Prospective consequential life cycle assessment : identifying the future marginal suppliers using integrated assessment models

Prospective consequential Life Cycle Assessment:

Identifying the future marginal suppliers using Integrated Assessment Models

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Abstract

Previous research efforts have focused on developing prospective life cycle inventory databases that build upon projections from integrated assessment models but were limited to attributional system models. A novel approach is required to construct consequential LCI databases that can be applied consistently on a large scale. To this end, the heuristic approach from Bo Weidema was selected as a basis for this study. This approach has been validated with historical data and was adapted in this study to identify the marginal suppliers in a prospective context. The different steps within the approach were analyzed, and alternative techniques for each step within the heuristic method were proposed. The techniques were tested on the future electricity sector using projections from two integrated assessment models (IMAGE and REMIND). Results show the sensitivity of results on the modelling technique selected in each step. The most sensitive step is the selection of the time interval, with even small changes resulting in a noticeable difference. In addition, the results also showed a substantial difference between the projections of the two models. The relevance and goals of the alternative techniques for each step were discussed to guide users in forming the heuristic method for their study.

Highlights

- Development of a prospective consequential database
- Review on consequential approaches for marginal changes
- Work builds upon the commonly used heuristic approach
- Prospective approach is applied to the electricity market using IAM projections
- Results are incorporated into *premise*

Keywords

Consequential LCA, prospective LCA, integrated assessment model, electricity sector

Word count

7485 words (excluding title, author names and affiliations, keywords, abbreviations, acknowledgements and references)

List of abbreviations

Abbreviations	Definition	Unit
ABM	Agent-based model	
GWP	Global warming potential	
IAM	Integrated assessment model	
LCA	Life cycle assessment	
PEM	Partial equilibrium model	
RCP	Representative concentration pathways	
SSP	Shared socio-economic pathways	
S_LT	Short-lasting changes using lead time as a time interval	
S_RANGE	Short-lasting changes using a range as a time interval	
L_WHOLE	Long-lasting changes	
L_SPLIT	Long-lasting changes in split time intervals	
GEN	General lead time	
IND	Individual lead time	
MYOP	Myopic	
PERF	Perfect foresight	
TECH	Use of technology levels	
SLOPE	Slope technique	
REGR	Regression technique	
AREA	Area technique	
WEIGH	Weighted technique	
HOR	Horizontal baseline	
CRR	Capital replacement rate as a baseline	
$t_{i,b}$	Start of the time interval for technology i	yr
$t_{i,f}$	End of the time interval for technology i	yr
$t_{i,c}$	Starting point of the additional slope	yr
J	Timestep between points	yr
P_i	Production volume of technology i	EJ
m_i	Slope of technology i	EJ/yr
$A_{i,total}$	Area under the curve	EJ*yr
$A_{i,baseline}$	Area under the baseline	EJ*yr
$A_{i,growth}$	Area of growth	EJ*yr
w_i	Weight for technology i	EJ
S_i	Share of technology i	%

1. Introduction

Limiting the extent of climate change will require substantial efforts from governments and industries. Decisions on actions should preferably be based on information regarding their environmental consequences. To this end, consequential life cycle assessment (LCA) is a valuable tool that allows users to quantitatively assess the environmental implications of their decisions (1). However, since the consequences can only materialize in the future, it is also fundamental to account for the expected evolutions of the socio-economic context, which affect the background system of an LCA.

Despite this need for a future-oriented rationale, only a few consequential LCA studies consider this future context when assessing the environmental impact of products and activities. Instead, the majority use background systems which were modelled relying on historical trends, assuming that these trends are representative of the future (2). However, the few studies integrating a prospective approach in the background system show this is not a valid assumption by default (3-5). For example, Vandepaer et al. (5) investigated the marginal electricity mix for several countries for multiple time intervals. The data projections were derived from reference scenarios (6) that estimate how the market might evolve if no further policy changes are implemented. The results showed, for the simple average, a 50% decrease in impacts on climate change for electricity when moving from 2015-2020 to 2030-2040. Results were also compared when switching from reference scenarios to climate policy scenarios. Switching to an ambitious climate scenario resulted in an average of 75% lower climate change impacts for electricity use. Maes et al. (3) compared several scenarios and time intervals for cement and electricity supply. For electricity, the results were similar to Vandepaer et al. (5), whereas, for cement, the GWP could differ by as much as 900% across scenarios and time intervals.

Such studies demonstrate the importance of incorporating future dynamics in consequential LCA. Yet, the biggest hurdle to integrating future trends into the background system is a lack of data on projections for the different industries and regions. Roadmaps are one potential prospective data source previously incorporated in LCA studies (3, 5). However, most roadmaps only focus on a select number of industries and regions, requiring several roadmaps to develop a prospective background system. These roadmaps rely on their assumptions, which do not consider how other sectors might evolve. It is, therefore, challenging to create a consistent economy-wide database starting from different roadmaps.

This issue is not present in process-based integrated assessment models (IAMs). IAMs project long-term transformation pathways by integrating energy, economic, land and climate models to do so consistently (7). A significant advantage is that IAMs operate on both a global and regional scale and take cross-sectoral interactions into account. Additionally, by integrating IPCC's shared socio-economic pathways (SSPs) (8) and representative concentration pathways (RCPs) (9) a consistent set of scenarios can be developed that consider potential future socio-economic developments and greenhouse gas emission targets. A downside of IAMs is that the results are spatially aggregated and aggregated across sectors. Additional efforts are required to disaggregate the results to the desired level of detail.

There has been excellent work on developing datasets considering the future context (3, 5, 10-15). In these projects, the LCI database ecoinvent (16) is transformed, using the IAM data to align the database with the investigated time horizon. This way, the extensive network of interlinked processes in the database can be preserved, only requiring a few additional processes to be modelled which are not yet out on the market. Cox et al. (17) and Mendoza et al. (11) initiated this work, which is currently extended with the development of the premise software package (12).

While these projects are an essential step forward in using a prospective background system, the transformation currently integrates the scenarios following an attributional approach. A prospective consequential background database is presently missing. Whereas attributional LCA considers the average impact contribution of the product system, consequential LCA aims at capturing the impact associated with a change in demand for the product (18). Hence, consequential modelling differs in two notable aspects. First, market mixes are no longer decided by the average production shares of the different suppliers on the market. Instead, the product system comprises suppliers along the supply chain likely to respond to a change in demand for said product. Second, multifunctionality is solved using system expansion, whereas attributional modelling uses allocation (19). For a comprehensive comparison, see Ekvall (20).

To apply a similar transformation of IAM data following a consequential approach, only the first aspect must be accounted for, as the second aspect is already considered taken care of by the consequential version of ecoinvent (16). There are several methods available to determine the affected suppliers. A small literature review was performed to select the optimal method for this study. A heuristic approach, also known as Weidema's 4-step procedure (29), was chosen as it is one of the few approaches that can be applied on a database-wide scale (16, 30).. The approach determines which suppliers are affected in the long term due to a small- scale change. These suppliers are known as "marginal suppliers" within the consequential framework. If more than one marginal supplier exists, a marginal mix is calculated. The shares of the mix represent their relative contribution to a change in demand. More information on the approach and the literature review can be found in the supplementary material.

Several studies have developed practical methods based on Weidema's theoretical framework (4, 5, 31). However, these have focused on identifying the marginal suppliers historically or in the near future. Some decisions made when developing those methods may not be optimal when determining the marginal suppliers in a future context. For example, how to choose the time horizon for a case study has never been adequately explored, as users are often constrained in their choice due to a lack of data (5, 21). Therefore, this study will first investigate the existing methods, identify the approach's critical parameters, and highlight issues and opportunities for improvement for each parameter. The findings from this investigation are then used to develop new techniques for the parameters. To determine their use, the existing and newly developed techniques will be tested on case studies.

