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Environmental impacts of the future German energy system from integrated energy systems optimization and dynamic life cycle assessment

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ABSTRACT

Mitigating climate change requires a fundamental transformation of our energy systems. This transformation should not shift burdens to other environmental impacts. Current energy models account for environmental impacts using Life Cycle Inventories (LCIs) that typically rely on historic processes. Thus, the LCIs are static and do not reflect improvements in underlying background processes, e.g., in the energy supply. Dynamic Life Cycle Assessment (LCA) incorporates changes in the LCI and allows for a consistent assessment of future energy systems. We integrate dynamic LCA in a national energy system optimization and discuss the differences between employing static and dynamic LCA in energy system optimization and assessment. Dynamic LCA leads to lower environmental impacts in most categories (e.g., climate change: -18%) and is required for a quantitative environmental assessment. However, our analysis shows that static LCA is sufficient to identify general trends in energy system optimization and assessment for Germany till 2050.

1. Introduction

Climate change mitigation requires a shift in energy supply, from fossil towards renewable energy resources. This shift fundamentally changes national energy systems all over the world. To plan the transition of national energy systems, long-term energy models support policymakers. One major challenge for the energy transition is the potential burden shifting from climate change to other environmental impacts (Algunaibet and Guillén-Gosálbez, 2019). To consider the environmental burden-shifting, energy models need to assess energy systems holistically, for which Life Cycle Assessment (LCA) is a well-suited method (Ringkjøb et al., 2018).

Today, LCA is typically employed subsequently to the energy system optimization (soft-linking approach, e.g., Blanco et al., 2020 and Junne et al., 2020). Integrating LCA directly in the optimization problem leads to more consistent results, as otherwise, the environmental constraints in the optimization are inconsistent to the assessment. However, direct integration is also more complex (Holz et al., 2016). Thus, only a few models integrate LCA directly into the energy system optimization (integrated approach, e.g., Volkart et al., 2018 and Tokimatsu et al., 2020).

Life Cycle Inventories (LCIs) describe the overall inputs and outputs of all processes within the respective system (ISO14044:2006). It can be divided in a foreground system, describing the direct emissions on-site, and a background system with environmental impacts related to the consumable input production (Saber et al., 2020).

Integrating LCA in long-term energy models faces the challenge that LCA typically relies on historical data (static LCA, Pehnt (2005)). Historical data does not represent the actual life cy-

Abbreviations: AC, alternating current; APOS, allocation at point of substitution; CNG, compressed natural gas; CPLEX, optimization package IBM ILOG CPLEX Optimization Studio; DC, direct current; GAMS, Generalized Algebraic Modeling System; GHG, greenhouse gas; IEA, International Energy Agency; ILCD2, Environmental Footprint 2.0; JRC, Joint Research Center; LCA, Life Cycle Assessment; LCI, Life Cycle Inventory; OECD, Organization for Economic Co-operation and Development; PV, photovoltaics; SecMOD, sector-coupled energy system model.

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cle inventories (LCIs), if the background processes change. For example, current inventories for the production of photovoltaic cells will poorly represent production in 2050 (Pehnt, 2005). In their recent review, van der Giesen et al., 2020 thus highlight dynamic LCA, i.e., the modification of background processes and their integration into integrated assessment models, as a significant challenge of applying LCA to future systems. The term dynamic LCA itself is currently not standardized. In this paper, we follow van der Giesen et al., 2020 and Pehnt (2005) and define “dynamic LCA” as LCA employing a time-dependent background system. Dynamic LCA considers changes in the background processes of the LCI and, therefore, allows for a consistent assessment of future environmental impacts, e.g., in Hertwich et al. (2015).

The full integration of dynamic LCA in national energy systems is challenging and thus currently not yet state of the art (e.g., Turconi et al., 2014; Rauner and Budzinski (2017); Algunaibet and Guillén-Gosálbez, 2019). On a national scale, García-Gusano et al., 2016 built a partly dynamic model to assess the Spanish electricity sector. However, the LCIs of the considered technologies remain static. Thus, global transitions in the energy systems are not reflected. Volkart et al., 2018 combine global energy systems optimization and LCA in an integrated model to include dynamic LCA model-endogenously. However, this integrated approach can not be transferred to national energy systems since global transitions are beyond the national models’ scope. In national models, global effects on the LCI data need to be integrated exogeneously into the national optimization model.

