Appendix to Chapter 2

A.1 Literature analysis

TABLE A.1: Overview of aspects of recyclability found in the literature, grouped by value chain stage.

Value chain stage	Group	Aspect
Overarching	Economies of scale	Quantity
		Economies of scale
		Investment inertia
	Environmental benefits	Environmental effects
		Human health impact
		Resource depletion
	Social benefits	Social externalities
		Labor conditions; Labor rights conditions
		Societal stability
		Job creation
	Supply chain alignment	Supply chain organization
		Supply chain cooperation
		Information exchange
	Uncertainty	Confidence level of future flows
		Future waste composition
		Uncertain waste quality
		Uncertain waste quantity
		Product information available
	Profitability	Net present value
	Costs	Awareness campaign costs
		Collection costs
		Transport costs
		Dismantling costs
		Investment costs
		Operating costs
		Processing costs
		Recycling costs
		Energy costs
		Labor costs

		Landfill costs
Manufacturing	Design approach	Eco-design
		Manufacturers vision
	Product design	Product complexity
		Product design variation
		Variety of components
		Compact design
		Dispersion
		Dismantability
		Joints; Fixation
Use & Collection	Collectability	Size
		Stock
		Property rights; Eligibility
		Ownership
		Ownership shifts
		Product lifespan
		Dissipation
	Collection participation	Collection rate
		Collection rate trends
		Consumer awareness
		Consumer attitude
	Infrastructure	Collection infrastructure
		Consumer facilitation
		Distance between collection points
		Geographic dispersion
	Policy	Extended producer responsibility (EPR) legislation
		Collection/recycling rules
		Collection enforcement
		Waste export
		Export regulation
		Informal/illegal recycling
Preprocessing	Preprocessing performance	Component identification; Material identification
		Contaminant detection
		Shredding time; Size reduction
		Dismantling time
		Liberation efficiency
		Separability after liberation
Recovery	Compatibility	Compatibility
		Co-recovery
		Contamination
		Coating
	Recovery performance	Recovery efficiency

		Concentration
		Variety of materials
		Metallurgical complexity
		Expertise required
		Technology availability
Preprocessing / Recovery	Environmental effects	Emissions to environment
		Toxic materials
		Toxic/hazardous process chemicals
		Energy consumption; Energy savings
		Process safety
	Policy	Economic incentives
	Recycling performance	Statistical entropy
		Material grade
	Technology availability	Technology maturity
		Current recycling rate
		Processing capacity
Secondary market	Criticality	Supply risk of metal
		Price volatility
		Depletion time
		Economic importance of metal; Importance of metal for emerging industries
		Resource independence
	Demand	Demand growth
		Market stability
		Confidence in recycled product quality
		Degradation; Purity of recycled materials
	Revenues	Recovered metal value
	Competition	Competing recycling processes

A.2 Proposed framework

A.2.1 Novel factors and indicators

The following factors and indicators have not been integrated in recyclability assessment frameworks before. The factors are mentioned in the literature, but not included in any framework. The indicators are novel ways to quantify an aspect.

- Factors
  - Design for recycling
  - Component design variation
  - EPR legislation
  - Export restriction
  - Safety risk
  - Expertise required
  - Confidence in quality
- Indicators
  - Fraction of actors involved in exchange
  - Number of product designs
  - Number of component designs
  - Identification accuracy
  - Technology readiness level
  - Price premium or discount

A.2.2 Score calculations

TABLE A.2: Formulas to calculate the score belonging to the value of quantitative indicators. Outcomes > 5 or < 0 are replaced by the maximum or minimum score.The formulas have been designed to return a number within the 5-point scale, by adjusting to the value ranges observed for minor metals. If an indicator and recyclability are inversely related, a minus sign was added. In the case that a range spanned several orders of magnitude, a log function was used.

Indicator	Unit	Formula
Annual waste flow	t/a	$\frac{x}{200} \cdot 5$
Recycling subsidy	\$/t	$x/20$
Disposal and raw material tax	\$/t	$x/20$
Standard deviation / future waste flow	%	$5 \cdot (1 - 2\|x\|)$
Labor rights indicator	–	$\frac{x}{2}$
Number of product designs	№	$5 - \frac{x}{4}$
Number of component designs	№	$5 - \frac{x}{4}$
Metal content per component	g/component	$\log(10 \cdot x)$
Product weight	kg/unit	$^5\log(5 \cdot x)$
Annual waste generation	units/capita/a	$^4\log(800 \cdot x)$
Collected fraction of EoL products	%	$5 \cdot x$
Fraction of aware consumers	%	$5 \cdot x$
Distance between collection points	km	$5 \cdot (1 - \frac{x}{100})$
Identification accuracy	%	$5 \cdot x$
Liberation efficiency	%	$5 \cdot x$
Dismantling time	h/t	$5 - \frac{x}{10}$
Recovery efficiency	%	$5 \cdot x$
Concentration after preprocessing	wt%	$^5\log(20,000 \cdot x)$
Value fraction of recoverable metals	%	$5 \cdot x$
Technology readiness level	TRL	$5 \cdot (x - 1)/8$
GHG emissions	% of virgin	$5 \cdot (1 - x)$
Target metal value	\$/t	$x/20$
Co-recovered metal value	\$/t	$x/400$
Price volatility	%	$5 \cdot (1 - \frac{x - 5\%}{25\%})$
Demand growth rate	%	$15 \cdot x + 1.75$

Quantities in tonnes (t) refer to waste input.

A

B Appendix to Chapter 3

B.1 Permanent magnet market

The market share of NdFeB magnets in the permanent magnet market was estimated on the basis of time series from three sources [1–3]. For ranges where these time series overlapped, the data were averaged.

