Journal of Cleaner Production 170 (2018) 260–268

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Is the optimal decarbonization pathway influenced by indirect emissions? Incorporating indirect life-cycle carbon dioxide emissions into a European TIMES model

Will McDowall [a,*], Baltazar Solano Rodriguez [a], Arkaitz Usubiaga [a], José Acosta Fernández [b]

[a] UCL Institute for Sustainable Resources, Central House, 14 Upper Woburn Place, WC1H 0NN, London, UK
[b] Wuppertal Institut für Klima, Umwelt, Energie, Döppersberg 19, 42103 Wuppertal, Germany

ARTICLE INFO

Article history:
Received 21 February 2017
Received in revised form
13 September 2017
Accepted 14 September 2017
Available online 17 September 2017

Keywords:
Energy system modelling
Life cycle assessment
TIMES model
Consequential LCA
Energy policy

ABSTRACT

Energy system optimization models (ESOMs) such as MARKAL/TIMES are used to support energy policy analysis worldwide. ESOMs cover the full life-cycle of fuels from extraction to end-use, including the associated direct emissions. Nevertheless, the life-cycle emissions of energy equipment and infrastructure are not modelled explicitly. This prevents analysis of questions relating to the relative importance of emissions associated with the build-up of infrastructure and other equipment required for decarbonization.

We have soft-linked an environmentally-extended input-output (EEIO) model to a European TIMES Model (ETM-UCL) with the aim of addressing the following questions:

- In what ways does the inclusion of indirect emissions change the optimal technology pathway for decarbonizing the European energy system?
- How much does the present value of key low-carbon technologies change when indirect emissions are accounted for in a decarbonization scenario for Europe?

We show that, although indirect emissions are a relatively small portion of overall power sector emissions (<10% in 2050), including them in the model leads to changes in the optimal power sector portfolio. Renewable energy technologies become relatively less attractive once indirect emissions are included within the optimization framework, and we quantify this effect, showing that it is not large. Changes to the relative attractiveness of specific renewable energy technologies are more pronounced than the reduction in attractiveness of renewable energy as a whole: in our main scenarios wind energy saw *increased* relative deployment in 2050 when indirect emissions are accounted for, since it displaced other technologies with higher life-cycle emissions (notably solar PV). Optimal cumulative installed capacity of PV in the EU 2050 is at least 7% lower when indirect emissions are included. We conclude that policy advice derived from ESOMs that focuses on the roles of specific technologies should ensure that it is robust to the possible effects of indirect emissions.

1. Introduction

Energy system optimization models (ESOMs) are used to support energy policy analysis worldwide (DeCarolis et al., 2017). They are used both to address questions relating to long-term strategic choices (such as decarbonization targets), and to inform energy technology policy (by illustrating the relative potential for different energy technologies) (Chiodi et al., 2015). For example, the UK has used both MARKAL/TIMES models and the similar ESME model to inform R&D priorities for energy technologies (Taylor et al., 2014).

ESOMs cover the full life-cycle of fuels from extraction to end-use, including the associated direct CO_2 emissions.[1] Nevertheless,

* Corresponding author.
E-mail address: w.mcdowall@ucl.ac.uk (W. McDowall).

[1] This paper addresses only CO_2 emissions. The term 'emissions', unless otherwise indicated, always refers only to CO_2.

https://doi.org/10.1016/j.jclepro.2017.09.132
0959-6526/

the emissions associated with manufacture or construction of the necessary *technologies and infrastructure* are not modelled explicitly. This prevents analysis of questions relating to the relative importance of emissions associated with the build-up of infrastructure and other equipment required to shift to a low-carbon economy. Unless the emissions arising from energy technology manufacture are considered explicitly, ESOMs will likely overestimate the mitigation potential of certain renewable technologies that are zero emitters during the use phase, but lead to higher emissions during the construction phase.

The magnitude of this effect is unknown, since ESOMs do not model the life-cycle emissions of energy infrastructure explicitly. In contrast, life cycle assessments (LCAs) – which do have a detailed representation of energy infrastructure – do not capture the complexities of the energy system and the interactions between technologies in a way that enables dynamic macro-level assessments of the whole energy system on their own (Gibon et al., 2015). The combination of different tools can help overcome the shortcomings of each type of model, as has been recently highlighted by Pauliuk et al. (2017).

Against this background, we have soft-linked an environmentally-extended input-output (EEIO) model to an ESOM. Indirect emissions from power sector technologies were obtained from a disaggregated EEIO model (see Usubiaga et al., 2017) and were then incorporated into the UCL European TIMES Model (ETM-UCL (Solano-Rodriguez and Pye, 2014);) with the aim to address the following questions:

- In what ways does the inclusion of indirect emissions change the optimal abatement pathway?
- How much does the present value of key low-carbon technologies change when indirect emissions are accounted for in a decarbonization scenario for Europe?

Models that can examine such questions can help inform R&D prioritization decisions, since they can reveal how the relative attractiveness of specific technologies changes when indirect emissions are taken into account. Hybrid models that combine the techno-economic realism of an energy systems model with the full environmental accounting of disaggregated environmentally-extended input-output (EEIO) analysis can thus contribute to the development of ‘consequential’ life-cycle analysis, in which models inform the possible consequences of adding or removing additional units of a technology to a system (Plevin et al., 2014).

This paper first reviews previous relevant efforts to bring energy system models and life-cycle assessments together. In section 3, we set out the method we have used, including the details of the EEIO model, the TIMES model, the procedures for linking them, and the scenarios examined. Section 4 then provides results relating to each of the research questions, while section 5 draws key conclusions. The paper is accompanied by a supplementary file that includes considerable further detail on the modelling approach, the data used, and the results.

2. Literature review

Bottom-up ESOMs (such as MARKAL [Loulou et al., 2004] and TIMES [Loulou et al., 2004]) and MESSAGE (Messner and Schrattenholzer, 2000)) provide a detailed depiction of the energy system, with explicit representation of primary extraction of energy resources, processing and conversion, delivery to consumers, and end-use (DeCarolis et al., 2017). Such models account for some emissions associated with upstream extraction (flaring, for example), and they account for the efficiency losses and energy inputs associated with conversion and processing (e.g. in refineries and power stations), with transmission and distribution (losses in electricity transmission lines, energy use in fuel distribution, etc.), and efficiency losses in end use devices. Many sources of fossil fuel chain indirect emissions are thus already included in the default setup of TIMES (see the supplementary file for further details). ESOMs are “demand-driven” in the sense that the energy service demands across the economy are a key exogenous input into the models. Energy service demands associated with residential consumption, transport, industry and service sectors are all key inputs (DeCarolis et al., 2017).

