Integrating Energy System Modelling and Life Cycle Assessment for both Cost and Environmental Optimisation of a Decentralised Residential Energy System

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Abstract

Environmental pressures already exceeded earth's system resilience. The energy sector, as one of the main contributors, therefore urgently calls for the design of sustainable solutions to meet energy security and environmental goals at the same time. Optimising energy system models allow to balance supply and demand for each time step and to simultaneously minimize costs by linear programming. Life Cycle Assessment provides a comprehensive tool to analyse environmental burdens of energy systems and services. In the current state Energy system models focus on cost optimisation and Life Cycle Assessment is meanwhile limited to a post assessment of specific systems. Out of this requirements we coupled a linear energy optimisation model with parametrised Life Cycle Assessments to achieve an integrated optimisation. The developed tool is used to analyse an expansion planning of a grid-connected decentralised residential energy system including households, photovoltaics, wind power, battery storage and combined heat and power. The optimisation model minimises both, total system costs and 18 Life Cycle Impact Assessment indicators. Moreover, both a single score and an economic-environmental objective is applied. Single score indicators have not been found to be recommendable for the assessment of energy systems by scientific standard. Our results also show that total system costs do not represent a sufficient objective for the optimisation of energy systems if environmental sustainability is demanded. Wind power with battery storage and combined heat and power show advantages in most of the impact categories. However, with the implementation of these technologies the total system costs increase significantly.

1 Introduction

On global level, particularly effects on climate change, biosphere integrity and biochemical flows, already exceeded the limits of earth's resilience (Steffen *et al.*, 2015). Energy related activities are the worldwide biggest contributor to environmental pressures such as climate change, particulate matter and NO_x emissions (IPCC, 2014; Umweltbundesamt, 2018a, 2018b). Consequently the energy sector demands for sustainable solutions to meet energy security and the preservation of earth system's stability simultaneously. Following the three dimensional perspective of sustainability, the Sustainable Development Goals (United Nations, 2018) define affordable, clean energy and climate action as main targets for the energy sector. At this juncture the development of scientific tools which support integrated economic, environmental and ideally social decision-making procedures is postulated.

Energy system models (ESMs) are common tools to represent a real world system and to assist decision making. ESMs allow to balance supply and demand for every time step and to simultaneously minimise system costs. Thus ESMs are able to address two main goals of the energy policy triangle (Doukas *et al.*, 2019; Schiffer, 2019) (i) security of supply and (ii) affordability. The third goal, (iii) sustainability is increasingly required by national and international energy planning (BMWi, 2010; European Commission, 2010) and therefore introduced into ESMs by the implementation of additional constraints, e.g. a limit of Greenhouse Gas (GHG) emissions allowed.

The aspired reduction of GHG emissions is usually connected to a shift to renewable energies such as solar and wind power. Because these renewables are available only intermittently, they increase the complexity to ensure energy security also in phases without wind or solar irradiance. Out of this reason renewables are implemented together with battery storage, Power-to-X[1] or biomass driven technologies which consequently increase the modelling effort. Furthermore, renewable energies and battery storages incorporate environmental impacts other than climate change. Thus, target conflicts which need to be acknowledged during the planning procedures and therefore within ESMs arise. In environmental sciences Life Cycle Assessment (LCA) has been established since the 1970s and 1980s as a standardised method to assess and analyse environmental impacts. LCA allows to identify environmental aspects and potential impacts of products or services throughout a product's life cycle. Hence for energy generation it enables to account for the whole life cycle impacts of i.a. fuel, facility and infrastructure production. (Klöpffer and Grahl, 2014) To address the sustainability dimension in energy planning an integration of LCA into ESM is intended.

The aim of this paper is to introduce a generic expansion planning tool with a high technical and timely resolution (bottom-up). The tool allows to investigate goal conflicts by the implementation of renewables and battery storage. First results are presented and assist the deduction of further research needs. In order to achieve this, the paper is outlined as follows: the next sections gives background information on ESMs and LCA before section 3 presents the developed tool and the assumptions made. Single indicator optimisations (total system costs and 18 environmental indicators) as well as multi-criteria optimisation deliver energy system compositions which are presented in chapter 4. A sensitivity analysis for crucial assumptions is used as basis for the discussion in chapter 5 considering methodological limitations and results. Chapter 5 draws conclusions and gives an outlook on further research activities.