Recently, dynamic LCA has been integrated into the assessment of national energy systems (Blanco et al., 2020; Junne et al., 2020) using a soft-linking approach. In general, energy models incorporating LCA are usually not publicly available, despite recent efforts (Vandepaer et al., 2020). Assessing future energy systems is crucial for planning of sustainable energy systems. For a consistent assessment, dynamic LCA should be adopted in energy system optimizations incorporating LCA. However, dynamic LCA requires modifications of the whole LCA database. Efficient approaches to directly integrate dynamic LCA in the optimization are is still missing. At the same time, the impact of dynamic LCA on the resulting energy systems has not been analyzed. This paper’s central goals are to integrate dynamic LCA in national energy system optimization and to analyze the differences between employing static and dynamic LCA in energy system optimization and assessment. To account for dynamic LCA, we modify the background processes of an integrated national energy systems optimization using global energy scenarios. The presented method to generate dynamic LCA Databases is provided as open-source code. We compare the resulting energy systems when using the static and dynamic LCA databases.

We combine an energy system optimization model for the German sectors electricity, heat, and transportation (Baumgärtner et al., 2021) with dynamic LCA: Baumgärtner et al., 2021 fully integrate LCA in an energy system optimization but are using static LCA. In this work, we integrate dynamic LCA in their model to account for changes in the exogenous electricity supply of supply chains. Hence, we reflect international developments caused by other countries’ changing electricity mix in the assessment of our national energy system. As part of the ESCAPE Special Issue, the present work extends the conference paper by Reinert et al., 2020 by providing the details, the open-source code to generate dynamic LCA Databases, and discussing the influence of modified background processes on the resulting sector-coupled energy system in detail.

In Section 2.1, we first introduce our case study, the SecMOD model. Section 2.2 comprises the modification of relevant background processes in the life cycle inventories (LCIs) of the technologies used in SecMOD. In Section 2.3, we discuss the issue of double counting.

In Chapter 3, we compare static and dynamic LCA in two steps: First, the transition pathways are analyzed that result from the optimization. Applying dynamic LCA results only in moderate changes in the transition path, as the optimization is only constrained by operational emissions.

Our environmental assessment, considering both infrastructural and operational emissions, shows significant differences between static and dynamic LCA of the optimized German energy system in the year 2050.

2. Including dynamic background processes in national energy systems optimization

In this Section, we discuss the integration of dynamic LCA in energy systems optimization (Fig. 1). Section 2.1 introduces our case study, a national energy systems optimization for the German energy system, and discusses its link between energy systems optimization and LCA. In Section 2.2, we modify the background processes of the LCIs for the technologies considered in the case study to account for changes in electricity generation in the background processes (Fig. 1).

2.1. Case study: Sector-coupled energy system model SecMOD

We perform a cost optimization of the German energy system consisting of the sectors electricity, domestic and industrial heating, and private transportation for the transition path from the year 2016 - 2050. The linear energy systems optimization model SecMOD is based on mass and energy balances (Baumgärtner et al., 2021), modeled in GAMS (GAMS, 2016) and solved with CPLEX (IBM, 2016). In a brownfield design optimization, we extend the currently existing German energy infrastructure (as in the year 2016). We consider exogeneous energy demands: electricity, centralized and decentralized heat at different temperature levels (domestic heat below 100 °C and industrial heat below 100 °C, between 100–400 °C and above 400 °C) and private transportation. As energy converters, we consider

- fossil-based and renewable electricity generation (e.g., conventional plants, photovoltaics, wind, and other renewables),
- heating on multiple temperature levels (e.g., oil-, methane- & electric boilers, and heat pumps),
- private transportation (e.g., diesel, compressed natural gas (CNG), battery electric cars), and
- power-to-X technologies (e.g., battery storage, power to gas, pumped storage, power to fuel).

We optimize the system stepwise, using five-year steps until 2050. For each optimization period, we update the emission constraints. Further, the costs for each component follow a learning curve (for details, see Baumgärtner et al., 2021).

Current emission reduction policies typically target direct emissions only. However, Lopion et al., 2018 stress the need to constrain all operational emissions, including direct emissions and the upstream emissions of the background processes (e.g., mining of energy carriers). Thus, we here constrain operational greenhouse gas (GHG) emissions of all energy technologies. To assess all operational emissions, we use LCA by going beyond direct emissions only. We decrease the GHG emission limit by up to 85% in the year 2050 (as in Baumgärtner et al., 2021). We chose the year 2050 as the year targeted in our work, as it is the target year for many policies and therefore the time period most commonly studied in energy systems models. Jaxa-Rozen and Trutnevyte (2021) recently examined 1550 energy scenarios, out of which 1488 scenarios consider the year 2050. Our model allows assessing the energy system at several points in time between now and 2050. However, the differences between employing static and dynamic LCA strongly de-