However, various relevant upstream processes are frequently not incorporated into the model in an explicit way. In particular, emissions associated with the manufacture of energy technologies[2] are not directly linked to the model's decisions to deploy energy technologies (Scott et al., 2016). Instead, the emissions associated with these activities are tracked through the satisfaction of exogenously specified energy demands in the industrial, service, agricultural and other sectors. The energy demands – and hence emissions – arising from the manufacture of energy technologies are implicitly assumed to be constant across scenarios. Yet in the real world, the indirect emissions associated with processes such as the construction and manufacture of low-carbon energy technologies differs from their high-carbon alternatives, and structural shifts to low-carbon technologies (such as wind, for example) might be expected to lead to increases in activity and hence emissions from the industrial sector relative to the case in which fossil fuels continue to be used (at least during periods of installation and deployment of low-carbon technologies (Usubiaga et al., 2017);). Such endogenous changes in industrial production implied by energy transition scenarios have previously been ignored by most ESOMs (including dominant modelling systems such as MARKAL/TIMES and MESSAGE), suggesting that there is value in integrating life-cycle or similar approaches with ESOM analysis.

Several recent papers have suggested a need to better integrate life-cycle assessment and energy system (or integrated assessment) modelling approaches (Pauliuk et al., 2017; Hertwich et al., 2015; Masanet et al., 2013). Two broad strands of research can be identified that respond to this call. One strand of research has responded to this challenge by using the outputs of ESOMs as an input into detailed prospective life-cycle assessment studies. Studies taking this approach have developed LCAs of long term energy scenarios, developing dynamic life-cycle inventories that are fully consistent with the energy mix depicted in the scenario, focusing for example on wind power (Arvesen and Hertwich, 2011), renewables in Australia (Wolfram et al., 2016) or in Europe (Peter et al., 2016), and low-carbon technologies more generally (Hertwich et al., 2015). These scenarios are typically generated using energy system optimization models, such as the IEA's ETP model, a member of the MARKAL/TIMES family, which was used by Gibon et al. (2015; 2017); Arvesen and Hertwich (2011); Hertwich et al (2015). These studies provide valuable insights into the relative environmental impacts associated with various technologies in different possible futures: they have shown that technologies with low use-phase carbon emissions also provide considerable co-benefits (Hertwich et al., 2015), as well as performing well in terms of whole-life-cycle carbon emissions (Wolfram et al., 2016). However, they have not addressed how the consideration of life-cycle emissions might influence the optimal decarbonization pathway, and thus the scenarios developed by the ESOM tools.

A second, smaller strand of research has approached the linkage

[2] The same is true for indirect emissions associated with the operation of energy technologies; or emissions associated with inputs used in the cultivation of bioenergy, such as fertilizer manufacture.

of life-cycle emissions and energy system optimization models from the other way around. This second strand of research (and the one to which the present paper makes a contribution) has used the outputs of life-cycle assessments as inputs into energy optimization models. In early studies, several authors used LCA as a basis for calculating the full life-cycle CO_2 associated with different electricity generation technologies and applied these as external costs in MARKAL models of the whole world (Rafaj and Kypreos, 2007), western Europe (Röder, 2001) and Val d'Agri in Italy (Pietrapertosa et al., 2009). These studies have aimed to show whether and how full life-cycle accounting for energy technologies can influence the techno-economically optimal energy system under a carbon constraint. However, while these studies have provided insights into system responses to life-cycle costs, the approach they use results in an internal inconsistency between the marginal CO_2 abatement cost generated endogenously within the model and the value of external costs of CO_2 applied exogenously.

More recently, Rentizelas and Georgakellos (2014) built an ESOM of the Greek power sector that used life-cycle emissions rather than those arising from the use-phase of technologies. There are clear limitations to their approach: the *direct* emissions from energy technology operation should be an endogenous variable within the model, since the model should determine how much to use each technology once built; whereas indirect emissions associated with construction should be fixed per unit capacity.

Three recent studies incorporate indirect emissions into an ESOM. Menten et al. (2015) and (García-Gusano et al., 2016) both incorporate emissions derived from process-LCA into TIMES models (of France and Norway, respectively). Their work represents an improvement on previous approaches to incorporating indirect emissions, but the resulting model suffers from double-counting of the indirect emissions (as explained in Menten et al., also see the Supplementary Information for a fuller explanation). In the third study Daly et al. (2015) have used indirect emissions from an EEIO model, and incorporated these into a TIMES model of the UK. The work presented in this paper builds on their approach. In particular, the work presented here uses indirect emissions factors derived from hybrid input-output based LCA, resulting in a more accurate mapping of indirect emission factors to specific energy technologies, realizing the strengths of both process-LCA and EEIO analysis. This enables greater insights into the extent to which indirect emissions influences the optimal technology portfolio under a carbon constraint. The work presented in this paper also offers a more consistent approach to overcoming the double-counting problem.

In the following sections we show the implications of incorporating the indirect emissions associated with the build-up of infrastructure and other equipment of energy technologies.

3. Method, data and scenarios

3.1. ETM-UCL: overview of the model

UCL's European TIMES model (ETM-UCL (Solano-Rodriguez and Pye, 2014; Solano Rodriguez et al., 2017);) is a cost optimization model that investigates decarbonization and energy technology pathways for 11 European regions covering the EU-28 countries plus Norway, Switzerland and Iceland. The Integrated MARKAL-EFOM System (TIMES) has been developed by the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency (IEA), and is used worldwide to implement both national and global models (Chiodi et al., 2015).

TIMES is a technology rich, bottom-up, linear programming model that minimizes total discounted energy system cost (Loulou et al., 2016). Energy service demands and carbon targets are exogenous inputs. The model then finds the least-cost energy system for meeting energy service demands subject to carbon constraints from its large menu of energy technologies and resources.

The model is calibrated to its base year of 2010, with energy service demand projected into the future using the exogenous drivers GDP, population, household numbers and sectorial output (linked to GDP), for each region. Energy consumption is available for each region for end-use sectors (transport, industry, agriculture, commercial and residential), and the upstream and power sectors.