TABLE B.1: Global permanent magnet production. Totals are calculated average of three market reports (1 in 4; 2; 3). NdFeB magnet amounts are based on Constantinides [5].

Year	Total (t)	NdFeB (t)
1990	306,865	1,254
1995	476,954	4,515
2000	552,104	17,560
2005	663,327	39,384
2010	627,255	80,525
2013	812,487	83,535
2014	877,587	90,057
2015	913,387	109,868
2016	981,423	117,437
2017	1,052,726	125,006
2018	1,125,414	132,576
2019	1,207,195	140,145
2020	1,295,094	147,714

B.2 Market share data

TABLE B.2: Market share of Nd-containing components. BEV: battery electric vehicle; FCC: fluid catalytic cracking; HEV: hybrid electric vehicle; PHEV: plug-in HEV.

UNU-Key	Product group	Assumption or sources
0001	Central heating (household)	Proxy: 1204
0102	Dishwashers	Proxy: 0104
0104	Washing machines	[6; 7]

UNU-Key	Product group	Assumption or sources
0105	Dryers	Proxy: 0104
0106	Heating and ventilation (household)	Proxy: 0201b
0108	Fridges	[6; 8; 9]
0109	Freezers	Proxy: 0108
0111	Air conditioners	[10; 11] EU market share is half that of Japan
0112	Other cooling	25% of 0111
0113	Cooling (professional)	Proxy: 0108
0114	Microwaves	50% of permanent magnet market share
0201b	Fans	Permanent magnet trend with 5% max.
0204	Vacuum cleaners	[11]
0205	Personal care	[11]
0205b	Shavers	Proxy: 0205
0301b	HDDs	See §B.3
0302	Desktop PCs	See Eq. 3 in main text
0303a	Laptops	idem
0303b	Tablets	100%
0304	Printers	Permanent magnet trend with 1% max.
0305	Telecom	Half of the market share of 0306a
0306a	Mobile phones	[8]
0306b	Smartphones	[8]
0307	Professional IT	Permanent magnet trend with 1% max.
0309	Flat screen monitors	Proxy: 0408
0401	Small consumer electronics	Half of the market share of 0401b
0401b	Headphones, earphones	[12; 13]
0403	Music instruments, radio, HiFi	Permanent magnet trend with 80% max.
0404b	Video players	[10]
0405	Speakers	[12; 14], [1]
0406	Cameras	[12]
0408	Flat screen TVs	[13; 15]
0702	Game consoles	Proxy: 0301b
0802b	MRIs	[16]
1002	Cooled vending machines	Proxy: 0108
1101	Cars	[11; 17]
1102a	BEVs	[6; 18]
1102b	PHEVs	100%
1103	HEVs	100%
1104	Snowmobiles, golf cars, etc.	Half of the market share of 1101

[1] Personal communication, B&C speakers

UNU-Key	Product group	Assumption or sources
1105	Trucks	75% of the market share of 1101
1106	Buses	75% of the market share of 1101
1107	Motorhomes	Half of the market share of 1101
1108	Electric bikes	[19]
1201	Industrial machines & motors	Permanent magnet trend with 2% max.
1202	Industrial pumps	Permanent magnet trend with 10% max.
1203	Lifting and conveying machines	Permanent magnet trend with 5% max.
1204	Shaping machines	0% [a]
1205a	Wind turbines, onshore	[20]
1205b	Wind turbines, offshore	[20]
1206	Industrial robots	Permanent magnet trend with 90% max. [a]
	Catalysts	
1101	Car catalytic converter	Nd phase-out between 1990–2000. [a]
1301	FCC catalyst	[21], Nd phase-out between 1995–2010. [a]
	NiMH batteries	
0204	Vacuum cleaners	Linear growth of products with a battery to 15.9% in 2012 [22].
0205	Personal care	Half of the products contain a battery. NiMH share as in Fig. 2.
0305	Telecom	Half of the products contain a battery. NiMH share as in Fig. 2.
0306a	Mobile phones	[23]
0406	Cameras	Twice the average market share of NiMH batteries.
0601	Power tools	Linear growth of products with a battery to 2% in 2009 [24].
0602	Tools (professional)	Half the value of 0601.
0701	Toys	Follows the average market share of NiMH batteries.
1103	HEVs	[23; 25; 26]

[a] Personal communication, Gareth Hatch (2020).

B.3 Data storage market

The market shares of HDDs and SSDs were based on market reports [27–30] reporting global unit shipments. Logistic curve fitting yielded an inflection point at 2018 and an ultimate market share of 85% for SSDs.

B

TABLE B.3: Global market data and forecasts for HDD and SSD sales, in million units per year.

Year	HDD sales [27]	SSD sales	SSD sales source	HDD market share	Fitted HDD market share
2003	251				
2004	295				
2005	368				
2006	424				99%
2007	486				99%
2008	521	2.0	[28]	100%	98%
2009	548	11.0	[28]	98%	98%
2010	632	14.0	[28]	98%	97%
2011	600	17.3	[28]	97%	95%
2012	548	39.0	[28]	93%	93%
2013	510				90%
2014	520				86%
2015	425	105	[29]	80%	80%
2016	377	140	[29]	73%	74%
2017	355	190	[29]	65%	66%
2018	310	232.2	[30]	57%	58%
2019	279	317.8	[30]	47%	49%
2020	249	354.3	[30]	41%	41%
2021	223	408.2	[30]	35%	35%
2022	182	451.8	[30]	29%	29%
2023	168	488.2	[30]	26%	25%
2024	158	508.9	[30]	24%	22%

B.4 Product lifespan

TABLE B.4: Weibull parameters describing the lifespan distribution of applications.