2 Energy System Modelling and Life Cycle Assessment

ESMs can be distributed into power flow models for electricity transmission network operation and planning, economic dispatch models for capacity planning and unit commitment models for power plant utilization. They can be large-scale transnational models (top-down), based on economic equilibrium models or technology-specific local models (bottom-up). Many models integrate sector coupling of electricity, heat and mobility. The models' methodology is generally didvided into three main categories simulation, optimisation and equilibrium models. Simulation models, based on specified equations and

[1] Power-to-X (PtX) as generic term for technologies which transform electrical energy to several energy carriers, such as gas (Power-to-Gas) or liquids (Power-to-Liquid)

characteristics, allow to test various system topologies, developments and scenarios. To optimise a resulting quantity of an energy system, optimisation models use an objective function which is either maximised or minimised (e.g. minimising of the total system costs). The majority of optimisation models uses a linear programming (LP) approach, further if variables of the LP are set to be integer this leads to a mixed-integer linear programming (MILP). Non-linear models are used if the objective function or constraints added to the energy system are non-linear. Heuristic optimisation models do not necessarily find the optimum solution but have further advantages such as improved calculation time and the possibility of a multi-objective optimisation (Jones *et al.*, 2002; Ren *et al.*, 2018). Equilibrium models determine the equilibrium of the energy sector or certain energy markets. (Biggar and Hesamzadeh, 2014; Hilpert *et al.*, 2018; Ringkjøb *et al.*, 2018; Wood *et al.*, 2013)

Most ESMs use costs as determining factor for the analysis of different scenarios, but more and more models include GHG emissions and pollutants such as CO_2, NO_X, SO_X or CH_4 as constraints to meet environmental policy requirements or goals. However, decision support for a sustainable development demands for the integration of new dimensions. This integration needs to go beyond cost optimisation and environmental constraints and requires to consider a sustainability assessment of the whole energy supply chain. For this purpose Life Cycle Assessment (LCA) is increasingly implemented into decision making methods (Luglietti *et al.*, 2016; Means and Guggemos, 2015; Meyer and Upadhyayula, 2014; Strantzali and Aravossis, 2016; Yilmaz *et al.*, 2015; Zhang *et al.*, 2016) and as a core element for environmental policies (European Parliament and Council of the European Union, 2009; United States Environmental Protection Agency). Within an LCA the whole life cycle is analysed from extraction of the raw materials to processing, usage, recycling and disposal of the materials. The international norms ISO 14040 and ISO 14044 standardise LCA initiating a comparable and reproducible procedure (International Standard Organisation, 2009, 2006). LCA organises its input and output (elementary) flows in the so called Life Cycle Inventory (LCI) that lists materials and emissions. The items of the LCI are aggregated and characterized following the Life Cycle Impact Assessment (LCIA) to estimate the final effect of each flow in the respective impact category. Impact categories represent the environmental intervention and are differentiated by the point of assessment on the underlying impact pathway. Midpoint impact categories such as CML (Bruijn *et al.*, 2004), ReCiPe[2] (Goedkoop *et al.*, 2013), ILCD/EF (Fazio *et al.*, 2018; Hauschild *et al.*, 2011) are located at an intermediate point on the impact pathway. Exemplary impact categories on midpoint level are i.a. climate change, water use and fossil resource depletion. In general, midpoint impact categories provide a higher certainty but a lower force of statement compared to endpoint impact categories. Hence, in the environmental assessment of energy systems, a LCIA at midpoint level delivers a comprehensive but partly ambiguous result array. Endpoint methods indicate stressors which lay at the endpoint of the impact pathway (e.g. damage to human health, damage to ecosystems) and therefore are able to focus on less impact indicators or deliver a single score e.g. by aggregation of various indicators. Though, weighting and aggregation procedures can distort the initial results and therefore are not compliant to DIN ISO standards in LCA. Due to their distance from the original impact, endpoint methods such as Eco-indicator (Goedkoop and Spriensma, 2000), LIME[3] (Itsubo and Inaba, 2005) and EPS (Steen, 1999) don't reach a sufficient level of scientific quality and therefore are not recommended for LCA practice (Hauschild *et al.*, 2013). Similarly the application of external costs as endpoint indicator is restricted and not recommended to substitute

[2] ReCiPe is also available as endpoint method (derived from the midpoint assessment) but is commonly used on the midpoint level.