Each region in ETM-UCL has its own energy system. These regions are described and modelled in their supply sector (fuel mining, primary and secondary production, exogenous import and export), their power generation sector and their demand sectors (residential, commercial, industrial, etc.). The 11 regions are linked through the trade in crude oil, hard coal, pipeline gas, LNG (liquefied natural gas), petroleum products (diesel, gasoline, naphtha, heavy fuel oil), biomass and electricity.

A wide range of energy supply and demand technologies for future years are included in the model. For example, power sector technologies are modelled considering investment and operating cost parameters, efficiency factors, construction time, utilization factors, etc. Subject to resource, technology and policy constraints such as the EU 2050 greenhouse gas (GHG) emission target, the model then chooses the cost-optimal set of electricity generation technologies to meet demand in each time period up to 2050.

3.2. Developing indirect emission factors for power sector technologies

The indirect CO_2 emission factors (IEF) associated with the construction of power sector technologies have been calculated by means of input-output based hybrid LCA – a variant of EEIO analysis (full details of the method are reported in Usubiaga et al. (2017). This method consists of a disaggregation of an input-output table and its environmental extension(s) based on data from life-cycle inventories (LCI), and the use of EEIO analysis to calculate consumption-based pressures (Suh and Huppes, 2005) – in this case, CO_2 emissions. Disaggregating an EEIO model using LCI data allows overcoming the main limitations of each of them, i.e. the high aggregation of EEIO models and the incomplete system boundaries in LCA (Lenzen, 2000).

In this exercise, the 2007 EU27 Eurostat symmetric input-output tables (Eurostat, 2011) and the corresponding carbon emission accounts (Eurostat, 2014a) have been disaggregated from the 59 original product groups to 125 product groups. The additional product groups depict either 18 electricity supply technologies or their most relevant life cycle stages, including the infrastructure required (Table 1). The resulting disaggregated EEIO table thus includes explicit representation of the sectors that produce energy technologies, enabling identification of the indirect emissions associated with the production of a unit of each energy technology.

The disaggregation has been carried out by combining direct input coefficient data (as a production recipe) and product output data such as annual capacity additions and power generated in the European power sector. The disaggregation process combines physical input coefficients of the representative technology taken from the Ecoinvent LCI database (Ecoinvent Centre, 2010, 2013), prices (Gaulier and Zignago, 2010) and monetary input coefficients the EXIOBASE v2 database (Wood et al., 2015) with their corresponding outputs, which are either calculated in the previous step or obtained from alternative sources such as Eurostat's Structural Business Statistics (Eurostat, 2014d, 2014b, 2014c). The direct input coefficients of manufactured products have been adapted to EU27 efficiencies with data from the International Energy Agency (IEA, 2013a, 2013b). As for the carbon emissions of each of these

Table 1
Detail of the infrastructure related to electricity production.

Technology	Description
Wind onshore	Wind power plant onshore - fixed parts
	Wind power plant onshore - moving parts
Wind offshore	Wind power plant offshore - fixed parts
	Wind power plant offshore - moving parts
PV	Inverter
	Multi-Si PV panel
	Multi-Si PV cell
	Multi-Si PV wafer
	Electric installation, photovoltaic plant, at plant
	Slanted-roof construction, mounted, on roof
Coal	Hard coal power plant - CHP
	Hard coal power plant - no CHP
CCGT	Combined cycle gas power plant - CHP
	Combined cycle gas power plant - no CHP
Conventional gas	Conventional gas power plant - CHP
	Conventional gas power plant - no CHP
Nuclear	PWR nuclear power plant
Hydro	Run-of-river hydropower plant
Oil	Oil power plant - CHP
	Oil power plant - no CHP
Biomass/Waste	Municipal waste incineration plant - CHP
	Municipal waste incineration plant - no CHP

Note: CCGT: Combined Cycle Gas Turbine; CHP: Combined Heat & Power; Multi-Si: Multicrystalline Silicon, PV: Photovoltaic.

subproduct groups, the direct emission intensities from Ecoinvent have been multiplied by the corresponding product output. More details are provided in the original source (Usubiaga et al., 2017).

In a last step, the standard formulation of EEIO analysis is used to estimate the direct and upstream CO_2 emissions related to the infrastructure associated with selected electricity production technologies as shown in the following equation.

$$m = B\cdot(I-A)^{-1}\cdot y$$

where m denotes direct and upstream pressures, B represents direct pressure intensity, $(I\text{-}A)^{-1}$ represents the Leontief inverse and y refers to the final demand of a good or service. In this case, the final demand y is set to 1 for selected energy technologies and related infrastructure in order to obtain the direct and indirect carbon emissions associated therewith.

The indirect emissions factors generated by (Usubiaga et al., 2017) were compared against emissions factors identified in the wider LCA literature (Masanet et al., 2013). By making assumptions about average load factors, the CO_2/MW factors generated by Usubiaga et al. were compared with those from Masanet et al. (which are expressed in terms of gCO_2/kWh). This comparison suggested that the estimates from Usubiaga et al. are at the low end of the range in the literature. Exploring sensitivity scenarios using higher emissions factors thus is useful both in testing the model and in exploring real-world uncertainty.

3.3. Mapping IO sectors to ETM-UCL technologies

For most existing power sector technologies, the mapping process was straightforward (i.e. the new sector in the disaggregated EEIO table that produces coal-fired power plants was mapped to the TIMES coal-fired power plant technologies). New technologies that were not included in the EEIO table (because they did not exist in 2007, the snapshot year from which the IEFs were developed) were assigned IEFs based on judgements about which other energy technologies they are most similar to in terms of physical characteristics, though it is acknowledged that this process introduces considerable uncertainty in the IEFs. A full mapping of IO sectors to TIMES technologies is included in the supplementary information.

The units for emissions factors from the EEIO table are in monetary units (tCO_2/Euro monetary output of the sector), and must be converted into physical units (tCO_2/MW capacity). In order to do this, estimation of the historical EU annual capacity additions, which corresponds to the years of the EEIO table, was used to convert output of each sector in monetary terms into output in physical terms.