UNU-Key	Product group	scale (β)	shape (α)	Source
0001	Central heating (household)	14.21	2	[31]
0102	Dishwashers	12.12	1.64	[31; 32]
0104	Washing machines	13.6	2.2	[31; 32]
0105	Dryers	14.6	2.58	[11; 31]
0106	Heating and ventilation (househ.)	13.47	2	[31]
0108	Fridges	16.71	2.2	[31]
0109	Freezers	18.55	1.28	[31; 33]
0111	Air conditioners	14.52	2.69	[31]
0112	Other cooling	13.36	2.36	[31]
0113	Cooling (professional)	15.36	1.6	[31]
0114	Microwaves	17.99	2.07	[31]
0201b	Fans	7.97	1.22	[31]

UNU-Key	Product group	scale (β)	shape (α)	Source
0204	Vacuum cleaners	8.7	1.45	[31; 32]
0205	Personal care	8.09	1.2	[31]
0205b	Shavers	9.5	1.5	[31]
0301b	HDDs	5.91	1.25	[31]
0302	Desktop PCs	8.95	1.58	[31]
0303a	Laptops	6.57	1.6	[31]
0303b	Tablets	6.8	1.6	
0304	Printers	9.31	1.88	[31]
0305	Telecom	7.22	1.24	[31]
0306a	Mobile phones	6.26	1.56	[31]
0306b	Smartphones	6.26	1.56	[31]
0307	Professional IT	7.78	1.46	[31]
0309	Flat screen monitors	7.39	2.33	[31]
0401	Small consumer electronics	9.87	1.3	[31]
0401b	Headphones, earphones	6.15	1.3	[31]
0403	Music instruments, radio, HiFi	15.54	2.09	[31]
0404b	Video players	8.33	1.14	[31]
0405	Speakers	11.5	1.49	[31; 34]
0406	Cameras	6.75	1.19	[31]
0408	Flat screen TVs	11.75	2.01	[31]
0702	Game consoles	4.78	1.14	[31]
0802b	MRIs	14	2.5	[31; 35]
1002	Cooled vending machines	15	2	[31]
1101	Cars	15.5	3.6	[10; 36]
1102a	BEVs	15.5	3.6	[10; 36]
1102b	PHEVs	15.5	3.6	[10; 36]
1103	HEVs	15.5	3.6	[10; 36]
1104	Snowmobiles, golf cars, etc.	15.5	3.6	[10; 36]
1105	Trucks	23	3.3	
1106	Buses	23	3.3	
1107	Motorhomes	17	1.8	[32]
1108	Electric bikes	10	1.8	[11; 32]
1201	Industrial machines & motors	16.7	1.5	[37]
1202	Industrial pumps	27.1	2.2	[38]
1203	Lifting and conveying machines	16.7	1.5	[32]
1204	Shaping machines	16.7	1.5	[32]
1205a	Wind turbines, onshore	24.7	3	[11; 12; 38]
1205b	Wind turbines, offshore	24.7	3	[11; 12; 38]
1206	Industrial robots	13.6	2.7	[10; 38]
1301	FCC catalyst	2.3	1.5	[39]

B

B.5 Recyclability assessment

B.5.1 Data sources

The following data sources were used to quantify each of the quantitative indicators of the recyclability framework.

- Labor rights indicators from Kucera & Sari [40] were weighted using the shares in global production of rare earth elements.
- Price volatility was obtained from DERA [41].
- Target metal value, Co-recovered metal value: based on metal prices [41] and product composition data (§B.5.2).
- Value fraction of recoverable metals: §B.5.2.
- Annual waste flow, Annual waste generation: from MFA.
- Metal content per component, Product weight: Table 1 in main text.

B.5.2 Value of recoverable metals

The recovered metal value is calculated as the product of the recovery efficiency, the target metal content after preprocessing and the target metal price. The target metal, neodymium, has an average metal price of $61.53 (€50.45) [41].

For a view on the recoverable metal value fraction, a similar calculation was used. Price data were again obtained from Bastian [41], with data for iron from Focus-Economics [42]. For printed circuit board contained in HDDs, pumps and wind turbine nacelles, it was assumed that 25% of the value is recoverable.

TABLE B.5: Value of metals contained in EoL products.

EoL product	Composition source [b]	Total metals ($/t)	Neodymium ($/t)	Co-recovered metals ($/t)
EV motors	[43]	$ 3,296	$ 387	$ 2,883
HDDs	[44]	$ 7,159	$ 464	$ 6,308
Industrial pumps	[45]	$ 2,812	$ 315	$ 1,560
Speakers	[46]	$ 1,273	$ 276	$ 997
Wind turbines [a]	[47]	$ 3,301	$ 969	$ 1,341

[a] Nacelle is taken as reference. [b] Metal content of printed circuit board was taken from Holgersson et al. [48] and Wang et al. [49].

B.6 Nd content of waste flows

TABLE B.6: Nd content of waste flows in 2019, per country. This data is plotted in Fig. 5 in the main text.

Country code	Nd in waste (t)	Nd in waste (g/km²)	Land area (km²)
AUT	55.69	664	83,879
BEL	86.28	2,826	30,530
BGR	17.55	158	111,000
CYP	3.01	326	9,250
CZE	74.66	947	78,870
DEU	541.86	1,515	357,580
DNK	60.63	1,413	42,920
ESP	211.00	417	505,953
EST	4.01	88	45,340
FIN	28.43	84	338,460
FRA	378.26	689	549,087
GBR	482.37	1,980	243,610
GRC	49.97	379	131,960
HRV	10.91	124	88,073
HUN	31.54	339	93,030
IRL	40.69	579	70,280
ITA	260.58	863	302,068
LTU	7.09	109	65,290
LUX	4.54	1,752	2,590
LVA	4.81	75	64,594
MLT	2.08	6,490	320
NLD	142.20	3,423	41,540
POL	156.44	500	312,690
PRT	39.39	427	92,230
ROU	43.55	183	238,400
SVK	31.33	639	49,030
SVN	8.92	435	20,480
SWE	63.14	119	528,861