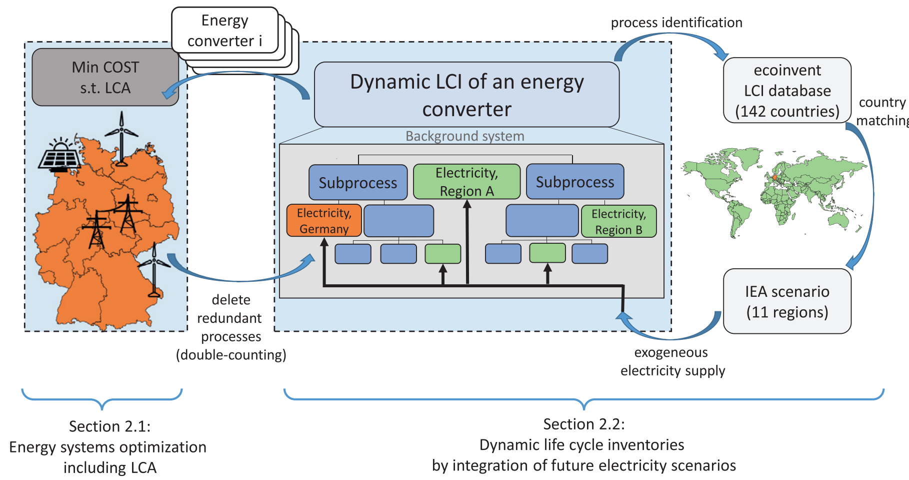

Fig. 1. Optimization of the German energy system using dynamic LCA (Section 2.1). We modify the electricity-related background processes of the life cycle inventories (LCIs) using the multiregional scenario of the International Energy Agency (IEA)(Section 2.2). We solve double-counting by deleting emissions in the LCIs, already accounted for in the German energy system.

pend on the developments of the electricity mix in other countries compared to the static case. Due to a continuous decrease in electricity emission intensity, the difference between static and dynamic results increases with time. In 2050, we can thus observe the largest differences between static and dynamic results to draw conclusions on the importance of dynamic LCA. As we consider Germany as an isolated energy system without negative emission technologies, a carbon-neutral scenario is not achievable within the given constraints.

The original time series is represented with an hourly resolution and aggregated to typical time series (Bahl et al., 2018) with 192 time steps (8 typical periods, subdivided into 24 time steps). We simultaneously optimize the design and operation of the energy system using the aggregated time series. The spatial resolution comprises 18 nodes (Dena-zones), interconnected by a power grid. The power grid is modeled using a direct current (DC) load flow approach (Egerer, 2016). The DC load flow approach is widely adopted in long-term energy models and simplifies the alternating current (AC) power flow. Alternative modeling approaches for the grid are a transshipment approach, which is simpler, or an AC power flow approach, which accounts for losses but is computationally more challenging. The DC load flow approach has been shown to combine computational simplicity with an acceptable level of accuracy (van den Bergh et al., 2014).

After the optimization, we evaluate the energy system's total environmental impacts (invest and operational). For the LCA of the resulting energy system, we employ data from ecoinvent 3.5 (Wernet et al., 2016). ecoinvent is a well-established LCI database and widely used in the assessment of energy models, as discussed in Astudillo et al., 2018. The data is provided following three system models: Cutoff, consequential, and APOS (allocation at the point of substitution). As ecoinvent system model, we chose APOS to consistently consider recycling of materials. APOS does not depend on marginal effects as the consequential approach and distributes the impacts from recycling along the value chain. Thus, APOS captures future energy systems best where material recycling will become increasingly important due to extensive infrastructure. Several methods are available for impact assessment. Popular impact assessment methods in energy modeling are CML (e.g., in Nabavi-Pelesaraei et al., 2017, ReCiPe 2016 (e.g., Mostashari-Rad et al., 2021), and Environmental Footprints 2.0 (ILCD2). We assess environmental impacts using ILCD2, the life cycle impact assessment method recommended by the European Commission's Joint Research Center (JRC) (Fazio et al., 2018; Joint Research Center, 2010). Beyond this official recommendation, ILCD2 provides quality levels and hence indicates uncertainties of environmental impacts.

In ILCD2, a quality level is given for each environmental category, regarding completeness, relevance, robustness, transparency, applicability, acceptance, and suitability. All impact categories with quality level I are recommended and satisfactory; quality level II is recommended, but with some improvements needed. Quality level III is recommended but needs to be applied with caution.

2.2. Dynamic LCI: integration of future energy scenarios in the background processes

The LCI data contains all processes that are required to provide a product. A large part of these processes (e.g., energy supply) changes over time so that historical LCIs cannot represent product supply in long-term scenarios. As the ecoinvent database consists of static LCI, it does not consider dynamic processes in the background system. We assume that while the process steps required to produce a product are relatively constant, the energy-related processes are likely to change strongly during the energy transition.

Since electricity is crucial to the climate change impact of the considered technologies (energy converters and grid elements), we focus on the electricity sector for the dynamic LCA. Further integration of heat and transport is possible by slightly modifying our code (provided as open-source code and documented in the supporting information).