3.4. Avoiding double counting

The system boundaries of the energy system model and EEIO model overlap: the EEIO table incorporates the whole economy including the energy system, while the energy system model includes detailed representation of the energy system alongside exogenous assumptions about energy demand in different sectors of the economy. This creates a double-counting problem, because some of the activities associated with manufacture of energy technologies (and hence the direct and indirect emissions associated with the energy inputs into those activities) are implicitly represented by the energy demands within ETM-UCL. In other words, the ETM-UCL end-use demands already include within them the demands that arise from the construction and operation of energy technologies – these are implicitly included within exogenously specified industrial energy service demand (e.g. steel production implicitly includes that steel required for power station construction), service sector demand (construction activities) and others. By including indirect emissions factors, the emissions associated with this energy are accounted for twice; once explicitly by the TIMES model through the various processes that satisfy sectoral energy demands, and once through the indirect emissions attached to the construction of energy technologies.

Daly et al. (2015) adjust for this double-counting by summing the indirect emissions, and relaxing the emissions target by this amount. In other words, the emissions and activities associated with them are not removed from the model; rather the emissions target is adjusted such that the marginal abatement cost of meeting a particular target is unchanged. Daly et al.'s method works around the double counting, but remains technically inconsistent, with overlapping system boundaries. A conceptually clearer alternative approach is to remove the energy service demands from the final demand sectors in ETM-UCL that correspond to these double-counted emissions. E.g. if 2% of the steel sector is producing steel that is ultimately destined to be used in wind turbine manufacturing, then the energy service demands of the steel sector in ETM-UCL should be reduced by 2%, since this activity is now represented by the IEF. To estimate this, one must identify the portion of steel demand that is specific to the construction and manufacture of energy technologies. This can be estimated from the disaggregated input-output table. A more detailed explanation of this approach is provided in the supplementary information.

Table 2
Typical TIMES model demand categories.

TIMES demand sector	Demand sub-sector
Agriculture	Agriculture
Services	Services
Industry	Pulp and Paper
	Chemicals
	Iron & Steel
	Non-metallic minerals
	Other industry
Transport	Heavy goods vehicles
	Light goods vehicles

Table 3
Illustrative mapping of IO sectors to TIMES exogenous demand categories.

IO Sector	TIMES equivalent demand
Products of agriculture, hunting and related services	Agriculture
Products of forestry, logging and related services	Agriculture
Coal and lignite; peat	N/A (demand created endogenously within TIMES)
Leather and leather products	Other industry
Wood and products of wood and cork (except furniture); articles of straw and plaiting materials	Other industry
Pulp, paper and paper products	Pulp & Paper
Printed matter and recorded media	Pulp & Paper
Coke oven products	N/A (demand created endogenously within TIMES)
Nuclear fuel	N/A (demand created endogenously within TIMES)
Chemicals, chemical products and man-made fibers	Chemicals
Rubber and plastic products	Chemicals
Other non-metallic mineral products	Non Metallic minerals
Fabricated metal products, except machinery and equipment	Other industry

It is helpful here to examine the demand structure of ETM-UCL. Table 2 illustrates ETM-UCL sectors that are equivalent to IO sectors that produce goods and services that are used in the construction, manufacture or operation of energy technologies.

ETM-UCL end-use energy demands that are associated with the energy used in the production of goods and services for intermediate consumption (rather than final energy consumption by households) can be matched to the IO sectors that describe those production activities. Note that a major exception is IO sectors that produce energy commodities (such as the IO sector "coke oven products"), since the demands for these commodities are produced endogenously by the energy system model, rather than being an exogenous input. A sample of such a mapping process is shown in Table 3 (the full mapping is provided in the supplementary material).

The second step is to calculate the share of intermediate consumption, for these aggregated sectoral categories, that is accounted for by the production of energy technologies for which IEFs are being derived. This step requires applying the 'structural path analysis' method. This is done to derive direct *and indirect* demands associated with the manufacture and construction of energy technologies, distributed across the industrial, service and transport demands in TIMES. Ideally, these indirect energy service demands should be calculated on an identical basis to the indirect carbon emissions that are represented by the indirect emissions factors.

Finally, the third step is to reduce the energy service demands for each of the aggregated sectoral categories. If the share of total agricultural output used in the manufacture of energy technologies is 1%, then the 'agriculture' demands in the TIMES model should be reduced by 1%, and so on with other sectors (see Table 4).

The approach is based on a snapshot of the intermediate demands associated with the production of energy technologies at a given point in time. Note also that this approach makes the assumption that there is a simple linear relationship between demand for production for these aggregated sectors and energy demand.

3.5. Limitations and simplifying assumptions

3.5.1. Assumptions on decarbonization of energy technology manufacture

In the real world, the IEFs associated with technologies are expected to decline over time, as both the economic structure and production processes change in response to decarbonization policies. It seems likely that decarbonization rates for the production of energy technologies are likely to be similar to those in other sectors. The analysis here explores both scenarios in which IEFs are assumed to be static across time (i.e. no technological change) and dynamic, in which IEFs decrease across time in a decarbonization scenario. The rate of decrease in IEFs is derived from the decarbonization rate of the TIMES industry sector in a model run that meets targets, i.e. the sectors producing energy technologies are assumed to decarbonize at the same rate as the rest of the industry sector. Further detail on these rates is given in the supplementary material.

3.5.2. Geographic system boundaries

The EEIO table used in this analysis is fully described in Usubiaga et al. (2017). It is a single region table covering all 27 countries of the EU (before the addition of Croatia). In estimating IEFs, Usubiaga et al., 2017 adopt the 'domestic technology assumption', i.e. they assume that production structures and technologies are identical globally. The IEFs thus include emissions from outside the borders of the EU, embodied in imported goods. This is a weakness of the current analysis, since it precludes strong conclusions about the importance of IEFs in the ability of the EU to meet targets.[3]

3.5.3. Sectoral coverage and model balancing

In the current analysis, IEFs were applied only to power sector technologies, which creates an imbalance in the model, since other sectors do not generate indirect emissions. As a result, the interpretation of results must be avoid drawing conclusions that could be distorted by this imbalance. For example, drawing conclusions about the relative attractiveness of electric vehicles vs. Biofuels in such a model would be unwise, since electricity will be effectively penalized by carrying the burden of indirect emissions, whereas biofuels would not. Ideally, a fully hybridized EEIO-ESOM model would include all indirect emissions factors for all technologies in the energy system model, including end-use technologies (lights, ovens, cars, etc.), conservation technologies (such as insulation) and upstream and industrial sector technologies (refineries, steel mills).