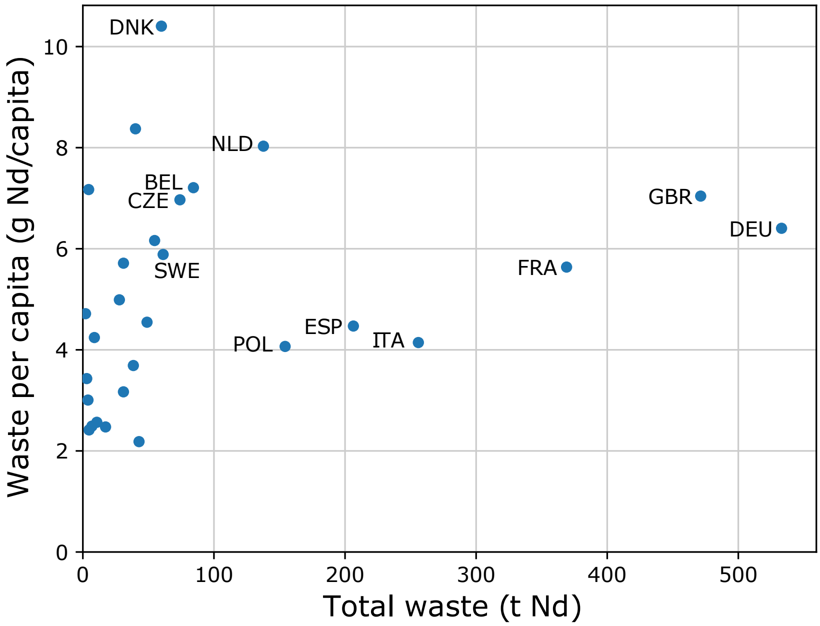

FIGURE B.1: Per capita Nd waste generation per country, in 2019.

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C Appendix to Chapter 4

C.1 Information on magnet wastes and applications

TABLE C.1: Weight of magnets and magnet assemblies in EoL products.

EoL product	Assembly weight (kg)	Magnet weight (g)	Source
EV drive rotor	10.9–14.6	1500–2000	[1]
HDD	0.488	15	[2]
Industrial pumps	1.6	132	INS*
Speaker assembly	4	500	B&C*
TV speaker	0.037	5	STENA*
Wind turbine drive (10 MW)	$149 \cdot 10^3$	$11.88 \cdot 10^3$	[3]

* SUSMAGPRO project partner.

TABLE C.2: Breakdown of demand and waste flows for NdFeB magnets by application, in the EU and the UK in 2019 (based on Chapter 3).

Application	Waste share	Demand share	Magnet type
HDDs	14.7%	2.5%	sintered
Speakers	10.4%	11.3%	sintered
Other small electronics	21.8%	9.8%	sintered
Electric vehicles	0.6%	3.6%	sintered
Wind power	0.4%	12.8%	sintered
Conventional cars	12.7%	14.8%	sintered, bonded
Industrial applications	21.6%	34.7%	sintered
HVAC	6.1%	4.3%	sintered, bonded
Large electric devices	8.5%	4.2%	sintered, bonded
Other	3.2%	2.0%	sintered, bonded

C.2 Unit process descriptions

C.2.1 General approach

As introduced in Chapter 4, we consider the following configurations: pilot process, process changes, size scaling, internal recycling, optimization, industrial reference process, and the thermodynamic or theoretical optimum.

For size scaling, equipment with an approximate capacity of 200 t/a was selected. For reference, the target capacity of both HyProMag plants is 100 t/a. Further scaling beyond 200 t/a is achieved mostly by parallel processing. Therefore it will only marginally change the process performance.

The equipment is operated 8 hours per day and 240 days per year. For processes that take more than 8 h per batch, 240 batches per year were assumed. The lifespan of machines was estimated by technical experts, and varies between 8 and 30 years. The upscaled process has 16 h per day, and optimized 24 h per day.

For comparison, also the industrial process performance and the thermodynamic or theoretical optimum were determined. The industrial reference is often a proxy, i.e. a similar unit process from a comparable sector. For example, metal injection moulding (MIM) of steel powders was used as a proxy for MIM of Nd-Fe-B powders. The theoretical optimum describes an ideal process, with an energy efficiency of 100%, and no material loss.

Table C.3 provides a data quality score for each process configuration, based on the pedigree matrix by Weidema [4].

C.2.2 Unit processes

The description of all unit processes can be found online at dx.doi.org/10.1016/J.JClePro.2024.142453, in Electronic Supplementary Information (ESI) 1.

C.2.3 Effective emission reduction

Table C.4 summarizes the contributions of improvements to lowering the environmental impacts of recycled magnets.

TABLE C.3: Data quality indicators for the life cycle inventory of each process configuration.

Indicator	Pilot process	Process change	Size scaling	Internal recycling	Optimization	Industrial reference
Reliability	1	2	2	3	4	1
Completeness	4	5	5	5	5	2
Temporal correlation	1	1	1	2	3	3
Geographical correlation	1	1	1	1	1	3
Further technological correlation	1	1	2	3	5	5
Average score	1.6	2	2.2	2.8	3.6	2.8

TABLE C.4: Process improvements grouped by their effectiveness for impact reduction.