To account for dynamics in the electricity sector, we integrate long-term electricity scenarios in the background system. Namely, we consider the "2 °C scenario" for regionalized technology mixes by the International Energy Agency, 2017 (IEA scenario). The "2 °C scenario" by the IEA targets to limit global warming to 2 °C. The 2 °C scenario includes considerable additional commitment of renewable energies compared to those currently in place. Above 2 °C, a tipping point of irreversible damage of the environment could be reached. The IEA provides scenarios for 11 world regions from 2014 to 2060 by estimating the annual electricity generation for the 16 most relevant energy conversion technologies. In SecMOD, we use linear interpolation to match years wherever necessary.

Using the IEA scenario, we modify the ecoinvent 3.5 database (Wernet et al., 2016) by updating electricity market processes in the background system to generate dynamic LCIs for the full transition path (2016–2050) considered in SecMOD.

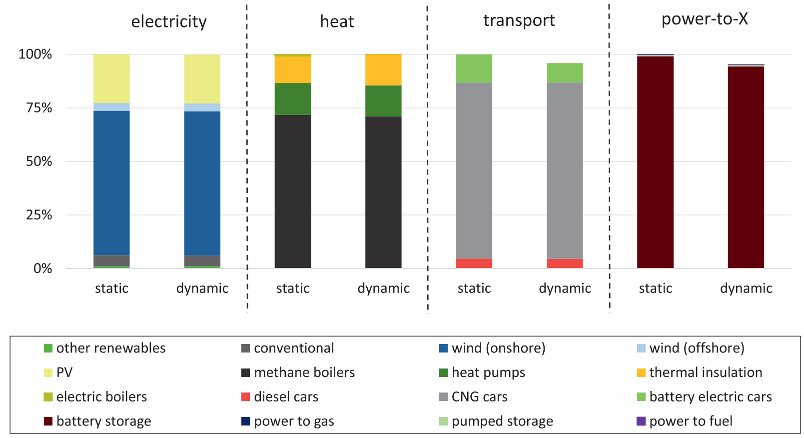

Fig. 2. Resulting capacity of the German energy system in the year 2050 for the optimization using static and dynamic LCA data. The capacity is subdivided by the sectors electricity, heat, transport, and power-to-X. For each sector, the capacity is normalized to the total capacity in the static optimization. Here, PV refers to photovoltaics and CNG cars to compressed natural gas cars.

The modification has three main steps (Fig. 1, right):

1. Identification of electricity market processes in ecoinvent 3.5.
Brightway2 (Mutel, 2017) and the wurst package (Mendoza Beltran et al., 2018) were specifically developed to modify background processes in ecoinvent. We use them to identify all electricity market processes in the aggregated ecoinvent database. We transform all low and medium voltage processes to high voltage, accounting for transformation losses (as in Mendoza Beltran et al., 2018). Hence, we obtain electricity markets for all ecoinvent regions on high voltage level.
2. Country matching between ecoinvent and IEA scenarios.
For each high voltage electricity market, we match the ecoinvent region (142 countries) to the respective IEA region (11 regions). Using the IEA scenario for the respective year, we update the electricity market mix with the regionalized IEA mix. If the ecoinvent region matches more than one IEA region, we use an average scenario. When there is no IEA region that matches the ecoinvent region available, we use lists to match the ecoinvent region to either a region which is a member of the Organization for Economic Co-operation and Development (OECD) or a Non-OECD region. If the ecoinvent region is in the OECD region, we use the OECD scenario. As a last option, if the ecoinvent region could not be matched to any list, we use the global IEA scenario.
3. Adaption of regional electricity market mix.
We use the wurst package to modify the regional electricity market mix in the database according to the respective IEA scenario electricity generation mix. Each electricity generation scenario is based on multiple energy conversion technologies. For each technology, we determine a matching LCI: First, we search for an LCI in the same ecoinvent region as in the electricity market mix. If not available, we search first for an LCI in the same IEA region, then for a global LCI and last for an LCI in any region. The IEA scenario considers some energy converters which are not yet modeled in the ecoinvent database. We thus added the following LCIs: carbon capture and storage (Volkart et al., 2013), wave energy converters (Thomson et al., 2011), hydroelectric power stations (Douglas et al., 2008), and concentrated solar power plants (Mendoza Beltran et al., 2018). After identifying all LCIs needed, we update the ecoinvent market mixes with the regionalized IEA scenario mix.

For each investment period of the SecMOD model, we generate dynamic LCIs based on the updated electricity market mixes in each region. The full code to modify ecoinvent is provided and extensively documented in the supplementary information (SI).

2.3. LCI modification: double counting

We additionally modify the background processes to solve one common issue of combining LCA and national energy systems optimization: double-counting (Blanco et al., 2020; Lenzen, 2008).