3.6. Scenarios

The first research question set out in the introduction is: *In what ways does the inclusion of indirect emissions change the optimal abatement pathway?* Addressing this question requires comparison of scenarios in which indirect emissions are included with those in which they are excluded, with various sensitivity tests to examine

[3] EU emissions targets are of course calculated on a production basis, not a consumption basis. However, if the indirect emissions associated with infrastructure can be estimated on a common geographic basis as production-based emissions, then the relative importance of infrastructure-related emissions could still be used to inform analysis of carbon targets.

Table 4
Energy service demands in TIMES attributable to the manufacture of energy technologies. NB: in the EEIO table, the ETM-UCL categories Iron & Steel and non-ferrous metals are represented by a single IO sector, 'basic metals'. We assume that the share of demand of these sectors associated with energy technologies is the same.

ETM-UCL demand sector	Total use by sectors manufacturing power sector technologies (m€)	Total use by all sectors at basic prices (m€)	Share of total use that goes to power sector tech.	Coefficient for energy service demands
Agriculture	223	413,850	0.05%	99.95%
Other industry	9228	4,390,832	0.21%	99.79%
Pulp & Paper	169	397,462	0.04%	99.96%
Chemicals	965	917,922	0.11%	99.89%
Iron & Steel; Non-ferrous	1780	359,346	0.50%	99.50%
Services	14,717	13,589,209	0.11%	99.89%
HGVs	707	497,000	0.14%	99.86%
Aviation	33	125,193	0.03%	99.97%
Shipping	360	98,369	0.37%	99.63%
Non-metallic minerals	3203	216,489	1.48%	98.52%

key uncertainties in both the time-path of indirect emissions, and the magnitude of emissions factors. The scenarios required to do this are presented in Table 5.

The high IEFs scenario examines the model's response to higher indirect emissions, which is useful because of the considerable uncertainty in the estimation of the emissions factors. In addition, EEIO-derived emissions factors exclude emissions associated with end-of-life and decommissioning processes. The resulting underestimation of the real values of indirect emissions across the full life-cycle, though not expected to be large, provides a further rationale for sensitivity testing with inflated emissions factors.

The second research question is: *How much does the present value of key low-carbon technologies change, when indirect emissions are accounted for in a decarbonization scenario for Europe?* Assessing the value of a single specific technology requires running scenarios in which that technology is excluded as an option, and comparing the total discounted system costs of that scenario with an equivalent scenario in which the technology is available to the model. The scenarios in which wind and solar PV are prevented from diffusing provide a way of estimating the change in value of the technologies to the energy system when indirect emissions are taken into account.

Note that these scenarios, while exhibiting key differences, hold a number of common assumptions:

- **Energy service demands:** The scenarios share common energy service demand projections, which are themselves based on projections for GDP, population growth and number of households. These values are taken from the IEA's "Energy Technology Perspectives 2012" (ETP) for the European Union (IEA, 2012).
- **Carbon targets:** Low carbon scenarios in this study constrain the model to reduce GHG emissions by 80% below 1990 levels by 2050.
- **Exogenous fuel import prices:** While the model generates prices of energy commodities within Europe endogenously, the rest-of-the-world prices (i.e. the price for imports into Europe of oil, coal and gas) are exogenous. In all scenarios, these prices are derived from the IEA ETP 2DS scenario prices for oil, gas and coal imports (IEA, 2012).

4. Results and discussion

4.1. Research question 1: does the inclusion of indirect emissions change the optimal abatement pathway?

Though the overall share of indirect emissions is relatively small in most scenarios (<10% of power sector emissions in the constant IEFs scenario), these additional emissions do result in changes in the optimal configuration of the power system – in particular in the sensitivity scenario with high IEFs. As expected, the overall power sector capacity is reduced when indirect emissions are included, and further reduced in scenarios with high IEFs. Recall that this is an expected result where the model is imbalanced (i.e. because indirect emissions have only been applied to the power sector).

The changes that occur within the power sector itself are more interesting. When indirect emissions are included, the model responds by reducing the deployment of solar PV (see Fig. 1). In the declining IEF case, in which IEFs are reduced over time, the optimal installed capacity of PV across Europe is around 30 GW less in 2050 than in a case in which indirect emissions are ignored. This is around a 7% reduction in cumulative installed capacity of PV in 2050—not dramatic, but certainly not negligible. This result is unsurprising: solar becomes less attractive under a decarbonization scenario once it is no longer a zero carbon energy source. This effect is strongly observed in the high indirect emissions sensitivity scenario.

This pattern is similar for renewables as a whole: the impact of including indirect emissions results in a 4% reduction in renewable energy installed capacity in 2050 (ranging from 1% in the declining IEFs scenario to 27% in the high IEFs scenario). These results provide a quantification of the intuition that accounting for the full life-cycle of the infrastructure of energy technologies will reduce the

Table 5
Summary of scenarios.

Scenario names	Description
No IEFs	Basic model run, with *direct* emissions constrained to meet carbon targets, but with indirect emissions not included in the scope of the emissions constraint.
Constant IEFs	As above, but with indirect emissions included in the scope of the emissions constraint. The IEFs used in this scenario are constant across time, based on the EEIO snapshot from the 2007 symmetrical EEIO table).
Declining IEFs	As above, but with declining IEFs, rather than static. In this scenario, IEFs are reduced according to the decarbonization trajectory of the ETM industry sector in the previous low-carbon runs)
High IEFs	This sensitivity scenario examines higher IEFs (five times higher than in the constant indirects scenario). Indirect emissions are included in the constraint in this scenario, and are constant over time.