2. Measuring prospective competitiveness

In the 4-step procedure proposed by Weidema et al. (29), the first two steps concern defining the time horizon and scale of the study and whether the extent of the change in demand affects the market structure. In step three the market trend is determined. The slope of the trend decides how the marginal suppliers are identified in the next step. Considering a market with an increasing, stable, or slightly decreasing supply volume, competitive suppliers are expected to answer the change in demand by investing in additional capacity. For markets with a definite declining trend, the least competitive suppliers are expected to respond to the change in demand by extending the lifetime of existing, albeit underperforming, technologies.

Step four aims to identify the affected suppliers. In this step, suppliers that are constrained in their ability to respond to a change in demand are thrown out, and the competitiveness of the unconstrained suppliers is determined within the time horizon. There are a variety of approaches in the literature on how to assess competitiveness, with studies adopting different indicators and measuring approaches (3-5, 32).

To apply the heuristic approach, the user must first determine the appropriate indicator for competitiveness for the study, the time horizon and the measuring approach.The following section will provide a short overview of existing variations of those parameters and highlight where there are opportunities to expand the approach, given the future-oriented outlook.

2.1. Indicator for competitiveness

Potential indicators for competitiveness are production cost, additional capital investments and trends in production volume. Due to data limitations, most consequential LCA studies use production volume as an indicator. Like other data sources, IAMs offer projections on production volume for most markets but rarely provide information on additional installed capital or production cost.

Typically, growth in production volume is measured against either the horizontal baseline or against the slope defined by the capital replacement rate (33) (see Figure 1). The two baselines imply different definitions of what is deemed competitive. With the former, any supplier that does not grow within the time horizon is seen as uncompetitive. With the latter, these suppliers could still be deemed competitive as long as the supplier is not phasing out.

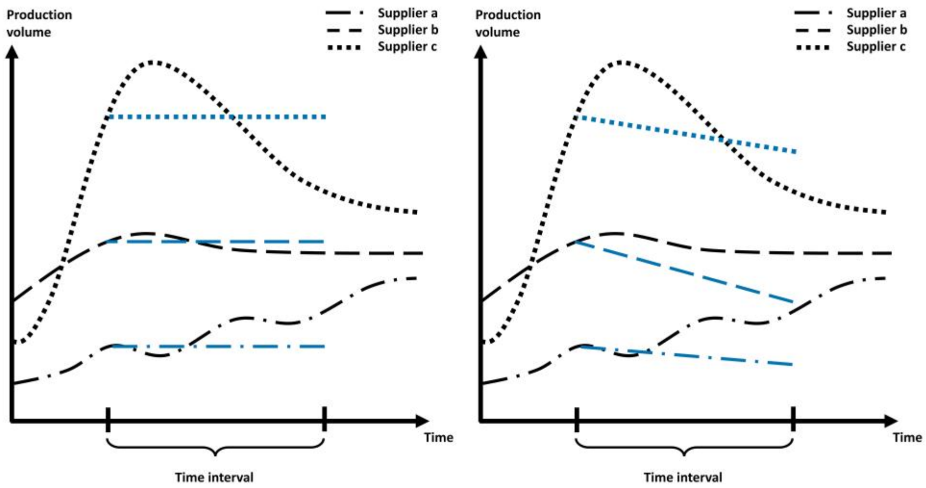

Figure 1: Left: growth against the horizontal baseline (in blue); right: growth against the slope formed by the capital replacement rate (in blue)

2.2. Time interval

In studies that include prospective data, the time horizon is often set between the latest available historical and the nearest available future data points (4, 5, 34). The measured trend within the time interval should indicate how competitive (or open to investment) the supplier is when it is expected to respond to a change in demand. Two elements play an essential role. First, when do suppliers react to the change in demand? This depends on how well suppliers can foresee and respond to changes in the market (35). Second, how long does it take to go from the decision to installing the additional capacity? This depends on the lead time of the technology. This is the time needed to plan, license, build and start an installation (36).

Furthermore, changes in demand can be further distinguished between single occurrences or short-lasting changes and continuous or long-lasting changes. Depending on the duration, the change in demand can potentially influence multiple investment decisions. The time interval should, therefore, also consider the duration of the change.

2.3. Measuring the indicator

Most studies measure only the difference between the beginning and end of the interval (3, 5). Other studies consider the growing trend of the suppliers using linear regression (4, 32). Both approaches are only valid if the production volume follows an almost linear pattern. However, in practice, suppliers' production outputs, in the long run, tend to follow an S-shaped pattern (37). To measure this non-linear growth, alternative approaches are needed.

In conclusion, this study aims to identify approaches and key criteria following the heuristic approach to identify marginal suppliers and to translate this into practical calculation protocols. The heuristic approach determines who the affected suppliers are by determining their level of competitiveness. While there are several potential indicators to measure competitiveness, using the trends in production growth is the most common and practical. There is, however, no consensus on when and how growth should be measured.

3. Methods

3.1. Overall approach

To develop a prospective heuristic approach, this study has tested several techniques to derive the three parameters: indicator for competitiveness, time interval and growth measurement approach. These techniques were combined to form heuristic methods to determine the marginal mix. These methods were then tested in a case study to assess the sensitivity of the approach to the different techniques.

3.2. Indicator for competitiveness

All measurements were done on production volume. To measure the absolute growth of suppliers, growth was measured against the horizontal baseline (see Figure 1). By measuring against the slope formed by the capital replacement rate, an estimate could be made of how much new capital is installed (33). The slope formed by the capital replacement rate is equal to:

$$-\frac{P_{i,t_{i,b}}}{L_i} \quad \text{(Eq. 1)}$$

with:

- $t_{i,b}$: start of the time interval for technology i
- P_{i,t_b} : production volume of technology i at year $t_{i,b}$
- L_i : lifetime of technology i

Both the measurement against the horizontal baseline (HOR) and against the capital replacement rate (CRR) were tested out in the case study.

3.3. Time interval

3.3.1. Supplier's foresight and technology's lead time

Similarly to economic models, to identify when suppliers are expected to respond, we assume a level of foresight for the suppliers (35). Two levels of foresight were selected for this study: myopic and perfect foresight. In the myopic approach, also called a recursive dynamic approach, the agents have no foresight on relevant parameters (e.g., energy demand, policy changes and prices). They will only act based on the information they can observe. In this case, the suppliers can respond to a change in demand only after it has occurred. In the perfect foresight approach, the future (within the studied period) is fully known to all agents. In this case, the decision to invest can be made ahead of the change in demand.

The lead time lies between the decision to invest in new capital and the installation of the new capital (see Figure 2)(36). Depending on the technology, this can take up to a year (e.g., photovoltaic farm) to even more than a decade (e.g., nuclear power plant).

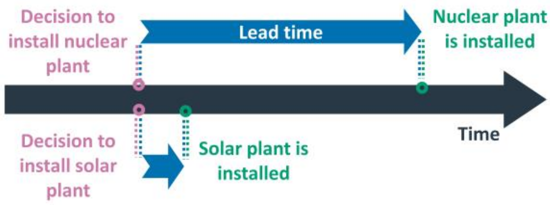

Figure 2 Example of difference in lead times between technologies within the same market

Suppliers will aim to install the additional capacity as soon as needed. For suppliers with perfect foresight (PERF), this will be right before the change in demand. For myopic suppliers (MYOP), a delay equal to the lead time is considered.

A general lead time for all technologies within the market can be used, or technology-specific lead times can be used. While the latter approach is more detailed, implementing it can be challenging. Therefore, the sensitivity of the lead time on the results is considered by comparing results when using the average lead time of the market (GEN) against the individual lead times for the technologies within the market (IND).