[3] LIME includes midpoint categories which are derived from the endpoint methodology.

commonly used midpoint indicators (Lazar and Tietze, 2019). Thus, other approaches prefer to attach weighting and normalisation factors following a comprehensive midpoint assessment to ensure both scientific quality and communicability (Huijbregts *et al.*, 2016). One approach in this field is the use of weighting and normalisation factors based on global emission estimations published by the European Commision's Joint Research Centre (JRC) (Huppes and van Oers, 2011; Sala *et al.*, 2017).

However, in addition to the challenges in the impact assessment, LCAs are limited to a post evaluation of specific and static systems. The need for an a priori integration of LCA into energy optimisation modelling is recurrently mentioned in literature and frameworks as well as models have been developed (Arvesen *et al.*, 2018; Azapagic and Clift, 1999; Carapellucci and Giordano, 2012; Onat *et al.*, 2016; Pauliuk *et al.*, 2017; Yue *et al.*, 2016; Zhang *et al.*, 2016). Focussing on electricity systems Azapagic *et al.* (2016) developed a decision support framework (DESIRES) integrating economic, environmental and social sustainability. Later on, they coupled sustainability assessment, optimisation and multi-attribute decision analysis and applied it on the electricity generation in the UK and Turkey (Atilgan and Azapagic, 2016). Moreover, from a model coupling perspective, García-Gusano *et al.* integrate life cycle indicators into energy optimisation models on the case of the Norwegian electricity system. They focus on the commonly used TIMES model. Their results demonstrate that in the Norwegian case most of the impacts are linked to the installation of new capacity. Rauner & Budzinski (2017) include life cycle based sustainability assessment into an energy system model, considering all relevant products and processes of the global supply chain. They furthermore categorize coupled models, following the definition of Hwang and Masud (1979), into *a priori*, *interactive* or *a posteriori* methods in the context of including life cycle based data into the energy system optimisation model. Rauner and Budzinski (2017) state that only the *a posteriori* method calculates the full spectrum of efficient solutions, which allows the decision maker to select the most preferred solution while being aware of the trade-off. As a consequence they integrate LCIA indicators into the energy system model and perform a multi objective optimisation using costs and a ReCiPe single score to represent the environmental dimension. They use a partial equilibrium model formulated as mixed integer linear programming problem allowing capacity expansion in Germany. Three pareto-point efficient solution are analysed further by their midpoint impact assessment indicators. (Rauner and Budzinski, 2017)

We can observe that frameworks for an integrated assessment of ESMs and LCAs have been developed and models with an application on national power grids are existent. However, the multi-criteria objective of an environmental assessment is either represented by cost optimisation solved under a limitation on GHG emissions or by weighting procedures of few selected indicators. A whole integration of the full array of impact indicators and their different outcomes, if optimised individually, is seen as necessity to deliver a holistic picture of the system and to develop communicable impact scores. Especially with a rising share of less CO_2-intensive renewable energies, the application of further impact categories is even more relevant to avoid undesired side effects. Moreover the implementation of renewables opens new opportunities for decentralised energy systems. With growing affordability we see a huge potential for an implementation of a sustainable energy system in residential areas financed sharingly by private capital. Community energy systems have been identified to have fewer technical, administrative and economic resources to devote to sustainability projects and therfore demand for decision-making tools (McKenna *et al.*, 2018). Thus, besides the national perspective in the energy system analysis the investigation of decentral systems is deemed necessary.

3 Life Cycle Asssement based Energy Decision Support Tool

The development of the ***L**ife Cycle **A**ssessment based **En**ergy **D**ecision Support Tool* (*LAEND)* is subdivided into (i) the techno-economic ESM, (ii) the parametrisation of the LCA data for an implementation into the ESM, (iii) the development of a link between the ESM and the LCA and (iv) the extension of the objective function of the ESM to implement a multi-criteria sustainability array (see also Figure 1). Recently, a growing number of models have opened their code base and allow to reuse and modify the models as well as to improve efficiency, scrutiny, reproducibility, reusability and transparency in energy system modelling (Hilpert *et al.*, 2018). Examples are calliope (Pfenninger and Keirstead, 2015), MESSAGEix (Huppmann *et al.*, 2019), oemof (Hilpert *et al.*, 2018), OSeMOSYS (Howells *et al.*, 2011), PyPSA (Brown *et al.*, 2018) and urbs (Dorfner *et al.*, 2017).[4] We focussed on models using python as programming language to ease the coupling of the model to LCA tools. Python is widely used in science and LCA tools are available for python, e.g. Brightway 2 (Mutel, 2016), olca-ipc (PyPi, 2019), and wurst (PyPi, 2019). Commonly used LCA software such as openLCA and Umberto growingly implements the support of python scripts (Di Noi *et al.*, 2017; ifu, 2016). In addition, python provides a decent basis for data handling and data analysis with additional modules such as numpy, pandas and matplotlib.