Improvements with significant effect	Improvements with moderate effect (or process level only)	Processes with marginal effect
Reduced loss at sieving	Choose binder with low melting point	ICP-OES analysis
Use recycled NdH2 from HDDR	Switch to ultrasonic sieving	QR-code scanner
Reduce the amount of NdH_2	Switch to induction demagnetization	Coating the magnet
Internal recycling of inert gases	More magnets per mould (MIM process)	Magnetization
Solvent distillation and reuse	Cooling water recycling	Parallel cutters for HDDs
Less rotations of HPMS vessel		
Size scaling of furnaces (e.g. sintering)		
Optimized sandblasting		

C.3 Life cycle impact assessment

The applied set of impact categories is listed in Table C.5. The corresponding characterization factors and methods are adopted from Fazio et al. [5].

TABLE C.5: Life cycle impact categories and indicators, as recommended by the EF 3.0 scheme.

Impact category	Indicator	Unit
Climate change	Global warming potential (GWP100)	kg CO_2 eq
Ozone depletion	Ozone depletion potential (ODP)	kg CFC-11 eq
Respiratory inorganics	Human health effects associated with exposure to $PM_{2.5}$	Disease incidences
Photochemical ozone formation	Tropospheric ozone concentration increase	kg NMVOC eq
Acidification	Accumulated exceedance (AE)	mol H^+ eq
Eutrophication, terrestrial	Accumulated exceedance (AE)	mol N eq
Eutrophication, aquatic freshwater	Fraction of nutrients reaching freshwater end compartment (P)	mol P eq
Eutrophication, aquatic marine	Fraction of nutrients reaching marine end compartment (N)	mol N eq
Ionising radiation, human health	Human exposure efficiency relative to ^{235}U	kBq ^{235}U
Human toxicity, cancer effects	Comparative toxic unit for humans	CTUh
Human toxicity, non- cancer effects	Comparative toxic unit for humans	CTUh
Freshwater ecotoxicity	Comparative toxic unit for ecosystems	CTUe
Resource use, energy carriers	Abiotic depletion potential (ADP): fossil fuels	MJ
Resource use, minerals and metals	Abiotic depletion potential (ADP): elements (ultimate reserves)	kg SB eq
Land use	Soil quality index (aggregating biotic production, erosion resistance, mechanical filtration, and groundwater replenishment)	–
Water use	Water depletion potential (not from EF, see Table C.6)	m^3

C.4 Characterization factors for water use

Water use was calculated as the depletion of surface water. The extraction of water from water bodies contributes to depletion, whereas emission of water (not to air) is counted as restoration. All quantities are in units of square meter.

TABLE C.6: Characterization factors for water use. The contributions are in cubic meters.

Biosphere exchange	Exchange categories	Contrib.
Water, cooling, unspecified natural origin	natural resource::in water	+1
Water, in air	natural resource::in air	+1
Water, lake	natural resource::in water	+1
Water, river	natural resource::in water	+1
Water, salt, ocean	natural resource::in water	+1
Water, salt, sole	natural resource::in water	+1
Water, turbine use, unspecified natural origin	natural resource::in water	+1
Water, unspecified natural origin	natural resource::in ground	+1
Water, unspecified natural origin	natural resource::in water	+1
Water, unspecified natural origin	natural resource::fossil well	+1
Water, well, in ground	natural resource::in water	+1
Fresh water (obsolete)	water::surface water	−1
Water	water::surface water	−1
Water	water::ground-	−1
Water	water::fossil well	−1
Water	water::ground-, long-term	−1
Water	water	−1

C.5 Relative impacts

Supplementing Figure 4.7 of this thesis, Figure C.1 below shows the relative impact of all 16 impact categories (listed in Table C.5). The gray data series indicate that the impacts mostly follow the trend of selected impact categories (in color).