3.3.2. Selecting the time interval

The additional capital is expected to be installed at a single point for single occurrences or short-lasting changes in demand. For suppliers with perfect foresight, we assume this is in the same year the change in demand occurs (see Figure 3, left-hand side). For suppliers without foresight, capital will show a lead time later (see Figure 3, right-hand side). To measure the trend around the point where the additional capital will be installed, a range of *n* years before and after the point is taken as the time interval. For this study, a range of two years is taken (see Figure 3), resulting in a four-year time interval4. This value closely mirrors the recommended time interval in ecoinvent's consequential database, which is three-to-four3-4 years (21). This time interval is long enough to measure an actual trend, not an abnormality or single occurrence, but also short enough to represent the chosen time reference.

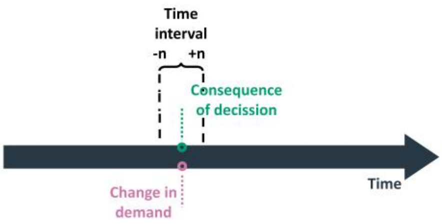

Figure 3: time interval for a short-lasting change in demand, assuming the supplier has perfect foresight (left side) or no foresight (right side)

For long-lasting changes in demand, the interval will follow the entire duration of the change. As with the short-lasting changes, the delay in response is considered for suppliers with no foresight (see Figure 4). Two techniques were used to measure growth within the time interval. The first technique takes the time interval, and the trends are measured once over the entire interval (L_WHOLE). In the second technique, the time interval is split up into smaller sections. The marginal suppliers within each section are determined separately, after which the average marginal mix for the entire time interval is calculated (L_SPLIT). For this study, the time interval was split into its smallest form, each section having a time interval of 1 year.

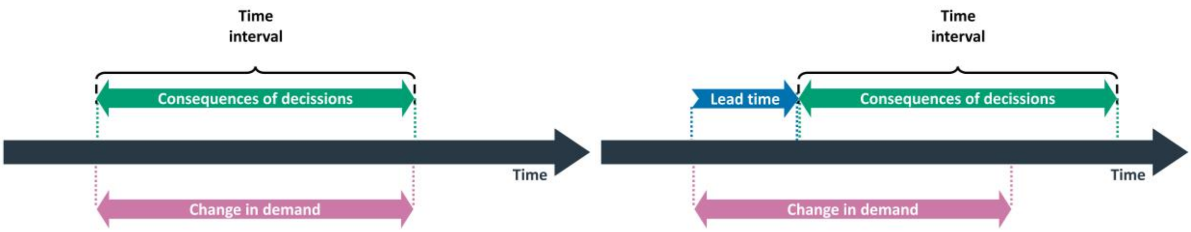

Figure 4 time interval for a long-lasting change in demand, assuming the supplier has perfect foresight (left side) or no foresight (right side)

3.4. Calculating growth

According to previous studies (3, 5) the marginal suppliers' mix can be calculated using the slope of the time interval for each supplier (SLOPE). In these studies (3, 5), the slope is calculated by dividing the difference in production volume compared to the initial volume or capital replacement rate by the time interval duration (see Eq. 2). Identifying the marginal suppliers depends on the market trend. Marginal suppliers are the most competitive if the market trend lies above the baseline. In this case, any supplier with a negative slope is left out. The approach described in the literature was also adopted in this study to calculate the supply shares of the short-listed suppliers (eq 3). If the market trend lies under the baseline, the least competitive suppliers are the marginal ones. In this case, suppliers with a positive slope are left out.

Using the slope only considers the production volume of the suppliers at the start and end of the time interval. Three techniques are used to evaluate the entire growth of the suppliers within the time interval. The first was taken over previous studies (4, 32), and the second and third were developed for this study.

The regression technique (REGR) applies linear regression on all points within the interval. After that, the calculation is similar to using the slope, except the slope is now not calculated using equation 2 but comes from the linear trendline.

The area technique (AREA) accounts for the entire path of the supplier's production volume within the time horizon. It is done by measuring the area of the additional production volume using midpoint Riemann Sums (see Eq. 4-6). This approach favors suppliers with early growth over those with late growth.

The weighted technique (WEIGH) uses weighting factors. A first slope ($m_{i,long}$) is calculated within the entire time interval. A second, shorter slope ($m_{i,short}$) is then calculated at the end of the time interval (see Figure 5, left side). The second slope is divided by the first slope. The growth is exponential if the ratio x is higher than 1, linear if equal to 1, logarithmic if lower than 1, and if lower than zero, the supplier experiences a decline in growth near the end. The calculated value x is passed through a logistic model to restrict how much the weight can affect the weighted score. In the example shown in Figure 5, the boundaries of the logistic model are [-1:+1]. The resulting value is then multiplied by a weight *w* and added onto the first slope (see Eq. 11). For this study, the weight is $m_{i,long}$, so that the weighted score is at maximum double the value of the slope calculated in Eq. 2. and at the minimum, zero. The weighted score is in the following step used to calculate the share in the mix, similar to equation 3.