For the further development of a linear optimisation model, we use the open source energy system modelling framework oemof (Hilpert et al., 2017) together with the commercial Gurobi optimization solver[5]. Oemof provides the main prerequisites in terms of the technical resolution of a decentralised residential energy system and economic variables such as operational and investment costs. Furthermore, it offers an adjustable timely resolution, wide flexibility, sophisticated feed-in packages (demandlib, feedinlib, tespy) and is open for modifications. In benchmark studies, amongst others, the commercial solver Gurobi has proved advantages in run time (Gurobi, 2013; Meindl and Templ, 2012) and therefore was chosen to reduce the calculation time. To allow an expansion planning up to the year 2040, we extended the functionality of the economic tools integrated in oemof to include cost degression of future investments.

For the link to the environmental assessment, we use olca-ipc (PyPi, 2019) connected to openLCA (Greendelta, 2018). This allows to benefit from the whole usability of the openLCA interface and in the same time to communicate with python-based software via Inter Process Communication (IPC). Figure 1 shows an overview of the *LAEND* model framework, composed of an energy system with the corresponding input data, LCA tools and the optimisation objectives.

[4] A full list can be accessed through the openmod initiative, see also Richstein (2019).
[5] Gurobi optimisation solver, available at http://gurobi.com/products/gurobi-optimizer

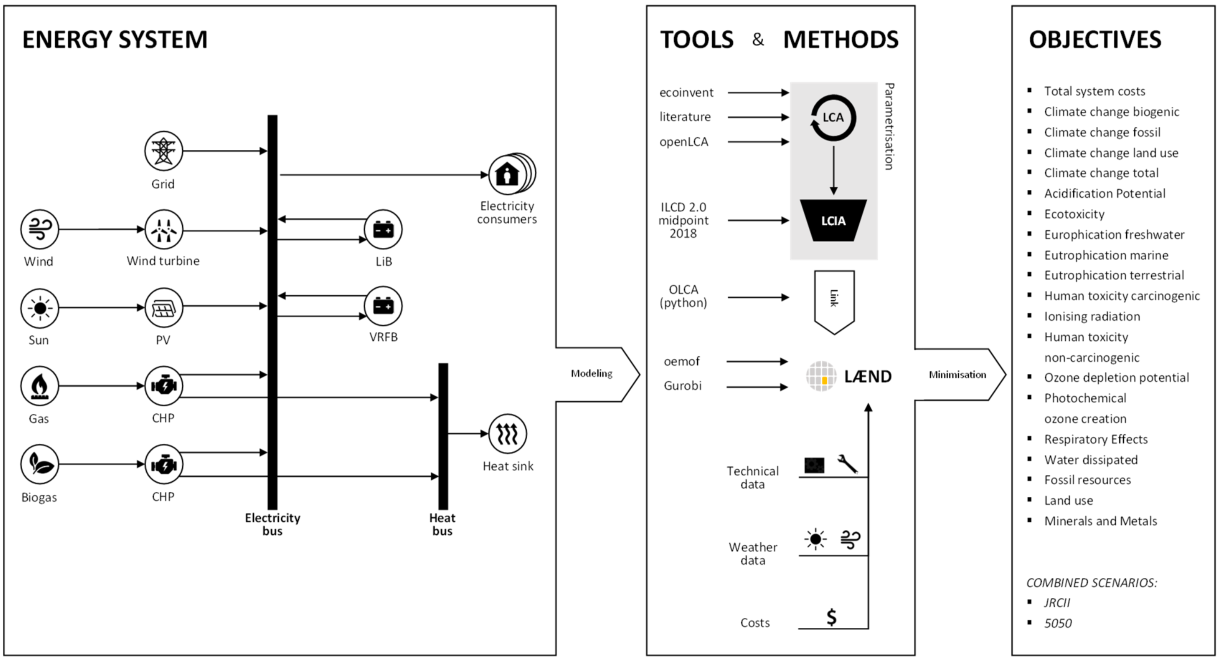

Figure 1 Representation of the energy system, tools, methods and objectives. PV = Photovoltaics, CHP = Combined heat and power, LiB = Lithium iron phosphate/lithium titanate Battery, VRFB = Vanadium redox flow battery, JRCII= Combined environmental scenario with weighted and normalised indicators as suggested by the European Commission's Joint Research Centre (JRC), 5050 = 50 % Total system costs, 50% JRCII. Icons by Icons8 (2018).