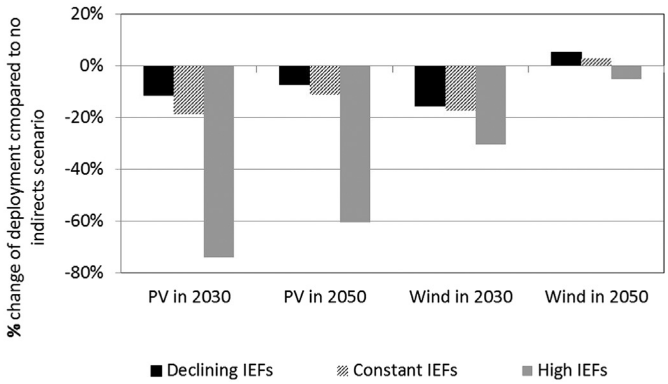

Fig. 1. Change in PV and Wind capacity relative to No IEFs scenario, in which indirect emissions are not constrained. A version of this figure showing absolute changes in GW is available in the supplementary material.

apparent attractiveness of technologies that have zero emissions in the use-phase. It is worth noting that in the most plausible scenario (empirically derived indirect emissions that fall as the wider economy is decarbonized) the effect is small, both for renewables in general (1% reduction in cumulative installed capacity in 2050) and for PV in particular (a 7% reduction in 2050).

The results are more interesting for wind. In 2030 the installed capacity of wind decreases between 35 and 100 GW when indirect emissions are included (Fig. 1). However, in 2050 the reduction in PV is compensated by *increases* in wind deployment at baseline indirect emissions factors. This occurs even when emissions factors are constant across the time horizon (which implicitly assumes that while the rest of the economy decarbonizes, the production of wind turbines generates identical indirect emissions in 2040 as it did in the EEIO base year of 2007). This is a surprising finding: one would expect that adding indirect emissions to a zero-carbon technology would result in a decrease in its optimal levels of deployment in a carbon-constrained scenario, and that this pattern would be consistent across the model time horizon. Here, instead, the low-carbon technology portfolio shifts as a whole, such that the decline in PV is partially offset by relative increases in wind deployment. Wind also appears to be subject to a threshold effect in these 2050 results: in sensitivity runs with higher levels of indirect emissions, wind follows the pattern of PV and shows declines in deployment.

One possible explanation for the reductions in PV shown in Fig. 1 is that the addition of indirect emissions results in a reduction of power generation as a whole (for example, the model may use less electricity in the transport sector, since the addition of indirect emissions to electricity will result in higher emissions burdens associated with electricity consumption). Thus the reduction in PV could be a response to a smaller overall power sector, rather than a result of the model preferring other power generation technologies over solar. This could occur if solar PV is the marginal technology that the model is deploying in order to meet power generation requirements. If that were the case, then when the overall power sector is reduced, solar PV would be disproportionately reduced. A similar effect might be expected to occur for renewable energy technologies on aggregate.

In order to confirm that the reduction in the contribution of particular power sector technologies to the electricity generation capacity of the system under different scenarios is not solely due to the reduction in power sector capacity, we have also run scenarios in which power sector capacity has been fixed in all scenarios to the level found in the scenario without indirect emissions constraints. In other words, the model is forced to continue to use the same size of power sector across scenarios in these runs, and can only respond to the introduction of indirect emissions by changing the power sector technology portfolio. The results (shown in Fig. 2) show that even under the same power capacity there is a change in the optimal power sector portfolio chosen by the model. The figure shows that the overall patterns remain unchanged, though the magnitude of the effects is reduced.

In addition to altering the model's choices with respect to installed capacity, the addition of capacity-related indirect emissions shifts the way in which power generation plants are used. As might be anticipated, in general dispatchable technologies have a higher load factor when indirect emissions are included. This is illustrated in Fig. 3, showing usage of Europe's coal generating capacity in the high indirect emissions scenario and the scenario in which indirect emissions are not constrained.

Since the introduction of new power generation assets now results in indirect emissions, the model prefers to use existing assets more intensively. In the No IEFs scenario, coal fired power stations are being retired long before the end of their technical life, as it is techno-economically optimal under a carbon constraint to switch away from coal to other power generation options. In the High IEFs case, many of these coal plants remain operational, since shutting them down would require the construction of alternative power generation technologies, incurring indirect emissions. Moreover, the no IEFs scenario sees higher deployment of renewables, resulting in higher levels of part-load operation of coal-fired plants.

A similar result is found across all dispatchable technologies: the lowest load factors are found in the scenario when indirect emissions are unconstrained. In scenarios where indirect emissions are constrained, the lowest load factors are found where the IEFs reduce over time, while the highest load factors are found in scenarios in which IEFs are highest.

4.2. Research question 2: changing value of specific technologies

ESOM analysis can be used to generate a direct measure of the value of a particular technology to the energy system (or, equivalently, the cost of excluding that technology from the energy system). Such measures can be used by policymakers to inform analysis of R&D portfolios and prioritization for energy innovation support. Here, we explore how the inclusion of indirect emissions

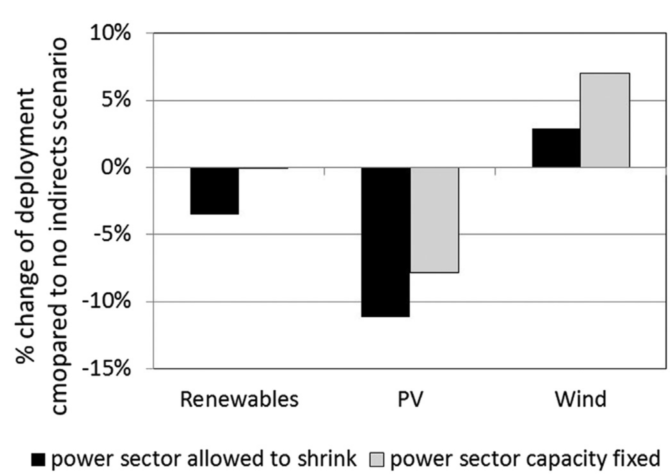

Fig. 2. Difference in capacity in the ‘constant IEFs’ scenario in 2050, relative to the ‘no IEFs’ scenario. The figure shows both the case in which power sector size is fixed, and when the power sector is allowed to shrink. A version of this figure showing absolute changes in GW is available in the supplementary material.

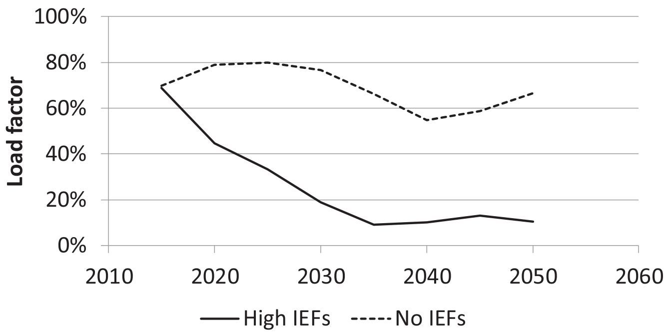

Fig. 3. Load factor of European coal plant (%).

effects the value to the energy system of solar PV and wind.