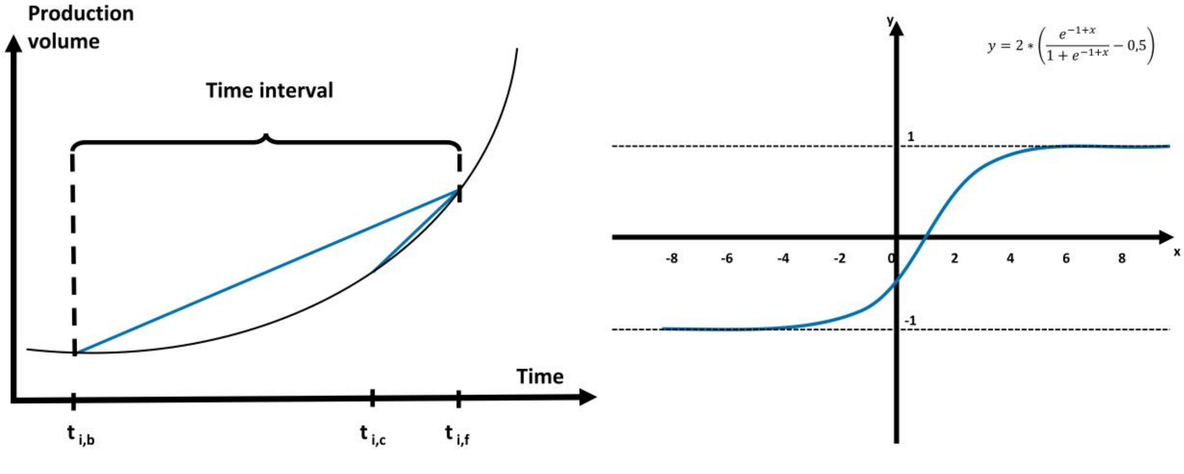

Figure 5 left: measuring the slopes, right: logistic model

Table 1. Overview of the equations used in the measurement techniques

	Eq. #	Equation	Variables
SLOPE	Eq. 2	$m_i = \frac{P_{i,t_{i,f}} - P_{i,t_{i,b}}}{t_{i,f} - t_{i,b}}$	$t_{i,b}$: start of the time interval for technology i $t_{i,f}$: end of the time interval for technology i $P_{i,t_{i,b}}$: production volume of technology i at year $t_{i,b}$ $P_{i,t_{i,f}}$: production volume of technology i at year $t_{i,f}$ m_i: slope of technology i S_i: supply share of technology i
	Eq. 3	$S_i = 100 * \frac{m_i}{\sum_i^n (m_i)}$	
REGR	/	$P_i = m_{i,regr} * t$ Slope calculated using least squares regression line on values within the time interval	P_i: production volume of technology i t: year $m_{i,regr}$: slope of technology i
AREA	Eq. 4	$A_{total} = \frac{J * (2 * \sum_j^n P_{i,t_{i,j}} - P_{i,t_{i,f}} - P_{i,t_{i,b}})}{2}$	J = timestep between points $P_{i,t_{i,j}}$: production volume of technology i at year j within the time interval $A_{i,total}$: total area under the curve $A_{i,baseline}$: area under the baseline $A_{i,growth}$: area of growth
	Eq. 5	$A_{i,baseline} = P_{i,t_{i,b}} * (t_{i,f} - t_{i,b})$	
	Eq. 6	$A_{i,growth} = A_{i,total} - A_{i,baseline}$	
WEIGH	Eq. 7	$m_{i,long} = {P_{i,t_{i,f}} - P_{i,t_{i,b}}} \Big/ {t_{i,f} - t_{i,b}}$	$m_{i,long}$ = slope of the time horizon $m_{i,short}$ = additional slope $t_{i,c}$ = starting point of the additional slope w_i = weight (can be chosen by the user) $m_{i,weighted}$ = the weighted slope
	Eq. 8	$m_{i,short} = {P_{i,t_{i,f}} - P_{i,c}} \Big/ {t_{i,f} - t_{i,c}}$	
	Eq. 9	$x_i = \frac{m_{i,long}}{m_{i,short}}$	
	Eq. 10	$w_i = m_{i,long}$	
	Eq. 11	$m_{i,w} = m_{i,long} + 2 * \left(\frac{e^{(-1+x_i)}}{1 + e^{(-1+x_i)}} - 0.5\right) * w_i$	

3.5. ecoinvent's consequential methodology

As the approach will be applied to the ecoinvent database, ecoinvent's current methodology is discussed and compared with the proposed alternatives. EcoinventE uses two methods within the LCI database to determine the mix of marginal suppliers within a market. The first approach was introduced in ecoinvent v.3 alongside the consequential system model version of the database (16, 30). The second approach was introduced later in v.3.4 and is only used for the electricity sector (5).

3.5.1. Ecoinvent's general methodology

In the first method, the marginal mix largely resembles the average mix found in the attributional system model. The critical difference is that suppliers constrained in their ability to respond to a change in demand are excluded from the market mix. Two types of constraints are considered (21). First, suppliers whose process relies on an input resource which depends on the demand for another product are excluded (= by-product constraint). Second, the technology level of a supplier, combined with the market situation, is a selection variable (TECH) (see Table 2). Considering a market whose supply volume is increasing, stable or slightly decreasing, suppliers using modern technologies can respond to a change in demand. For fast-declining markets, suppliers using old technologies are seen as unconstrained and able to respond to a change in demand.

Table 2 ecoinvent's assigned technology levels

Technology level of an activity	Requirement
New	A novel technology that is not yet commonly used
Modern	A technology that is used when installing new capacity
Current	A technology that sits between the old and modern requirements
Old	A technology that is being decommissioned
Decommissioned	A technology that is no longer in use

Technologies are considered modern if they are used when additional capacity is required and old if the technology is phasing out. Historical data or expert judgement was used in ecoinvent to identify the technology level. In this study, the technology level of the suppliers will be decided using the production growth of the supplier against the capital replacement rate.

3.5.2. ecoinvent's method for the electricity sector

In the second method, the marginal mix is determined following the method described in Vandepaer et al. (5). The method assumes suppliers have no foresight and provide a direct response to the change in demand. The general lead time of the market is taken as the time interval (S_LT). Growth and share are calculated using the difference in growth between the start and end of the time interval, as in equations 1 and 2.

3.6. Heuristic method description

Heuristic methods to determine the marginal suppliers were constructed by combining the discussed techniques for the different parameters. This resulted in a total of 56 combinations. For the discussion, this was shorted down to 17 methods which only change on technique each time, plus the two methods from ecoinvent (see Table 3). The results for all other combinations can be found in the supplementary material. The first two methods in Table 3 follow ecoinvent's methodology. Methods 3-9 focus on assessing the marginal suppliers for short-lasting changes in demand. Methods 10-19 focus on determining the marginal suppliers for long-lasting changes in demand. For this study, the change in demand will last for 20 years. This value was chosen as it is close to the maximum lifetime for transport equipment and computer appliances in industries and only slightly lower than the average lifetime for machinery (38). Methods 17-19 split the time interval into small sections, calculating the time interval for each section and then calculating the average marginal mix. This technique requires all suppliers to share the same time interval, which is why only the general lead time is used. Because the time interval was split up in its smallest form, techniques that measure the entire growth were not applied for this technique.

Table 3 Overview of the investigated heuristic methods

	Methods	**Time interval**	**Lead time**	**Foresight**	**Measurement**	**Indicator**
1	e.v.3.0	S_LT	GEN	MYOP	**TECH**	**CRR**
2	e.v.3.4	S_LT	GEN	MYOP	SLOPE	HOR
3	S_BASE	S_RANGE	GEN	MYOP	SLOPE	HOR
4	S_IND	S_RANGE	**IND**	MYOP	SLOPE	HOR
5	S_PERF	S_RANGE	GEN	**PERF**	SLOPE	HOR
6	S_REGR	S_RANGE	GEN	MYOP	**REGR**	HOR
7	S_AREA	S_RANGE	GEN	MYOP	**AREA**	HOR
8	S_WEIGH	S_RANGE	GEN	MYOP	**WEIGH**	HOR
9	S_CRR	S_RANGE	GEN	MYOP	SLOPE	**CRR**
10	L_BASE	L_WHOLE	GEN	MYOP	SLOPE	HOR
11	L_IND	L_WHOLE	**IND**	MYOP	SLOPE	HOR
12	L_PERF	L_WHOLE	GEN	**PERF**	SLOPE	HOR
13	L_REGR	L_WHOLE	GEN	MYOP	**REGR**	HOR
14	L_AREA	L_WHOLE	GEN	MYOP	**AREA**	HOR
15	L_WEIGH	L_WHOLE	GEN	MYOP	**WEIGH**	HOR
16	L_CRR	L_WHOLE	GEN	MYOP	SLOPE	**CRR**
17	Ls_BASE	L_SPLIT	GEN	MYOP	SLOPE	HOR
18	Ls_PERF	L_SPLIT	GEN	**PERF**	SLOPE	HOR
19	Ls_CRR	L_SPLIT	GEN	MYOP	SLOPE	**CRR**

3.7. Using IAM projections to determine the marginal suppliers

The heuristic methods are applied to the projections of two IAMs currently used in *premise*. The first one, REMIND, uses a computable global equilibrium model with perfect foresight (39, 40). The second one, IMAGE, uses a partial equilibrium model with a myopic view (39, 41). While the suppliers have no perfect foresight in the model, they use heuristic forecasting approaches to guide their decisions (42, 43). Both models' projections extend to 2100; the data is provided in time steps of 5 years till 2050 and after in 10 years.

For testing and validating the proposed procedures, electricity production in the regions of Europe and China is selected as case studies. The two regions were chosen as their current power systems differ substantially in the penetration rate of low-carbon technologies: 57% in Europe (44) against 26% for China (45) in 2019. The regions' differences could affect the decisions made in the future, which in turn could affect the results of the heuristic approach.

There is a difference in spatial scale between the two models. For IMAGE, Europe is disaggregated into Western and Central Europe, and China is aggregated with Mongolia (41). In REMIND, Europe comprises EU-28 and non-EU-28 countries (40). For this study, Western Europe and the EU-28 are selected from IMAGE and REMIND, respectively, to represent the European region.

Regarding scenarios, the socio-economic trajectory SSP-2 is known as the '*Middle of the road'*. It is combined with two climate mitigation targets: a *Baseline* target (i.e., RCP 6.5), representing a global temperature increase of 3.5°C by 2100 with respect to pre-industrial levels, as well as a Paris Agreement-compliant target (i.e., RCP 1.9), limiting the global temperature increase to 1.5 C. These two scenarios, referred to throughout the rest of the study as *+3.5°C* and *+1.5°C*, respectively, provide a moderate and extreme case of climate mitigation efforts.