3.1 Integration of Life Cycle Assessment

To include environmental impacts, we coupled oemof (Hilpert *et al.*, 2018) and the olca-ipc package (PyPi, 2019) with the open source LCA modelling software openLCA (Ciroth, 2007). Ecoinvent 3.5 database (Wernet *et al.*, 2016) and ILCD 2.0 midpoint 2018 Impact Assessment also called EF 2.0 (Fazio *et al.*, 2018) are used for the analyses. Following the economic scheme the Life Cycle Inventory data is paramterised into construction (investment) and operational environmental intervention for the integration into the ESM. The LCAs are following ISO 14040, 14044 (International Standard Organisation, 2009, 2006) and recent ILCD recommendations (European Commission, 2010). Because the data for battery storage is very basic in ecoinvent, we used data from literature[6] to extend the database by two promising battery technologies: lithium iron phosphate lithium titanate (LiB) and vanadium redox flow batteries (VRFB).

To consider environmental impacts within the objective function, we include an environmental attribute to the objective function. This attribute can either represent a single environmental impact or the (weighted) sum of several indicators. Thereby we can assess total system costs and each environmental impact separately to calculate minima scenarios for each indicator on the one hand. On the other hand this extention allows to apply combined economic-environmental scenarios by using weights. The altered term for the variable costs within the objective function consists of the originally implemented costs term

[6] Baumann *et al.* (2017); Baumann *et al.* (2018); Peters *et al.* (2017); Bauer (2010); Weber *et al.* (2018); Zackrisson *et al.* (2010); Peters and Weil (2018).

(costs multiplied by the flows of the edges E and nodes K (Hilpert *et al.*, 2018; oemof, 2018)) and the extended environmental term as follows:

$$\min \sum_{t \in T} \sum_{(i,o) \in E} [c_{(i,o)} \cdot w^{c}_{(i,o)}(t) + e_{(i,o)} \cdot w^{e}_{(i,o)}(t)] x_{(i,o)}(t) + \sum_{t \in T} \sum_{k \in K} [c_{(n)} \cdot w^{c}_{(i,o)}(t) + e_{(i,o)} \cdot w^{e}_{(i,o)}(t)] x_{(i,o)}(t) \tag{1}$$

where c are the variable costs, e the environmental interventions, x denotes the flow and t the time step, and k the node. The weight w is given to costs and environmental intervention. The time is set by t and the indices (i, o) denote start and end node. If costs were optimised the weight of the environmental intervention is set to zero and vice versa. In combined scenarios separate weights for the costs and the respective environmental indiciator can be applied.

For an expansion modelling oemof requires the inclusion of investment costs which are added to the objective function. Therefore, in the investment mode oemof calculates the annuity a by (oemof, 2018):

$$a = C \cdot \frac{WACC\,(1 + WACC)^{n}}{(1 + WACC)^{n} - 1} \tag{2}$$

where capital expenditures C, weighted average cost of capital WACC and years n are set. Additionally we added fixed costs f and a cost decrease d to allow an additional factor for technical progress resulting in the equivalent periodical costs epc:

$$epc = \frac{a + f}{(1 + d)^{n}} \cdot n \tag{3}$$

Finally, the original investment term of the objective function provided by (Hilpert *et al.*, 2018; oemof, 2018) is altered as follows:

$$\min \sum_{n \in N} \sum_{(i,o) \in E} [epc_{(i,o)} \cdot w^{c}_{(i,o)}(n) + e_{(i,o)} \cdot w^{e}_{(i,o)}(n)] x_{(i,o)}(n) + \sum_{t \in T} \sum_{k \in K} [epc_{(n)} \cdot w^{c}_{(i,o)}(n) + e_{(i,o)} \cdot w^{e}_{(i,o)}(n)] x_{(i,o)}(n) \tag{4}$$

Both terms (1) and (4) of the objective functions are summed up to reflect total system costs and environmental interventions and constitute the objective function to be minimised.