Double-counting occurs when the impacts of infrastructure produced within the system boundaries are counted once in the LCI of the infrastructure and once in the operational emissions.

For instance, if steel for a wind power plant is produced in Germany, energy-related impacts for the steel production in the LCIs are already accounted for in the operational emissions of the industrial system producing the steel. To avoid double counting, the impacts which are potentially double-counted must be removed either from the operational emissions in the energy system model by accurately reducing the energy demand, or from the inventories of the infrastructure by modifying the LCIs.

Volkart et al., 2018 first solved the issue of double-counting by modifying LCIs. Their approach can be readily integrated into our problem since we already modify the LCIs to integrate dynamic LCA.

3. Results and discussion

In this Section, we first discuss the influence of incorporating dynamic LCA as constraints in the optimization (Section 3.1). Second, we discuss the influence of dynamic LCA on the different technologies (Section 3.2). Finally, we explore the effects of including dynamic LCA instead of static LCA in the environmental assessment (Section 3.3).

3.1. Influence of dynamic LCA on technology choice in SecMOD

Fig. 2 shows the German energy system's infrastructure in the year 2050 for both the static and dynamic optimization. For each sector, we normalize the capacity to the total capacity in the static optimization. In 2050, the electricity sector is largely relying on low-carbon technologies, such as wind and photovoltaics. The heat and transport sectors are partly decarbonized by sector-coupling technologies, such as heat pumps, battery electric cars, and power-to-X technologies.

Despite attempting to represent reality, complex energy systems models rely on numerous assumptions, e.g., spatial and temporal resolution, technology availability or cost (Lopion et al.,

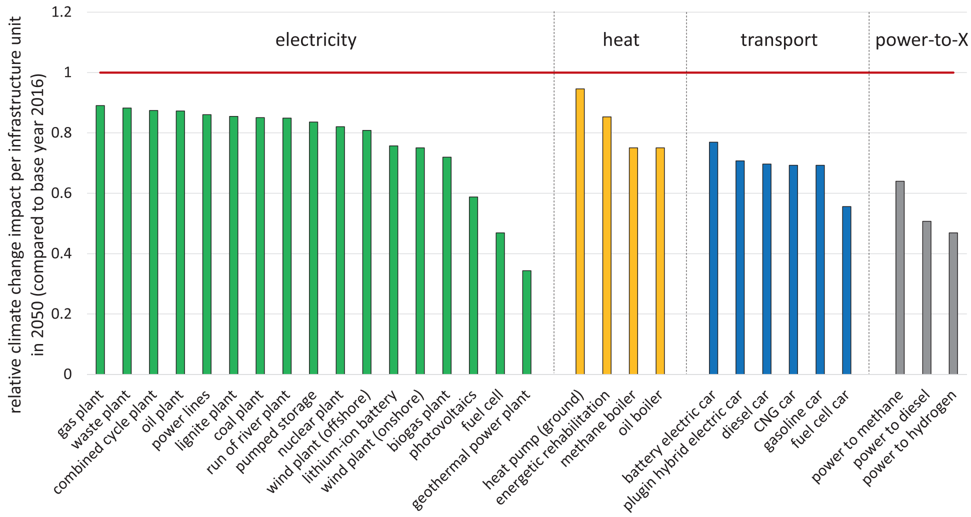

Fig. 3. Relative climate change impact per infrastructure unit in the year 2050, compared to 2016. The electricity sector is shown in green, the heat sector in yellow, transport in blue and power-to-X technologies in gray. CNG refers to compressed natural gas. For the year 2016, we calculated each infrastructure unit's impacts by regionalization and modified the LCI using the IEA energy mix of 2016 for each region. We further corrected for double counting. For the year 2050, we used the same method with the energy mix of 2050. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2018). All these assumptions influence the resulting system. It is thus important to be aware that the results of our optimization model are just one possible transition scenario under the given model assumptions (Neumann and Brown, 2020). With our findings, we hope to contribute to the debate about in what sense employing dynamic LCA will make a significant difference.

The results from the energy systems optimization for Germany till 2050 are rather similar for static and dynamic LCA. However, we observe lower capacities in the transport sector and for power-to-X technologies with dynamic LCA. The overall system cost in the year 2050 is 3% smaller in the dynamic case. Dynamic LCA leads to economic benefits since the operational emissions of background processes become less emission-intensive, such that some expensive emission-reduction measures can be avoided in the foreground system. While we believe that this trend will hold in general, the exact amount of cost savings still depends on numerous assumptions.