The marginal mix was calculated for each scenario over several time points, from 2020-2050, in 10-year timesteps. As the IAMs' data is not detailed enough to compare approaches that change the time interval, the data was disaggregated into yearly data, using cubic spline interpolation to fill in the missing data points (46).

4. Results

4.1. Exploratory analysis of raw IAM data

4.1.1. REMIND

For the EU, both the +3.5°C and +1.5°C scenarios show a significant increase in the demand for energy after 2020, which is mainly answered using wind and solar energy. In both scenarios, fossil fuels are primarily phased out, though natural gas is still present in the +3.5°C scenario.

The electricity sector in the EU and China shows very similar trends. In China, wind and solar are the primary electricity sources in the future, and a decline in fossil fuels is expected. Despite an overall reduction in coal, an uptake in Coal integrated gasification combined cycle (IGCC) is projected for China in the 3.5°C scenario. A temporary increase in nuclear energy and natural gas is expected for both the +3.5°C and +1.5°C scenarios. Hydro energy remains stable throughout the time horizon. In the +3.5°C scenario, the market slowly declines after 2035. In the 1.5°C scenario, this decline is also present only temporarily. In the +1.5°C scenario, the phase-out of fossil fuels occurs faster, and carbon capture and storage (CCS) is adopted for the combustion of natural gas, though its use remains small.

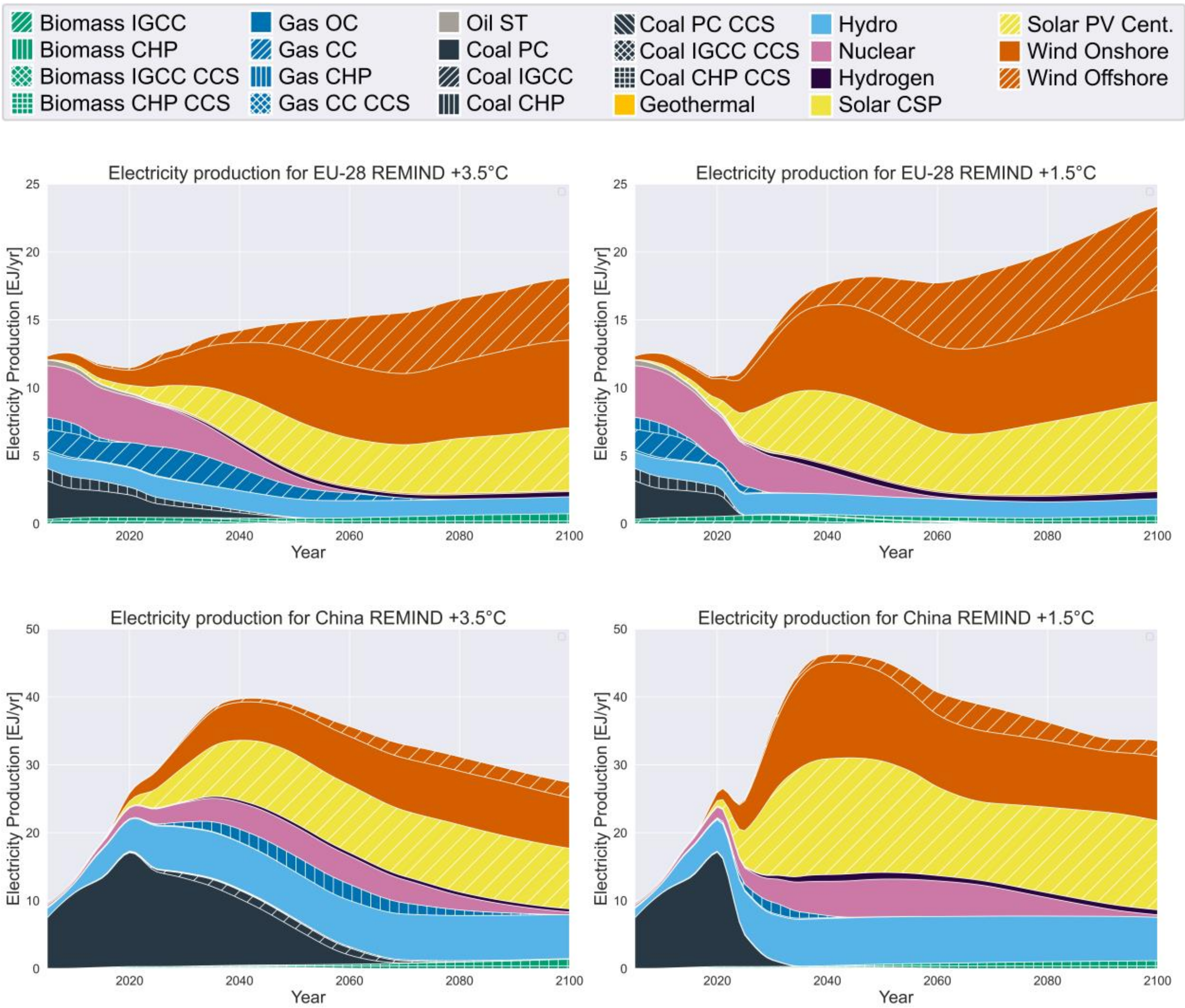

Figure 6 REMIND's projections for the electricity sector

4.1.2. IMAGE

IMAGE's projections are noticeably less consistent than those of REMIND. For both the EU and China, fossil fuels and nuclear energy remain essential in both scenarios. All scenarios project a switch from coal to natural gas. Wind and solar energy are still significant, though far less than in REMIND. Like REMIND, a market decrease is projected for China, though much later.

