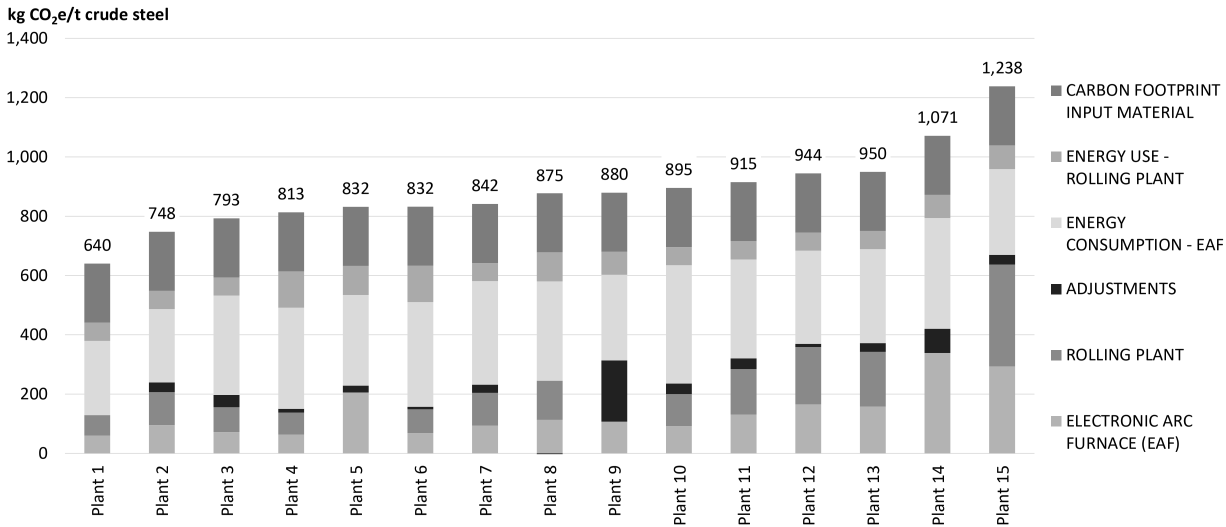


Figure B-2: Results of the examined, German secondary steel (EAF) plants after the emission adjustment

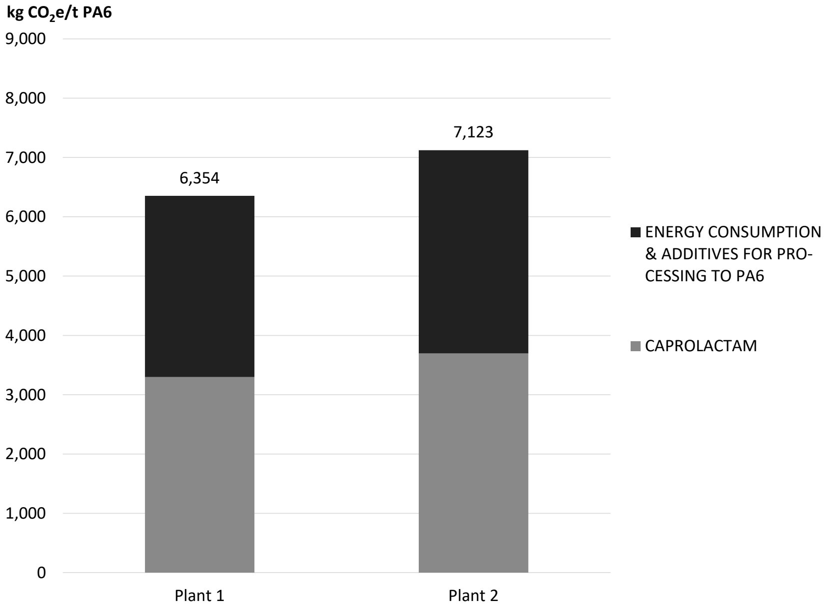


Figure B-3: Results of the examined, German chemical plants

Table B-13: Sample application different cost rates and emission limits

Scenario						
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	a)	34.2 kg CO_2 (≙ -10% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.15	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	b)	30.4 kg CO_2 (≙ -20% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.30	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	c)	26.6 kg CO_2 (≙ -30% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.46	280.21	291.02	299.02	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	d)	22.8 kg CO_2 (≙ -40% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.61	280.21	291.17	299.17	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	e)	19 kg CO_2 (≙ -50% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.76	280.25	291.32	299.32	281.08
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000