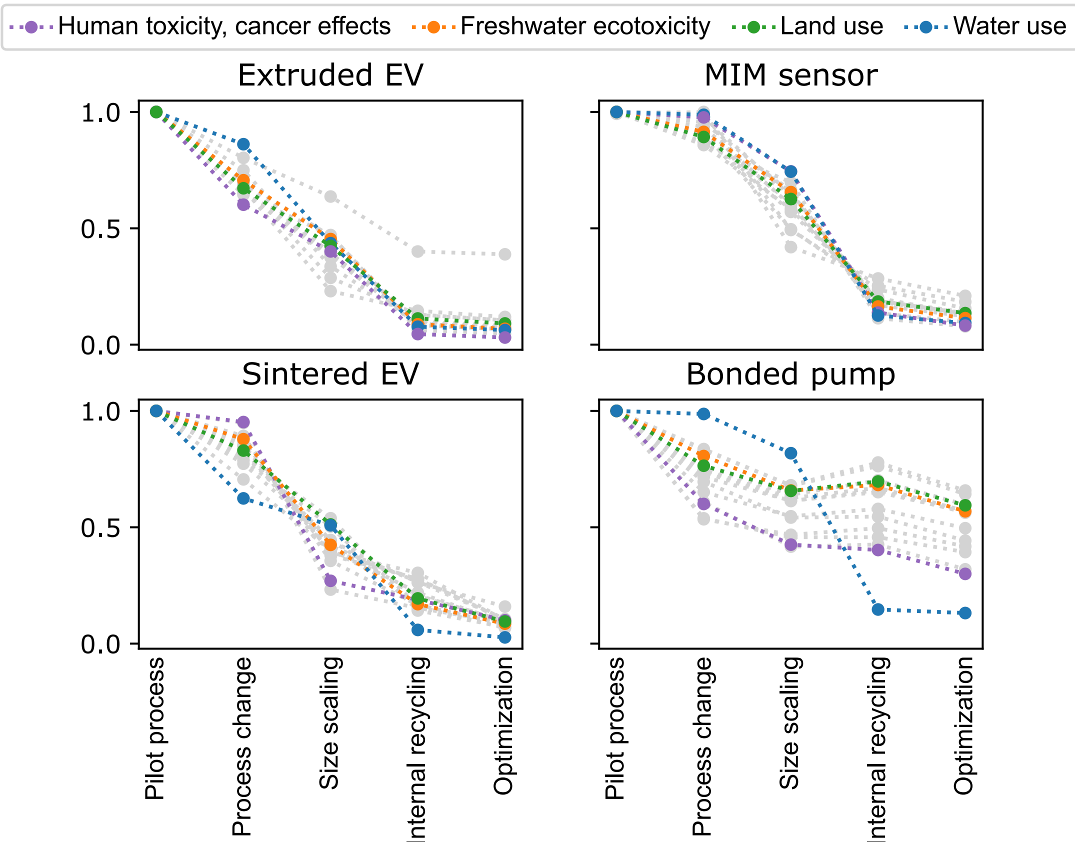

FIGURE C.1: Environmental impact changes due to projected technology developments for recycled demonstrator magnets, for all 16 impact categories. The values are plotted relative to the impacts at pilot scale.

To show the sensitivity of the LCA results to the electricity mix, a sensitivity analysis was conducted for the scenario of recycled sintered magnets for EV motors, produced from a mix of EoL magnets using industrial reference technology. The effect on different impact categories is shown in Figure C.2. In the default scenario, recycling processes use the average European electricity mix. In China and Poland, a large share of electricity is generated by coal-fired power plants, resulting in higher impacts in several categories. On the other hand, France uses mostly nuclear energy, therefore the ionizing radiation impacts are higher while most other impacts are below the base case.

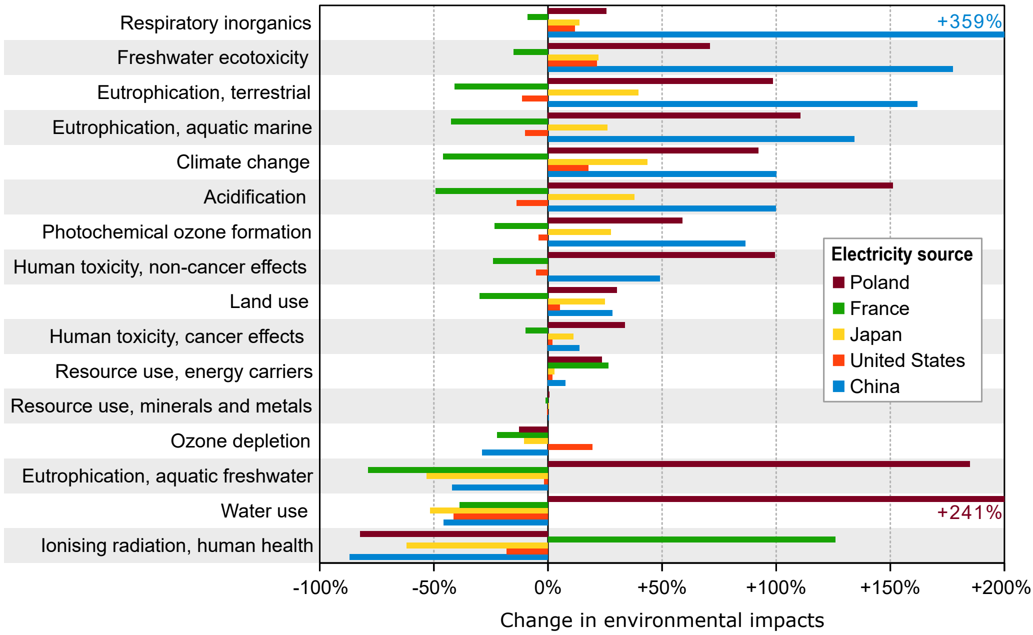

FIGURE C.2: Change in environmental impacts resulting from different electricity mixes. The base case is 1 kg recycled sintered magnets for EV motors, produced from a mix of EoL magnets using industrial reference technology and the European electricity mix.

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Appendix D: Appendix to Chapter 5

D.1 Modeling approaches

D.1.1 Modeling learning effects

Table D.1: An overview of methods to estimate future costs of technologies, as presented by Santhakumar et al. [1]. For each development phase, they recommend to use a different experience curve approach, complemented with bottom-up modeling of the production process and optionally other approaches.

Development phase	Experience curve approach	Complementary approaches
Prototype and Demonstration	Component-based model utilizing learning assumptions	Qualitative approaches (TIS theory)
Initial build-up phase	Single-factor model utilizing empirical observations	Qualitative approaches (TIS theory)
Upscaling and Growth phase	Multi-factor model	Technology diffusion curves, Scenario analysis
Saturation	Multi-factor model or single-factor model for aggregated learning rate	

TIS: technological innovation system.

D.1.2 Modeling size scaling

Size scaling of products or processes can be modeled using scaling relations, as presented by Caduff et al. [2, 3] and Piccinno et al. [4]. Two approaches are described below.

Empirical scaling laws are derived from empirical observations and data collected during the scaling of similar processes or technologies. These laws help to extrapolate technology performance indicators, such as energy consumption or production efficiency, to larger scales.

Equation D.1 gives a scaling law that relates the production capacity (or size) of equipment to environmental impact. Here EI_2 is the environmental impact of equipment

2; EI_1 is the environmental impact of equipment 1; X_2 is the capacity factor of equipment 2; X_1 is the capacity factor of equipment 1 and b is the size scaling factor.

$$I_2 = I_1 \cdot \frac{X_2}{X_1}^b \tag{D.1}$$

Reported cost scaling factors are typically between 0.5 and 1. If no specific data are available, a scaling factor of 0.6 is recommended [3].

Theoretical models are based on thermodynamic frameworks or mathematical models to predict how changes in size or scale influence the inputs and outputs of a process. These models typically integrate knowledge from physics, chemistry, and engineering.