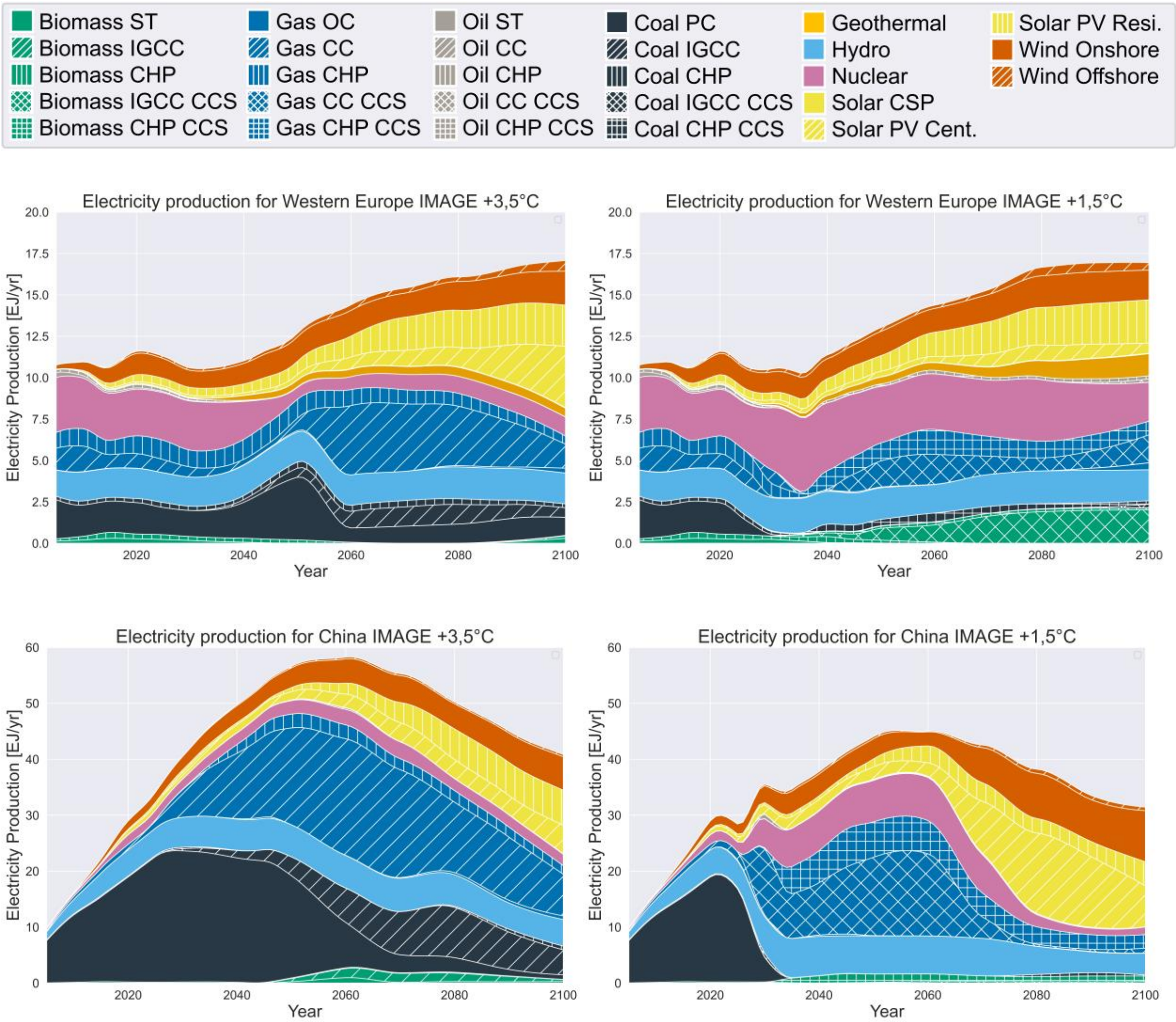

Figure 7 IMAGE's projections for the electricity sector

4.2. Impact of IAM scenarios on the marginal mix

A select number of results are shown in the following section. First, we investigate the impact of the heuristic method choice on the marginal mix using Figures 8 and 9. Second, we compare the marginal mix for each scenario using Figures 10 and 11. All results not covered in this section can be found in the supplementary material.

Despite REMIND's consistent trends, the marginal mixes can substantially differ between the years and methods. The marginal mixes for the EU are the most stable ones, including only two or three marginal suppliers (see Figure 8, left side). For China however, the marginal mixes fluctuate more due to the decline in total production volume that occurs midway through the investigated time horizon (see Figure 8, right side). The differences between the marginal mixes are on average more pronounced in IMAGE, with many marginal suppliers throughout the period considered (see Figure 9).

Of the 19 methods that were tested, the biggest difference lies between methods that focus on identifying the consequences of short-lasting changes and those that concentrate on long-lasting changes. In some cases, such as the 2040 mix for Western Europe (see Figure 9, left side), there is only a small overlap of marginal suppliers.

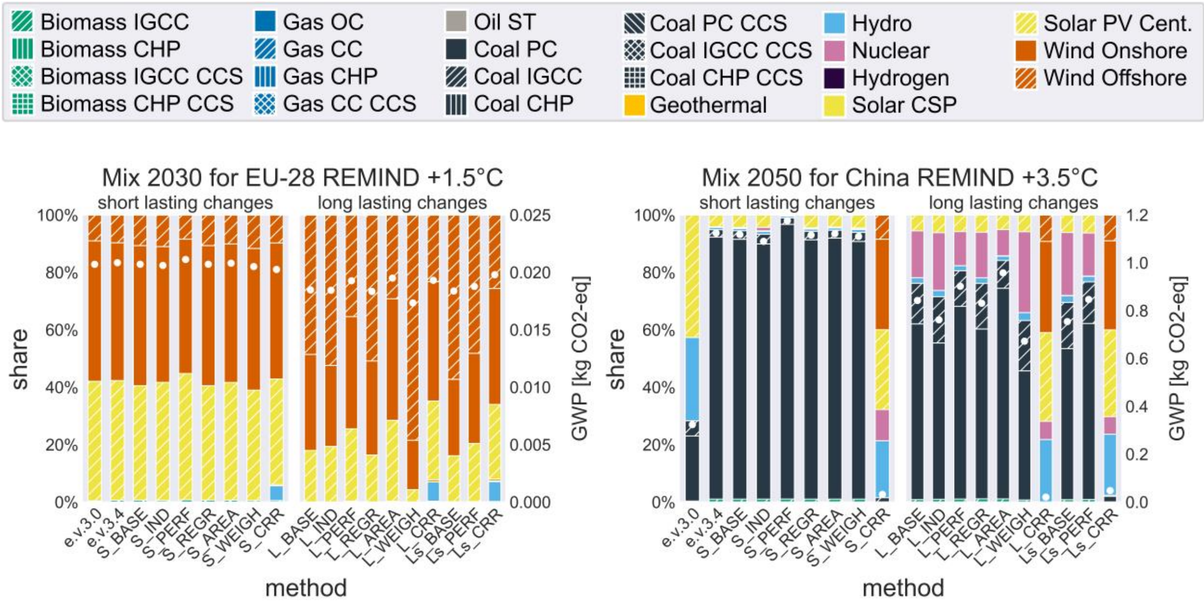

Figure 8 Comparison of methods using REMIND's projections (the year in the title notes the year the change in demand first occurs)

A general trend we observe in the data is that there is only a slight difference between methods that split the time interval (Ls-BASE, -PERF and CRR) and those that take the entire time interval (L-BASE, -PERF and CRR). However, the effect is more noticeable for time intervals that encapsulate rapid changes in marginal suppliers. For instance, IMAGE projects for Western Europe a temporary increase in electricity from coal PC from 2040 to 2050. This results in a noticeable difference between those methods that split the time interval and those that take the entire time interval for the 2040 mixes (see Figure 9, left side).

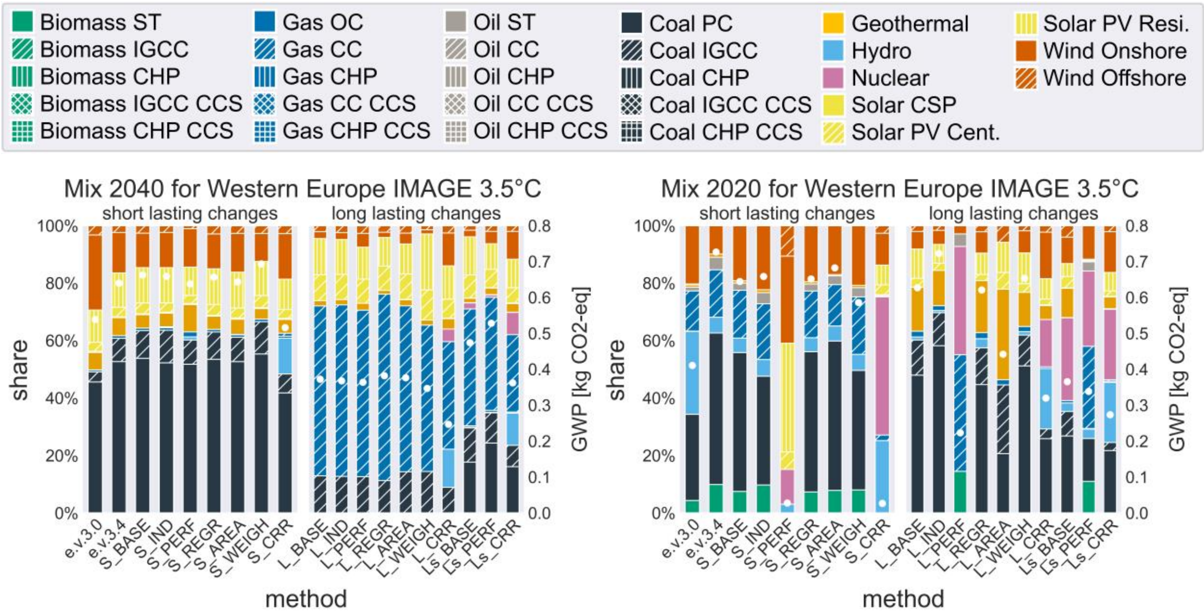

Figure 9 Comparison of methods using IMAGE's projections

The capital replacement rate has the most significant effect on both short- and long-lasting changes. For methods using the capital replacement rate, technologies decreasing at a slow pace or stable are included (e.g., hydro in most cases). The use of capital replacement rate also substantially affects only slightly growing technologies (e.g., solar PV in Figure 8, left side).