Scenario						
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	a)	34.2 kg CO_2 (≙ -10% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.30	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	b)	30.4 kg CO_2 (≙ -20% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.61	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	c)	26.6 kg CO_2 (≙ -30% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.91	280.21	291.03	299.03	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	d)	22.8 kg CO_2 (≙ -40% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.22	280.21	291.34	299.34	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	e)	19 kg CO_2 (≙ -50% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.29	281.52	291.64	299.64	281.16
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000

Scenario						
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	a)	34.2 kg CO_2 (≙ -10% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.46	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	b)	30.4 kg CO_2 (≙ -20% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.91	280.21	291.00	299.00	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	c)	26.6 kg CO_2 (≙ -30% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.37	280.21	291.05	299.05	281.00
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	d)	22.8 kg CO_2 (≙ -40% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.21	281.82	291.50	299.50	281.00
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	e)	19 kg CO_2 (≙ -50% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.33	282.28	291.96	299.96	281.24
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000

Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	f)	15.2 kg CO_2 (≙ -60% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		280.91	280.40	291.47	299.47	281.23
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	g)	11.4 kg CO_2 (≙ -70% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.06	280.55	291.62	299.62	281.38
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	h)	7.6 kg CO_2 (≙ -80% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.22	280.71	291.78	299.78	281.54
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	i)	3.8 kg CO_2 (≙ -90% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.37	280.86	291.93	299.93	281.69
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000
Scenario	1)	Cost of CO_2 - 40 €/kg CO_2 (UBA)				
	j)	0 kg CO_2 (≙ -100% reduction)				
Ranking		1	2	3	4	5
Supplier		S1	S3	S2	S5	S4
Projet Cost		281.52	281.01	292.08	300.08	281.84
CO_2e Project (total)		38,000,000	20,000,000	27,000,000	27,000,000	21,000,000

Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	f)	15.2 kg CO_2 (≙ -60% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.59	281.82	291.94	299.94	281.46
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	g)	11.4 kg CO_2 (≙ -70% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.90	282.13	292.25	300.25	281.77
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	h)	7.6 kg CO_2 (≙ -80% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		281.20	282.43	292.55	300.55	282.07
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	i)	3.8 kg CO_2 (≙ -90% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		281.51	282.74	292.86	300.86	282.38
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	2)	Cost of CO_2 - 80 €/kg CO_2 (UBA)				
	j)	0 kg CO_2 (≙ -100% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		281.81	283.04	293.16	301.16	282.68
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000

Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	f)	15.2 kg CO_2 (≙ -60% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		280.79	282.74	292.42	300.42	281.70
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	g)	11.4 kg CO_2 (≙ -70% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		281.24	283.19	292.87	300.87	282.15
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	h)	7.6 kg CO_2 (≙ -80% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		281.70	283.65	293.33	301.33	282.61
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	i)	3.8 kg CO_2 (≙ -90% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		282.15	284.10	293.78	301.78	283.06
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000
Scenario	3)	Cost of CO_2 - 120 €/kg CO_2 (UBA)				
	j)	0 kg CO_2 (≙ -100% reduction)				
Ranking		1	2	3	4	5
Supplier		**S3**	**S1**	**S2**	**S5**	**S4**
Projet Cost		282.61	284.56	294.24	302.24	283.52
CO_2e Project (total)		20,000,000	38,000,000	27,000,000	27,000,000	21,000,000

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