Comparing the resulting technologies for the year 2050 in the static and dynamic cases, we do not observe significant differences in the electricity and heat sectors (Fig. 2, left). However for some technologies, the background process modification shifts technology preference. In the transportation sector, the technology preference changes most strongly: The share of battery electric cars in the car fleet is reduced by 4% with dynamic LCA. In absolute terms, the number of battery electric cars is reduced by 32% compared to the static case. For the other transport technologies, the fleet is similar in the static and the dynamic case. The overall transportation demand is identical in both cases; however, in the dynamic case, the operational impact of CNG car is reduced compared to static LCA and CNG thus becomes more favorable. A higher utilization of the CNG cars due to lower operational impacts in the dynamic LCA reduces the need for additional battery electric cars.

Furthermore, in the power-to-X sector, we observe a reduction in battery storage capacity in the dynamic case. However, the annually stored energy is comparable in our study. The lower overall capacity extension of battery storage is caused by higher system flexibility: In both cases, battery electric cars are charged following a fixed load curve, contrary to CNG cars. Thus, employing CNG cars rather than battery electric cars slightly reduces the fixed electric load, as buying or producing CNG is more flexible.

Overall, only few technologies majorly contribute to the operational emissions that are constrained in our model. These main contributing technologies - mostly fossil-based - improve, when we use dynamic LCA. In year 2050, there are only few fossil-based technologies left, mainly in the transport sector. The global reduction in GHG emissions reduces the technology-specific operational GHG emissions for these technologies in Germany. The lower specific emissions reduce the necessary financial and technological effort to meet national emission targets. The influence of dynamic LCA in energy systems optimization is significant for the technologies with highest marginal GHG abatement cost, in our case battery electric cars. While leading to a higher share of technologies with smaller GHG emissions in the future supply chain, the overall decrease in technology-specific GHG emissions lowers the necessary share of technologies with high marginal GHG abatement cost. However, the general technology trends do not change significantly when we use dynamic LCA to constrain operational GHG emissions in the optimization.

SecMOD accounts for additional costs for a modified charging infrastructure for battery electric and fuel cell cars, leading to relatively high costs of these new technologies. In comparison to our results, Baumgärtner et al., 2021 observe significantly higher shares of battery electric cars in 2050 (13% vs. 82%). However, during the energy transition, they also identify CNG cars as transition technology. Baumgärtner et al., 2021 also use static LCA, but prove system feasibility with a full time series and longer foresight. Longer foresight favors battery electric vehicles: Despite high costs, they further reduce GHG emissions and hence their share increases with stricter GHG limits. As all other model assumptions are identical to our model, the effect of temporal resolution and foresight thus exceeds the influence of choosing static or dynamic LCA in the optimization.

3.2. Technologies in SecMOD: infrastructure-related emissions

Decreasing operational GHG emissions during the energy transition results in a higher relative importance of infrastructure emissions for the overall GHG emissions: In our model, infrastructure accounts for only 6% of total GHG emissions in 2016. Using static LCA, this share rises to more than 50% in 2050. The overall infrastructure-related GHG emissions increase by almost a factor of four from 2016 to 2050 in static LCA. It is currently discussed that the whole supply chain, including infrastructure-related emissions, should be considered in the optimization of future energy systems

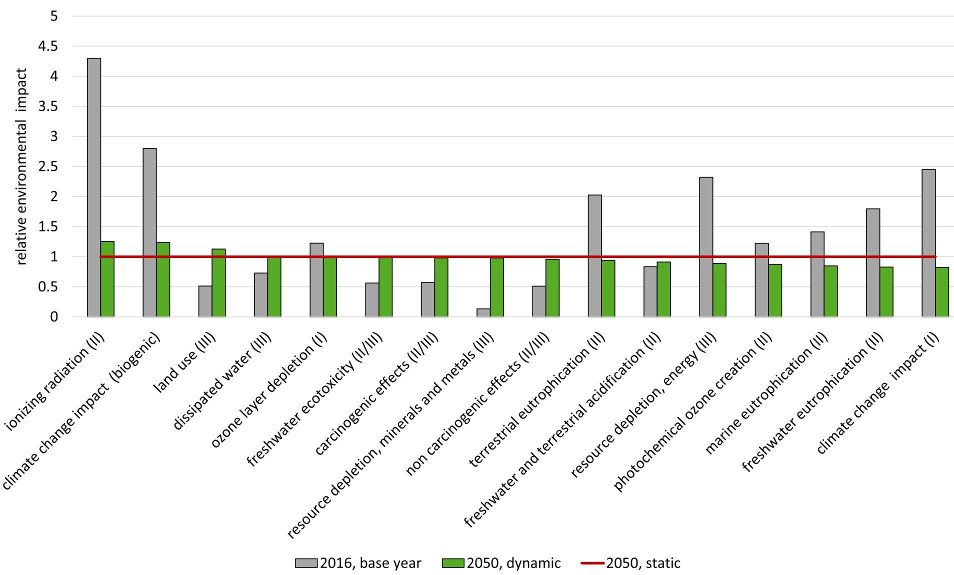

Fig. 4. Total environmental impacts of the energy systems optimized and assessed with static and dynamic LCA for 2016 and 2050, relative to the static case in 2050. We sorted the environmental impact categories by decreasing influence of the dynamic LCA. The quality level of each category according to the JRC is indicated in brackets (Joint Research Center, 2010; Fazio et al., 2018, see Section 2.1).

to identify optimal transition pathways (McDowall et al., 2018). As it is currently common to only constrain operational emissions, reductions of infrastructure-related impacts are not yet influencing technology choice during the optimization. However, if infrastructure emissions are incorporated in GHG emission constraints, we expect a considerable increase in the importance of using dynamic LCA in energy systems optimization.