The baseline has the most effect when the market decreases slowly, as is the case for China. For methods that use the horizontal baseline, the market is deemed uncompetitive. The least competitive suppliers are included instead of including the most competitive suppliers in the mix. However, for methods that use the capital replacement rate as a baseline, the market is still deemed competitive, as the rate of decline is lower than the weighted average capital replacement rate (see Figure 8, right side), resulting in a completely different set of marginal suppliers within the mix.

Overall, the techniques that affect the lead time or foresight have a negligible effect. There are some cases where the effect becomes more pronounced. This occurs when a technology's or market's production volume exceeds the baseline. In those cases, only a small change in the time interval can have a substantial effect, as it can alter whether the market or technology is deemed competitive.

An example of this can be seen in the 2020 mix for Western Europe (see Figure 9, right side). While IMAGE's projections show an overall growing market volume for the EU, there is a dip in total production volume between 2020 and 2040. As a result, the slight change in the time interval between methods using myopic foresight and those using perfect foresight greatly impacts the mix as it changes whether the market is deemed competitive or not.

Alternative techniques to measure growth have the smallest effect of the techniques, except when the trends start to change midway through the time interval. This is especially the case for short-lasting changes, which will almost always appear quasi-linear due to the short time interval. For -changes, the change is more substantial.

Measuring growth using the area technique resulted in an increased share of technologies with high growth at the start. Unlike the split technique, suppliers must maintain their production volume throughout the time interval to be included. For example, the temporary peak in electricity supply from coal for Western Europe is not included for L_AREA but is for Ls_BASE (see Figure 9, left side).

The weighted technique is meant to increase or reduce the share of suppliers based on their growth pattern. While no suppliers underwent expansive growth in the projections, several suppliers experienced a logarithmic growth or a temporary peak in growth. In those instances, the weighted method correctly identified the growth type and reduced the suppliers' share.

The general methodology (e.v.3.0) shows the most significant difference compared to all other methods. It is also the only method that uses production volume instead of growth to calculate the share of the marginal suppliers. The method that was developed in v.3.4. is very similar to S_BASE, with the only difference being the chosen time interval. The changes are relatively small but noticeable, as with the other methods that vary the time interval selected (S_IND and S_PERF).

The global warming potential (GWP) was calculated for each marginal mix (see white points on each bar). When comparing the difference in GWP between methods, the differences are minor for the EU in the REMIND scenarios (see Figure 8, left side). This is even the case when the mixes are substantially different. This is because the marginal suppliers are all renewable technologies with a similar GWP. In all other cases, the difference in GWP is substantial, as power plants using fossil fuels are included as marginal suppliers.

Figures 10 and 11 show the marginal mix for each scenario for 2020 and 2050 to allow for comparison. Results are shown for S_BASE, S_CRR, L_BASE and L_CRR, as the timespan of the change and the baseline had the most impact on the results.

In REMIND, the EU has a high adoption rate of renewable technologies starting around 2020 (see Figure 10). Simultaneously, China also experiences a substantial uptake of renewable technologies in the REMIND scenarios. However, due to its decline in total energy consumption, the market falls below the horizontal baseline. As a result, most combinations of heuristic methods include non-competitive suppliers if the horizontal baseline is used over the capital replacement rate. Overall, the marginal mixes for remind are stable throughout the decades, especially when looking at L_CRR.

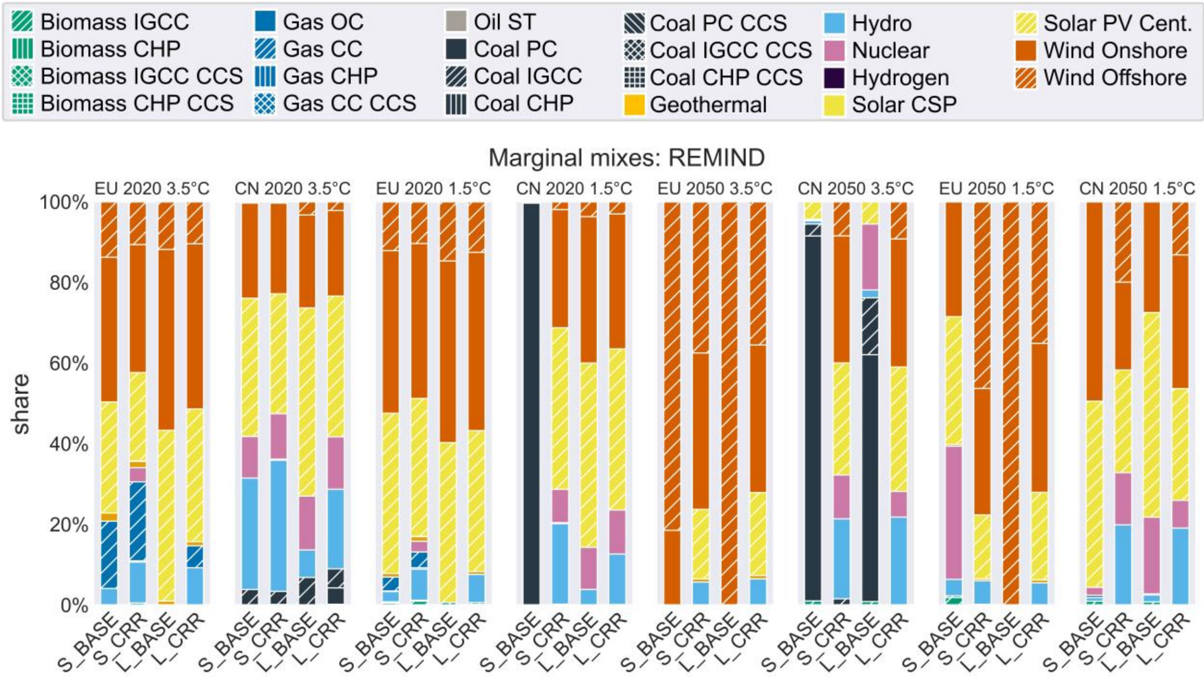

Figure 10 marginal mixes using REMIND's projections (EU = EU-28, CN = China)

The marginal mixes for IMAGE have a far lower share of renewable technologies. Instead, the mixes are dominated by fossil fuels in 2020. In 2050 the shares of renewable technologies slightly increase, and a large share of technologies use CCS in the 1.5°C scenarios.