D.2 Empirical data

To find studies with empirical evidence, we compiled search queries using the keywords in Table D.2. Each query included keywords from all columns.

TABLE D.2: Keywords used to search literature on empirical evidence for environmental learning.

Technological learning	+	Industrial technology	+	Environment
experience curve		industrial process		carbon intensity
learning	+	manufacturing	+	ecotoxicity
learning curve		manufacturing industry		efficiency
progress ratio		process		embodied energy
technological learning		technology		emissions
				energy
				environmental
				eutrophication
				historical emissions
				material inputs
				materials, resources
				ozone
				SOx
				waste reduction

Empirical data from previous studies are listed in Table D.3. These are environmental learning rates; cost-based learning rates are provided in Table D.4.

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Table D.3: Learning rates for environmental indicators, supporting Figure 3 in the main text. The learning rates for efficiency are negative, because the efficiency increases. Note that only a selection of the results from Stamford & Azapagic [5] are listed; see the source publication for full details.

Product [b]	Indicator [b]	LR	σ	R^2	Source
Ammonia, BAT	SEC [c]	28.9%		0.997	Ramírez & Worrell [6]
Ammonia, BAT	SEC	19.0%		0.951	Ramírez & Worrell [6]
Ammonia, average	SEC	23.1%		0.925	Ramírez & Worrell [6]
Urea, BAT	SEC [c]	11.4%		0.856	Ramírez & Worrell [6]
Urea, average	SEC [c]	8.9%		0.724	Ramírez & Worrell [6]
Ethanol from corn	SEC	17.3%		0.825	Hettinga et al. [7]
Pulp and paper	SEC, primary	9.0%	1.5%	0.84	Brucker et al. [8]
Clinker	SEC, primary	12.5%	3.0%		Brucker et al. [8]
Cement	SEC, primary	9.5%	2.0%	0.93	Brucker et al. [8]
Crude steel	SEC, primary	9.5%	1.5%	0.8	Brucker et al. [8]
Primary aluminum electrolysis	SEC, primary	3.5%	1.0%		Brucker et al. [8]
Poly-Si PV	GHG emission	16.5%	2.3%		Louwen et al. [9]
Mono-Si PV	GHG emission	23.6%	1.9%		Louwen et al. [9]
Poly-Si PV	CED	12.6%	0.9%		Louwen et al. [9]
Mono-Si PV	CED	11.9%	1.0%		Louwen et al. [9]
CdTe PV	GHG emission	12.8%	0.3%		Bergesen & Suh [10]
CdTe PV	Efficiency (W/m^2)	-5.7%			Bergesen & Suh [10]
CdTe PV	Electricity use	26.3%			Bergesen & Suh [10]
CdTe PV	CdTe use (g/cell)	8.9%			Bergesen & Suh [10]
CdTe PV	CdTe use (g/W)	13.8%			Bergesen & Suh [10]
Steel wire	Waste rate	11.7%			Lapré et al. [11]
PV	Si use (g/cell)	5.9%	0.8%	0.85	Louwen et al. [12]
PV	Ag use (g/cell)	28.1%	1.7%	0.95	Louwen et al. [12]
Mono-Si PV	Efficiency (W/m^2)	-4.7%	0.5%	0.93	Louwen et al. [12]
Poly-Si PV	Efficiency (W/m^2)	-3.9%	0.1%	0.99	Louwen et al. [12]
Mono-Si PV	Si use (g/W)	10.1%	1.3%		Louwen et al. [12]
Poly-Si PV	Si use (g/W)	9.4%	0.9%		Louwen et al. [12]
Mono-Si PV	Ag use (g/W)	31.3%	2.2%		Louwen et al. [12]
Poly-Si PV	Ag use (g/W)	30.8%	1.8%		Louwen et al. [12]
Mono-Si PV	GHG emission	10%			Stamford & Azapagic [5]

Product [b]	Indicator [b]	LR	σ	R^2	Source
Mono-Si PV	ODP (kg CFC11-eq.)	24%			Stamford & Azapagic [5]
Mono-Si PV	ADPe (kg Sb-eq.)	13%			Stamford & Azapagic [5]
Mono-Si PV	FAETP (kg DCB-eq.)	8%			Stamford & Azapagic [5]
Poly-Si PV	GHG emission	11%			Stamford & Azapagic [5]
Poly-Si PV	ODP (kg CFC11-eq.)	26%			Stamford & Azapagic [5]
Poly-Si PV	ADPe (kg Sb-eq.)	13%			Stamford & Azapagic [5]
Poly-Si PV	FAETP (kg DCB-eq.)	8%			Stamford & Azapagic [5]
Pig iron	SEC	12.3%		0.950	Gutowski et al. [13]
Aluminum smelting	SEC	8.9%		0.983	Gutowski et al. [13]
PV modules	CED (MJ/W)	20%			Görig & Breyer [14]
Mono-Si PV	CED (MJ/W)	18%			Görig & Breyer [14]
Poly-Si PV	CED (MJ/W)	24%			Görig & Breyer [14]
CdTe PV	CED (MJ/W)	7%			Görig & Breyer [14]
Mono-Si PV	CED (MJ/m^2)	14%			Görig & Breyer [14]
Poly-Si PV	CED (MJ/m^2)	22%			Görig & Breyer [14]
CdTe PV	CED (MJ/m^2)	3%			Görig & Breyer [14]
Thermal powerplant construction	CO_2 (kg/MW)	2.4%		0.951	Yuan et al. [15]
Hydropower construction	CO_2 (kg/MW)	48.4%		0.954	Yuan et al. [15]
Nuclear powerplant construction	CO_2 (kg/MW)	23.7%		0.955	Yuan et al. [15]
Wind construction	CO_2 (kg/MW)	17.4%		0.985	Yuan et al. [15]
Solar construction	CO_2 (kg/MW)	9.9%		1	Yuan et al. [15]
CO_2 absorption	Energy use (GJ/t)	23.2%		0.539	Rochedo & Szklo [16]

[a] LR: learning rate, σ: standard deviation, R^2: coefficient of determination.
[b] BAT: best available technology, CED: cumulative energy demand, SEC: specific energy consumption, GHG: greenhouse gas, ODP: ozone layer depletion potential, ADPe: abiotic depletion potential—elements, FAETP: freshwater ecotoxicity potential, DCB: *1,4*-dichlorobenzene.
[c] Curve fitting accounted for the theoretical minimum impact I_{min}.