In order to do this, scenarios were run in which PV and wind are excluded from the energy system. When a technology is excluded, the model must identify a replacement, and the additional cost of doing so is captured by differences in the total discounted energy system cost between the scenario in which the technology is available, and the scenario in which it is excluded.

When constant IEFs are included, the additional energy system costs in a scenario in which PV is excluded are $32bn. This rises to $41bn when indirect emissions are ignored. In other words, the present value of solar PV to the European energy system is $9bn less when indirect emissions are taken into account, a reduction of around 20%. Importantly, these numbers are based on a constant emissions factor that ignores the potential for the decarbonization of the sectors that produce energy technologies. When IEFs are reduced in line with industry sector emissions, the reduction in the net present value of PV arising from indirect emissions is halved, to $4.5bn.

For wind, the findings are completely different. When indirect emissions are included, the deployment of wind is higher than when they are ignored, since higher levels of wind compensate for the reduction in solar PV. The value of wind is thus increased in a scenario in which indirect emissions are included, though the effect is small (less than 1%).

5. Conclusions & limitations

The analysis conducted here demonstrates the feasibility and value of incorporating indirect emissions into an energy systems optimization model. The analysis provides a novel perspective and highlights previously neglected issues. In particular:

1. Indirect emissions are a relatively small portion of overall power sector emissions, but including them in the model leads to changes in the optimal power sector portfolio.
2. Renewable energy technologies (with zero *direct* emissions) become relatively less attractive once indirect emissions are included within the optimization framework. However, the effect is not large (1% change in installed capacity in 2050 in the most plausible case, using empirically-derived IEFs and declining emissions factors).
3. The changes to the relative attractiveness of specific renewable energy technologies are more pronounced than the reduction in attractiveness of renewable energy as a whole: In our main scenarios wind energy saw *increased* relative deployment by 3% in 2050 when indirect emissions are accounted for, since it displaced other technologies with higher life-cycle emissions (notably solar PV, which had cumulative deployment 7% lower in 2050 when indirects were taken into account).
4. The net present value of solar PV (a technology with zero direct emissions) is reduced by around 20% once indirect emissions are included within the emissions constraint; though this is subject to considerable uncertainty.
5. The model responds to indirect emissions not only by adjusting the capacity mix, but also by changing the operational profile of dispatchable plants resulting in higher load factors when indirect emissions are taken into account.

The results do not overturn the key insights of other attempts to evaluate the full life-cycle implications of long-term energy system scenarios. Renewable energy sources remain a key part of the optimal power sector mix, and contribute to a cost-effective decarbonization of the European economy. However, the results do suggest that existing analytic tools, including the IEA's Energy Technology Perspectives model, may overestimate the extent to which renewables contribute to a cost-optimal decarbonization pathway.

The analysis shows that the results of ESOMs, which are widely used by policymakers to inform climate policy development (Chiodi et al., 2015), are influenced by assumptions about the relative burden of life-cycle emissions. While the effects are not large for most technologies, the results highlight that indirect emissions are not negligible for some technologies. Where ESOMs are being used to inform policy: whether informing long-term abatement strategies (e.g. Strachan et al., 2009), or technology-specific R&D policies (e.g. (LCICG, 2014), analysts should ensure that results are robust to this effect.

Several key assumptions must also be understood in interpreting our results. In particular, the scale of uncertainties in input assumptions is very large. This is true for the indirect emissions factors, which here consider both the domestic and nondomestic emissions – but no less true for other technology data, such as costs and efficiencies. Moreover, the model operates according to a linear optimization procedure across time horizons—it is not an accurate depiction of how energy systems evolve over time, but an illustration of what is technically possible and economically cost-optimal. The insights are in the comparison between scenarios and the relative orders of magnitude and types of dynamics, rather than the precise quantitative outputs.

Acknowledgements

This work was carried out as part of the European Commission FP7 project “EMInInn” (grant number 283002). The authors would like to thank Hannah Daly and Isabela Butnar, as well as participants at a project workshop in London in November 2014 for their comments and suggestions for the work.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2017.09.132.

References

Arvesen, A., Hertwich, E.G., 2011. Environmental implications of large-scale adoption of wind power: a scenario-based life cycle assessment. Environ. Res. Lett. 6 (4), 045102.
Ecoinvent Centre, 2010. Ecoinvent Data v2.2. Dübendorf, Switzerland.
Ecoinvent Centre, 2013. Ecoinvent Data V3. Dübendorf, Switzerland.
Chiodi, A., Taylor, P.G., Seixas, J., Simões, S., Fortes, P., Gouveia, J., Dias, L., Ó Gallachóir, B., 2015. Energy policies influenced by energy systems modelling—case studies in UK, Ireland, Portugal and G8. In: Giannakidis, G., et al. (Eds.), Informing Energy and Climate Policies Using Energy Systems Models. Springer International Publishing, Switzerland.
Daly, H.E., Scott, K., Strachan, N., Barrett, J.R., 2015. The indirect CO2 emission