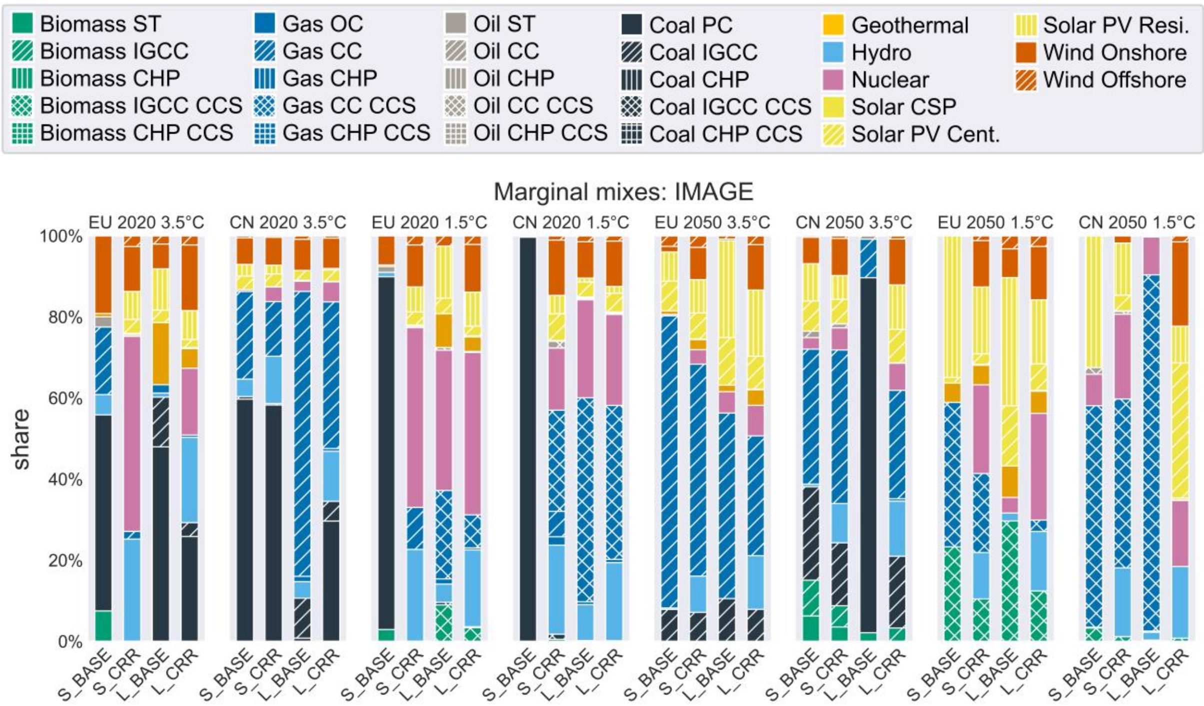

Figure 11 marginal mixes using IMAGE's projections (EU = Western Europe, CN = China)

5. Discussion

Projections or electricity production mixes obtained from the two IAMs used in this study are substantially different despite using the same pathways and focusing mainly on the same regions the different levels of foresight cause the suppliers' difference in the IAMs (47). As REMIND, all agents have perfect foresight. Because of this, the agents can set up long-term plans without risking disruption by unexpected changes. As a result, the trends in REMIND are consistent and only focus on a few technologies. On the other hand, IMAGE-modelled agents have no foresight, trending in more considerable volatility in production volume.

The level of foresight used seems to be linked to the goal of the IAM. Models with perfect foresight, such as REMIND, are most used to determine optimal transition pathways (35). Myopic models, such as those of IMAGE, are designed more closely to simulate reality as suppliers operate in asymmetric markets in real life and tend to be short-sighted when making decisions. IMAGE's model may be more appropriate for studies focusing on short-lasting changes that will occur in the near future. Both can be used for long-lasting changes or changes that happen in the far future. This study focused on two IAMs which are based on equilibrium models. However, multiple types of models have been used to develop IAMs (48). Examples are MUSE (49), which is agent-based and ANEMI (50), based on the system dynamics simulation approach. Projections are expected to differ significantly depending on the model type the IAM is based on. It is recommended to use a combination of IAMs and scenarios to deal with the uncertainty of future projections.

Results showed how sensitive the heuristic method is to the different parameters. The techniques to use depend on the focus of the study and are to be decided by the user. The following paragraphs discuss the various techniques, and recommendations are made on when to use each to help guide users in this decision.

The most significant differences were between methods focused on short-lasting changes and those focused on long-lasting changes. Multiple changes will occur in a single LCA study, which can differ in starting point and duration. It may therefore be interesting to use separate time intervals for changes that significantly affect the environmental impact.

The baseline selection is essential for both short- and long-lasting changes. This is especially the case when the market is slightly decreasing. The use of the capital replacement rate is recommended as it leans closer to the idea of measuring competitiveness through investments and to the other potential indicators.

The level of foresight had a small but noticeable effect on the results. As mentioned earlier, IAMs also assign a level of foresight to the supplier. It is recommended that the heuristic approach and IAM align with this assumption. If a myopic approach is taken, the lead time must be considered. It is recommended to use individual lead times of the technologies in the market as they influence the results.

For short-lasting changes, the results are only slightly affected by the measuring technique. For long time intervals, this is not the case. The technique to use depends on the focus of the study.

Linear regression is most useful for historical data to filter out potential outliers, which can influence the results if growth is measured using the slope in production volume. It is less useful for prospective data, which does not have these types of outliers. While the results do sometimes show a difference between using the slope or the linear trendline, this difference is caused by applying linear regression to a non-linear trend.

If the outlook is essential, then the weighted technique is advised. This technique can determine the growth trend the technology is going through. The type of growth trend, in turn, can indicate how the supplier may grow. This technique can also aid when historical data needs to be used, as it only requires a limited number of data points to determine the type of growth. This type of model could also be interesting when estimating suppliers' investment plans in a myopic model. As these suppliers do not know how the future may evolve, they might use indicators such as the growth trend to make predictions and guide their investment decisions.

Using the area under the curve to measure growth puts the focus instead on early development. This can be interesting, and in the early stages, the most impact may be felt due to the initial change in demand. Also, while the change in demand can technically influence investment decisions until the end, this is not the case for the use phase. Additional capital that appears at the end will barely be used to respond to that change in demand, directly or indirectly. By focusing on early growth, the use of additional capital within the time interval can be considered. This also avoids scenarios where novel technologies appear at the end of the time horizon with a high adoption rate and dominate the marginal mix. At the same time, they barely overlap with the lifetime of the investigated product or activity.

As with alternative measuring techniques, splitting the time interval into sections can consider non-linear growth. The differences are that no focus is laid on either the end or the beginning and that any investment in technology is considered even if the technology phases out later in that same time interval.

6. Conclusions

This work focused on developing a consistent prospective background database following a consequential approach. This study aimed to create an approach that is simple and flexible enough to be used systematically at a database scale. This study has shown that it is possible to consistently use the heuristic approach by Weidema et al. (29) to determine the long-term consequences of small-scale changes in a future context. The study has also shown the sensitivity of the different parameters within the heuristic approach. It has developed several techniques allowing users to modify the method depending on the focus of the study. For this study IAMs were used to model the background system. These models offer projections consistent on a scenario level and a global scale. However, their data is aggregated across geographies and sectors for use in the LCA context. For example, additional work will be required to disaggregate the data on the level of ecoinvent's detailed inventories for the study of specific and geographically limited sectors, such as the cement sector. In addition, the IAM incorporates several innovative technologies that are not yet out on the market. These technologies are absent from ecoinvent's database and should be manually added, which should be the subject of future research. Future work should also investigate how foreground changes can be modelled on top of the database in a way that is consistent with the underlying scenario of the database.

The results of this study were used in *premise* to transform the consequential ecoinvent database using IAM projections. As no one approach fits all, all techniques discussed were made available in the tool. The transformation is limited to the electricity mix, but this will be expanded. Whatever method is used will have a noticeable effect on the database. This is not just because of the use of the IAM projections but also because most of the markets within ecoinvent still measure share based on production volume instead of growth.

To conclude, this study has shown how projections can be integrated on a database-wide scale for the consequential approach. Several techniques are provided to allow users to freely choose their method based on the focus of their study. Future work will focus on expanding the approach in *premise* to integrate IAM projections for industries besides the electricity sector. In addition, future work will focus on how to disaggregate the IAM data and how to model foreground changes in a way consistent with the IAM scenarios.

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