To quantify the effect of dynamic LCA on the infrastructure-related emissions, Fig. 3 shows the relative change in infrastructure emissions when the background processes are modified using dynamic LCA. The climate change impacts reduce considerably for almost all sectors and technologies. Overall, the infrastructure-related GHG emissions in 2050 are reduced by more than 30%, when dynamic LCA instead of static LCA is employed. For each technology, the reduction ranges between 5% and 65%.

For power plants, the infrastructure-related impacts in our model are reduced by mostly around 20% for the scenario in 2050, compared to the base year. However, for energy-intensive infrastructures, such as photovoltaics, we observe a decrease in infrastructure impacts of 40% in the dynamic LCA. This strong dependence has in fact motivated the introduction of dynamic LCA (Pehnt, 2005). We see the highest climate change impact reduction for the geothermal power plant (- 65%), as electricity is the main contributor to its climate change impacts. Similar to the electricity sector, we observe reductions in infrastructure-related emissions for the year 2050 in all sectors.

3.3. Life cycle assessment of the low-carbon German energy system: static vs. dynamic

After the optimization, we assess the environmental impacts of the resulting energy systems, consisting of optimized infrastructure and operation. Fig. 4 shows the environmental impacts for the base year 2016 and the final year 2050 for both the static and the dynamic GHG constraints. The results are normalized to the static case, because static LCA is more commonly used in energy systems optimization.

When we compare the development of the environmental impacts from year 2016 to year 2050, the results of static and dynamic LCA are qualitatively similar. In both cases, impacts decrease in 10 out of 17 impact categories. However, we observe an increase in seven impact categories. Thus, both static and dynamic LCA identify similar environmental burden-shifting and co-benefits in the future energy system.

Importantly, the overall climate change impact is 18% lower when using dynamic LCA. Compared to the static case in 2050, environmental impacts are up to 18% lower for most environmental categories (9 out of 17). Five categories are not significantly influenced by applying dynamic LCA.

In a quantitative comparison to static LCA, applying dynamic LCA results in higher impacts in ionizing radiation (+ 25%), biogenic climate change (+ 24%), and land use (+ 13%) for year 2050. The higher ionizing radiation is caused by some regions increasingly relying on nuclear power as a low-carbon technology in the IEA scenarios. Further, the global intensification of biomass usage leads to higher land use and biogenic climate change. Dynamic LCA is able to reflect these global developments in a national energy system.

3.4. Critical discussion

Large-scale models rely on many assumptions, e.g., in the optimization model, the scenarios used for the dynamization, and the LCA method. These assumptions lead to uncertain results. In this section, we discuss factors influencing the results.

The learning curves for both costs and environmental impacts of the technologies used in our model underlie high uncertainties. Baumgärtner et al., 2021 show that introducing optimistic cost estimates for key technologies in 2050 could reduce energy systems cost by 40%. Despite different key assumptions in energy system models, the overall trends are often similar: In future energy systems, fossil fuels will be replaced by renewables, predominantly wind and photovoltaics. Further, the energy transition leads to large amounts of additional electricity storage. The dynamization of the LCIs is technology-dependent, but independent of the energy model used. Qualitatively, the results that follow from the dynamization, i.e., the slight change in technology preference and the larger differences in expected environmental impacts, are therefore presumably transferable to other energy models. By providing the open-source code to generate dynamic databases as model input, we hope to enable the integration of dynamic LCA in further energy models.

Another source of uncertainty is due to the available LCI. E.g., LCI data assumes a certain size for the assessed component, which is used as reference to calculate the costs and LCI. Bahlawan et al. (2020) show that component sizing can significantly impact environmental impacts. The LCIs we use are dimensioned on current typical technologies and then scaled in our linear model, however, the typical sizing of energy converters may change in the future. New types and sizes of energy converters could change costs, environmental impacts, and technology preferences.

Dynamic LCA can be further extended by prospective LCA, which reflects technical advances in the LCIs, e.g., new technologies, and efficiency improvements. As prospective LCA requires specific knowledge of individual technologies, we excluded such considerations in this work. However, recent efforts allow to simplify and share prospective scenarios, which will likely enhance data availability and applicability of prospective LCA in the future (Joyce and Björklund, 2021).When technology-specific improvements are taken into account, we expect them to further reduce environmental impacts in general, but trade-offs may still occur.