D.3 Supplementary examples

The following sections provide examples belonging to the steps of the proposed procedure. Environmental hotspots for step 2, stakeholders and incentives for step 3, technology changes and economic effects for step 4, and learning rates for step 5.

D.3.1 Environmental hotspots

- Process energy use
- material use
- waste or discard rate
- waste treatment
- equipment use
- use-phase material or energy use

D.3.2 Stakeholders

- Customers and consumers
- Investors
- Value chain partners (suppliers)
- Societal organizations (NGOs, labor unions)
- Governments and regulators
- Competitors

D.3.3 Incentives

External forces that influence company decision on technological change:

- Customer preferences (normative pressure)
- Competitive pressure (mimetic pressure)
- Restrictive environmental regulation (coercive pressure)
- Market-stimulating regulation
- Preferences of investors and value chain partners (normative pressure)

D.3.4 Technology changes

- Improved resource and energy efficiency of processes
  - Accumulation of experience by workers and machine optimization [17]
  - Optimization of logistics, operating parameters, feedstock compositions, etc.
  - Learning about redundant steps or superfluous safety measures [18]
  - Increased equipment productivity due to better tuning and more operating hours
  - Process automation: shift from human labour to electric equipment [19]

- Improved design of process equipment [20]
  - Less conservative design (no oversizing, lower safety margins)
  - Less spare or redundant equipment
  - Automation of equipment production
  - Maintenance and repair for service life extension
- Product improvement for better performance during the use phase [21], e.g. higher energy efficiency, material efficiency, or longer lifespan.
- Implementation of end-of-pipe solutions [22]
- Size scaling to increase production capacity [3; 4]
- Product improvement to meet the preferences of environmentally conscious consumers [23]
- Shift to inputs[1] or suppliers with lower impacts [10]
- Material or process substitution [24]

D.3.5 Economic learning effects

The following financial parameters decrease with growing experience and larger scales, thus contributing to cost reduction [1; 18; 25]:

- Budget overruns due to delayed construction or production
- Cost of capital (interest payments)
- Regulatory fees (permitting)
- Commercial and legal risk mitigation,
- Insurance costs
- Overhead costs
- Marketing expenditures for new products
- Single orders rather than bulk purchases

Besides, outsourcing to low-income countries reduces labor costs [19], while the environmental impacts may increase due to lower environmental standards in these countries. Raw material price fluctuations may also distort the observed trend.

[1]Inputs include feedstock materials, energy carriers, and equipment.

D.3.6 Learning rates

TABLE D.4: Mean learning rates for production costs at company-level for US manufacturing industries, by two-digit standard industrial classification (SIC) code. Learning rates for lower-level SIC sectors and standard deviations are provided in the source publication [26].

SIC	Description	Mean learning rate
20	Food and kindred products	0.361
22	Textile mill products	0.256
23	Apparel	0.285
24	Lumber and wood products	0.223
25	Furniture and fixtures	0.261
26	Paper and allied products	0.235
28	Chemicals and allied products	0.417
29	Petroleum refining	0.350
30	Rubber and misc. plastic	0.282
31	Leather and leather products	0.154
32	Stone, clay, concrete	0.290
33	Primary metal industries	0.229
34	Fabricated metal (excl. machinery)	0.257
35	Machinery (incl. computers)	0.286
36	Electrical and electronic equipment	0.304
37	Transportation equipment	0.263
38	Measuring instruments	0.356
39	Misc. manufacturing industries	0.272
	All	0.288

D.4 Illustrative example for copper

D.4.1 Cost decomposition

Costs of copper production were broken down by inputs to the main processes, as shown in Figure D.1 below. The added value of each process was calculated as the difference in costs between inputs and output. Added value is the combination of labour costs and profits, and may also include taxes and levies. In the case of mining, added value could be spend on mining taxes or the acquisition of land.

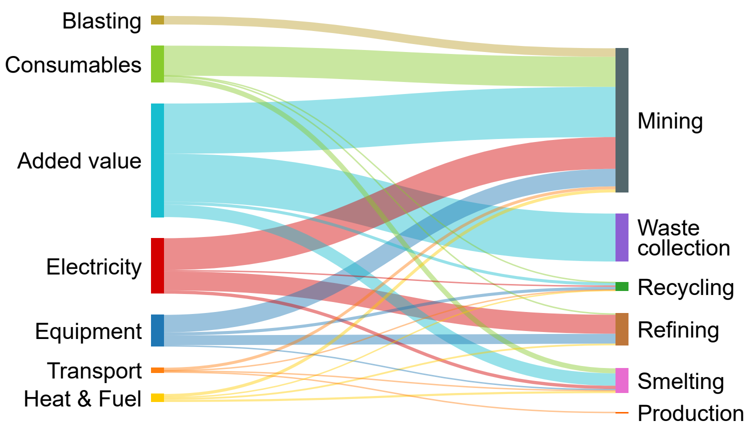

FIGURE D.1: Cost breakdown for the production of copper, by input (left) and by process (right).

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