3.2 Assumptions for the analyses of a typical residential quarter

The energy system in the model is designed to cover the electricity demand of a typical residential quarter near Pforzheim, Germany by multicrystalline silicon photovoltaics (PV), gas/biogas combined heat and power (CHP), wind power, and electricity from the grid. Two battery storage technologies are offered to the model: lithium iron phosphate/lithium titanate battery (LiB) and vanadium redox flow battery (VRFB). The period under consideration is 2018 to 2040 and the timely resolution is set to one hour.

The electricity demand for the residential quarter is represented by electrical load profiles of residential buildings in Germany. The data provided by (Tjaden *et al.*, 2015) covers the time frame of one year and is assumed not to change over the following years. As our first analyses focus on the electricity sector, the heat demand of the residential quarter is not considered. An additional sink is therefore modelled for the heat as by-product from the CHP units. A credit for this heat is considered in the environmental assessment due to the inherent ecoinvent structure which allocates CHP by exergy. In economic terms a credit for the heat was not considered.

The photovoltaic geographical information system (PVGIS) (European Commission (2017), delivers solar irradiance data and feed-in profiles for the location Pforzheim in Germany for the last 10 years. Parameters in PVGIS are set to a fixed, optimized slope and azimuth, 14 % efficiency and crystalline silicon modules. These time series from 2007 to 2016 have been extrapolated to cover the time frame up to 2040. Wind power is based on weather data from the German Meteorological Service[7]. Gaps within DWD data are interpolated and the completed time series from 2006 to 2017 is extrapolated to cover the period under consideration.

The energy technologies are based on the data implemented in ecoinvent 3.5 to achieve a maximum overlap of technical and environmental modelling. Life time is assumed with 20 years for CHP, PV and the wind turbine. Electrical efficiency of the natural gas fired CHP accounts to 37 %, thermal efficiency to 49%, using biogas it changes to 39 % (electrical) and 49 % (thermal) (ASUE, 2014). Wind power is calculated with the wind turbine power coefficient c_p for the turbine Nordex N50 800 kW, which represents data of wind turbines smaller than 1 MW in ecoinvent. The yield is calculated by the oemof feed-in modules feedinlib and windpowerlib and its basic model SimpleWindTurbine, which is sufficient for singular wind turbine installations. Efficiencies and cycle life time of the batteris LiB and VRFB are stemming from literature (Bauer, 2010; Baumann *et al.*, 2018; Baumann *et al.*, 2017; Peters *et al.*, 2017; Peters and Weil, 2018; Weber *et al.*, 2018; Zackrisson *et al.*, 2010). The charge rates (C-rates) have been assumed on a low level (C/6) to reach the expected cycle life time of the battery (Wikner and Thiringer, 2018).

The variable, fixed and investment costs used in the model can be found in Table 1. The weighted average cost of capital as well as the annual cost decrease, due to technical progress are assumed with 1 %, respectively. Additionally a natural gas price of 6 ct/kWh (Bundesnetzagentur, 2017; Verivox, 2019) and a biogas price of 10 ct/kWh (Bundesnetzagentur, 2014; naturstrom, 2019; Polarstern, 2019) are applied.

Table 1: Costs, efficiency and life time per energy technology, CHP = Combined heat and power, PV = Photovoltaics.

Costs / Technology	**Variable [€/kWh$_{el}$]**	**Fixed [€/kW$_{el}$/a]**	**Investment [€/kW$_{el}$]**	**Effi-ciency**	**Life time**	**Reference**
Grid electricity	0.14	N/A	N/A	N/A	N/A	Fraunhofer ISE (2019a), Vattenfall (2019)
CHP gas	0.01	N/A	module: 760, transport: 46, installation: 342	el. 37 %, th. 49 %	20 yr.	ASUE (2014)
CHP biogas	0.02	N/A	module: 764, transport: 46, installation: 342	el. 37 %, th. 49 %	20 yr.	ASUE (2014)

[7] Deutscher Wetter Dienst (2018).

PV	N/A	1 % of investment	1300	14 %	20 yr.	Wirth (2019), European Commission (2017)
Wind	0.03	59	1558	N/A	20 yr.	IRENA (2018) converted from USD (0.89 EUR/USD)
Lithium-ion battery (LiB)	≈ 0.11	25	Batt.mgmt.: 374, inverter: 500, installation: 125, approvals: 50	90 %, C/6	8000 cycles	Baumann *et al.* (2018; 2017), Peters *et al.* (2017)
Vanadium-redox flow battery (VRFB)	≈ 0.05	40	Batt.mgmt.: 374, inverter: 500, installation: 125, approvals: 50	75 %, C/6	8000 cycles	Baumann *et al.* (2018; 2017), Peters *et al.* (2017)

3.3 Single criterion and multi criteria optimisation of the residential quarter

The optimisation of the residential quarter in our analyses can be devided into two major classes:

- Optimisation for one single criterion and
- Optimisiation for multi criteria.