implications of energy system pathways: linking IO and TIMES models for the UK. Environ. Sci. Technol. 49 (17), 10701–10709.
DeCarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., McDowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., Yeh, S., Zeyringer, M., 2017. Formalizing best practice for energy system optimization modelling. Appl. Energy 194, 184–198.
Eurostat, 2011. Input-output Table at Current Prices, 60 Branches - EU Aggregates (Naio_17_agg_60. Luxembourg.
Eurostat, 2014a. Air Emissions Accounts by NACE Rev. 1.1 Activity (Env_ac_ainah_r1. Luxembourg.
Eurostat, 2014b. Annual Detailed Enterprise Statistics on Manufacturing, Subsections DF-DN and Total (NACE Rev. 1.1, D) (Sbs_na_2a_dfdn (Luxembourg).
Eurostat, 2014c. Annual Detailed Enterprise Statistics on Electricity, Gas and Water Supply (NACE Rev. 1.1, E) (Sbs_na_2a_el (Luxembourg).
Eurostat, 2014d. Annual Detailed Enterprise Statistics on Mining and Quarrying (NACE Rev. 1.1, C) (Sbs_na_2a_mi (Luxembourg).
García-Gusano, D., Iribarren, D., Martín-Gamboa, M., Dufour, J., Espegren, K., Lind, A., 2016. Integration of life-cycle indicators into energy optimisation models: the case study of power generation in Norway. J. Clean. Prod. 112 (Part 4), 2693–2696.
Gaulier, G., Zignago, S., 2010. BACI: International Trade Database at the Product-level. The 1994-2007 Version. Paris.
Gibon, T., Wood, R., Arvesen, A., Bergesen, J.D., Suh, S., Hertwich, E.G., 2015. A methodology for integrated, multiregional life cycle assessment scenarios under large-scale technological change. Environ. Sci. Technol. 49 (18), 11218–11226.
Gibon, T., Arvesen, A., Hertwich, E.G., 2017. Life cycle assessment demonstrates environmental co-benefits and trade-offs of low-carbon electricity supply options. Renew. Sustain. Energy Rev. 76, 1283–1290.
Hertwich, E.G., Gibon, T., Bouman, E.A., Arvesen, A., Suh, S., Heath, G.A., Bergesen, J.D., Ramirez, A., Vega, M.I., Shi, L., 2015. Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies. Proc. Natl. Acad. Sci. 112 (20), 6277–6282.
IEA, 2012. Energy Technology Perspectives 2012: Pathways to a Clean Energy System. International Energy Agency, Paris.
IEA, 2013a. Energy Balances of OECD Countries, 2012 ed. International Energy Agency, Paris.
IEA, 2013b. Energy Balances of Non-OECD Countries, 2012 ed. International Energy Agency, Paris.
LCICG, 2014. Coordinating Low Carbon Technology Innovation Support. Low Carbon Innovation Co-ordination Group. HM Government, London.
Lenzen, M., 2000. Errors in conventional and input-output—based life—cycle inventories. J. Ind. Ecol. 4 (4), 127–148.
Loulou, R., Goldstein, G., Noble, K., 2004. Documentation for the MARKAL Family of Models. Energy Technology Systems Analysis Programme (ETSAP. International Energy Agency, Paris.
Loulou, R., Goldstein, G., Kanudia, A., Lettila, A., Remme, U., 2016. Documentation for the TIMES Model. International Energy Agency Energy Technology and Systems Analysis Programme (IEA-ETSAP, Paris.
Masanet, E., Chang, Y., Gopal, A.R., Larsen, P., Morrow, W.R., Sathre, R., Shehabi, A., Zhai, P., 2013. Life-cycle assessment of electric power systems. Annu. Rev. Environ. Resour. 38 (1), 107–136.
Menten, F., Tchung-Ming, S., Lorne, D., Bouvart, F., 2015. Lessons from the use of a long-term energy model for consequential life cycle assessment: the BTL case. Renew. Sustain. Energy Rev. 43, 942–960.
Messner, S., Schrattenholzer, L., 2000. MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy 25 (3), 267–282.
Pauliuk, S., Arvesen, A., Stadler, K., Hertwich, E.G., 2017. Industrial ecology in integrated assessment models. Nat. Clim. Change 7 (1), 13–20.
Peter, B., Anders, A., Yvonne, S., Hans Christian, G., Edgar, G.H., 2016. Environmental impacts of high penetration renewable energy scenarios for Europe. Environ. Res. Lett. 11 (1), 014012.
Pietrapertosa, F., Cosmi, C., Macchiato, M., Salvia, M., Cuomo, V., 2009. Life Cycle Assessment, ExternE and Comprehensive Analysis for an integrated evaluation of the environmental impact of anthropogenic activities. Renew. Sustain. Energy Rev. 13 (5), 1039–1048.
Plevin, R.J., Delucchi, M.A., Creutzig, F., 2014. Using attributional life cycle assessment to estimate climate-change mitigation benefits misleads policy makers. J. Ind. Ecol. 18 (1), 73–83.
Rafaj, P., Kypreos, S., 2007. Internalisation of external cost in the power generation sector: analysis with Global Multi-regional MARKAL model. Energy Policy 35 (2), 828–843.
Rentizelas, A., Georgakellos, D., 2014. Incorporating life cycle external cost in optimization of the electricity generation mix. Energy Policy 65, 134–149.
Röder, A., 2001. Integration of Life-cycle Assessment and Energy Planning Models for the Evaluation of Car Powertrains and Fuels. Swiss Federal Institute of Technology, Zurich. PhD Thesis.
Scott, K., Daly, H., Barrett, J., Strachan, N., 2016. National climate policy implications of mitigating embodied energy system emissions. Clim. Change 136 (2), 325–338.
Solano Rodriguez, B., Drummond, P., Ekins, P., 2017. Decarbonizing the EU energy system by 2050: an important role for BECCS. Clim. Policy 17 (Suppl. 1), S93–S110.
Solano-Rodriguez, B., Pye, S., 2014. Documentation for the European Times Model at UCL (ETM-UCL. UCL Energy Institute, London.
Strachan, N., Pye, S., Kannan, R., 2009. The iterative contribution and relevance of modelling to UK energy policy. Energy Policy 37 (3), 850–860.
Suh, S., Huppes, G., 2005. Methods for life cycle inventory of a product. J. Clean. Prod. 13 (7), 687–697.
Taylor, P.G., Upham, P., McDowall, W., Christopherson, D., 2014. Energy model, boundary object and societal lens: 35 years of the MARKAL model in the UK. Energy Res. Soc. Sci. 4 (0), 32–41.
Usubiaga, A., Acosta-Fernández, J., McDowall, W., Li, F.G.N., 2017. Exploring the macro-scale CO2 mitigation potential of photovoltaics and wind energy in Europe's energy transition. Energy Policy 104, 203–213.
Wolfram, P., Wiedmann, T., Diesendorf, M., 2016. Carbon footprint scenarios for renewable electricity in Australia. J. Clean. Prod. 124, 236–245.
Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., de Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., Simas, M., Ivanova, O., Weinzettel, J., Schmidt, J., Merciai, S., Tukker, A., 2015. Global sustainability accounting—developing EXIOBASE for multi-regional footprint analysis. Sustainability 7 (1), 138–163.