In addition, the dynamization using scenario data itself is highly uncertain. As well as in our model of the German energy system, the scenario data from the IEA underlies uncertain assumptions about possible technological preferences. Although the 2°C scenario already includes considerable additional commitment of renewable energies compared to those currently in place, many studies propose even more ambitious climate targets (e.g., Intergovernmental Panel on Climate Change (2018)). Depending on the employed technologies, a more ambitious scenario would likely lead to a stronger reinforcement of the environmental effects stated in this work.

For the impact assessment, each method has different impact categories and metrics how inputs and outputs contribute to the overall impact. Some categories, such as global warming/climate change are relatively similar and should thus lead to similar results, even when other assessment methods are employed. To study this influence, we recalculated the study using ReCiPe 2008 (Goedkoop et al., 2009) as alternative impact assessment method. Using ReCiPe, we observe a high increase in agricultural land occupation (39%) when employing dynamic LCA. In comparison, ILCD2 shows 13% higher impacts in land use as well, but does not distinguish between different kinds of land use. The reduction in the climate change impact is comparable (18% reduction using ILCD2, and 21% using ReCiPe). As the JRC recommends using ILCD2, we show the full results of the assessment using ILCD2 in Fig. 4. Fig. 4 highlights a further source of uncertainty in the assessment: the impact assessment methods themselves. The JRC recommends to employ several methods only with caution (quality level III). Thus, improvements are needed - and may affect the analysis of future environmental impacts.

Overall, energy system optimization can only identify one possible future subject to the cost and environmental projections made. Game-changing effects, as the application of new technologies (e.g., carbon capture and storage), could change technology preference and hence lead to different energy systems and environmental impacts. Hence, our study describes one out of many possible futures. Jaxa-Rozen and Trutnevyte (2021) discuss a total of 1550 future energy scenarios and find large variations in technology-specific cost assumptions, assumed policies and constraints. Robust insights are therefore best derived by studying ensembles of models that span across levels of complexity and even organizational background.

3.5. Conclusion

In this work, we discuss a method to optimize and assess a sector-coupled, national energy system using dynamic LCA. Changes in the future electricity generation are incorporated by IEA global energy scenarios. The dynamic LCA is applied to an optimization for the cost-optimal energy transition in Germany till 2050. Here, dynamic LCA does not lead to significant technology shifts in the electricity and heat sectors since only operational emissions are constrained in the optimization. In contrast, technologies change especially in the transport sector when dynamic LCA is employed. In particular, the number of battery electric cars is reduced by 32% in the dynamic case, compared to the static case. Further, we show that dynamic LCA significantly reduces infrastructure-related climate change impacts, compared to static LCA: we observe climate change reductions for all technologies in all sectors.

Considering both investment and operational emissions shows significant differences between the static and the dynamic assessment: dynamic LCA leads to lower environmental impacts in most categories. While few categories are higher (e.g., ionizing radiation), many important categories (e.g., climate change) are up to 18% lower in the dynamic case.

Static LCA is a suitable choice as long as we only constrain operational emissions in the optimization. However, as there is a discussion to consider infrastructure emissions in future optimization models to further enhance the benefit of LCA in energy systems optimization and account for the increasing importance of indirect emissions, we expect dynamic LCA to become more important in the future. In our study, qualitative system trends are mostly similar for static LCA and dynamic LCA. However, choosing dynamic LCA quantitatively influences the resulting environmental impacts, reinforcing climate change reduction of the energy transition. Future studies should thus integrate dynamic LCA, especially if they discuss trends in individual technologies or impact categories, which are highly influenced by future energy systems, such as ionizing radiation.

Associated content

- The wurst package's code modification for integrating of the IEA scenarios in the life cycle inventories is provided and documented in a GIT repository. (https://git-ce.rwth-aachen.de/ltt/dynlca.git)
- We discuss the SecMOD model and all its supplementary information in Baumgärtner et al., 2021.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Christiane Reinert: Writing - original draft, Conceptualization, Methodology, Software, Investigation, Visualization, Data curation, Project administration. **Sarah Deutz:** Writing - review & editing, Conceptualization, Methodology, Data curation. **Hannah Minten:** Writing - review & editing, Methodology, Software, Investigation, Data curation. **Lukas Dörpinghaus:** Conceptualization, Software. **Sarah von Pfingsten:** Conceptualization, Methodology. **Nils Baumgärtner:** Writing - review & editing, Conceptualization, Methodology, Software. **André Bardow:** Conceptualization, Methodology, Writing - review & editing, Supervision, Resources, Funding acquisition.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.compchemeng.2021.107406

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