With regard to the optimisation for one single criterion, calculations were made for each of the 19 criteria individually. The results are of scientific interest even though they do not represent a likely future development as they may result in exorbitant total system costs and / or violate existing environmental constraints. Nevertheless, the resulting minimal value for each criterion is determined by these calculations and serves as basis for the further evaluation of the multi-criteria optimisation. Moreover, it is crucial to indicate goal conflicts which may potentially be cleared out in the multi-criteria optimisation.

For the multi-criteria optimisation two different objective functions considering multiple criteria have been applied to the model:

1. *JRCII*: For this integrated environmental optimisation, recent normalisation and weighting factors provided by the European Commission's Joint Research Centre (JRC) are used, based on the publications of Sala *et al.* (2017) and Huppes and van Oers (2011).[8] Therfore the environmental intervention e is build for all impact categories E:

$$e = \sum_{i \in E} \frac{e_i}{N_i} \cdot G_i \tag{5}$$

where N determines the normalisation and G the weighting factor. The environmental intervention e is used for the two terms of the objective functions (1) and (4). Analogously to the single-criteria optimisation the weight w^c in the objective functions is set to zero because total system costs are not assessed by these optimisation criterias.

[8] The impact categories Climate change biogenic, fossil and land use have not been considered in this scenario as weighting and normalisation factors are not available.

2. *5050*: The objective function from the *JRCII* optimisation is used together with the total system costs. The total system costs are normalised by the gross world domestic product at purchasing power parity taken from (IMF, 2019). The aggregated *JRCII* environmental criteria and the total system costs are weighted equally with 50 % in the objective function.

4 First results for a typical residential quarter

In the following at first the results for the optimisation considering one criterion are presented before the results for the integrated multi-criteria optimisation are introduced. The chapter closes with a short overview of results from a sensitivity analysis.

4.1 Results optimising single criteria

Figure 2 shows the optimal share of the generated electricity from each technology in total electricity production for the 19 single-criterion optimisations. When the minimisation of *Total system costs* or the impact category *Human toxicity carcinogenic* is the objective of the optimisation, electricity from the grid and a share of about 10 % PV power is chosen. Battery storage is avoided due to the flexibility of grid power and the higher total system costs involved. In contrast to that for the minimisation of the impact categories *Climate change (fossil & total)*, *Acidification potential*, *Eutrophication (marine & terrestrial*), *Photochemical ozone creation* or *Fossil resources*, the optimal solution is 100 % wind power with up to 37 % overall electricity from battery storage. Electricity from CHP is beneficial if the objective is the minimisation of *Climate Change (biogenic, land use)*, *Ecotoxicity*, *Eutrophication freshwater*, *Ionising radiation*, *Human toxicity non-carcinogenic*, *Respiratory effects*, *Water dissipated*, or *Land use*. Even though the share of electricity from CHP is subject to optimisation, battery storage of up to 8 % is part of the optimal solution to account for demand peaks and smaller CHP capacity. Gas driven CHP has been favoured to biogas CHP in the optimisation in all of the single-criteria optimisations except of *Human toxicity non-carcinogenic* which uses both. Moreover a mix of wind, PV and electricity from the grid with battery storage of up to 22 % is used for an optimal energy system in the impact category *Ozone depletion potential*. The results of *Total system costs* and *Human toxicity carcinogenic* objectives correlate, however they are outliers compared to the majority of the scenarios.

Wind power has been considered in seven out of 19 midpoint impact optimisation scenarios as sole generation technology and in three additional scenarios as certain share. CHP shows advantages in nine impact categories. These impact categories are mostly connected to mining activities and the production of metals. It can be observed that the total system costs of the energy system for the period until 2040 rise exorbitantly if battery storage and wind power are included. In the systems considering solely wind and battery storage the total system costs rise from around 2 Million in the optimal case to almost 990 Million Euros. If CHP or electricity from the grid are used, total system costs are in the low-field, however if battery storages are used, total system costs are rising quickly.

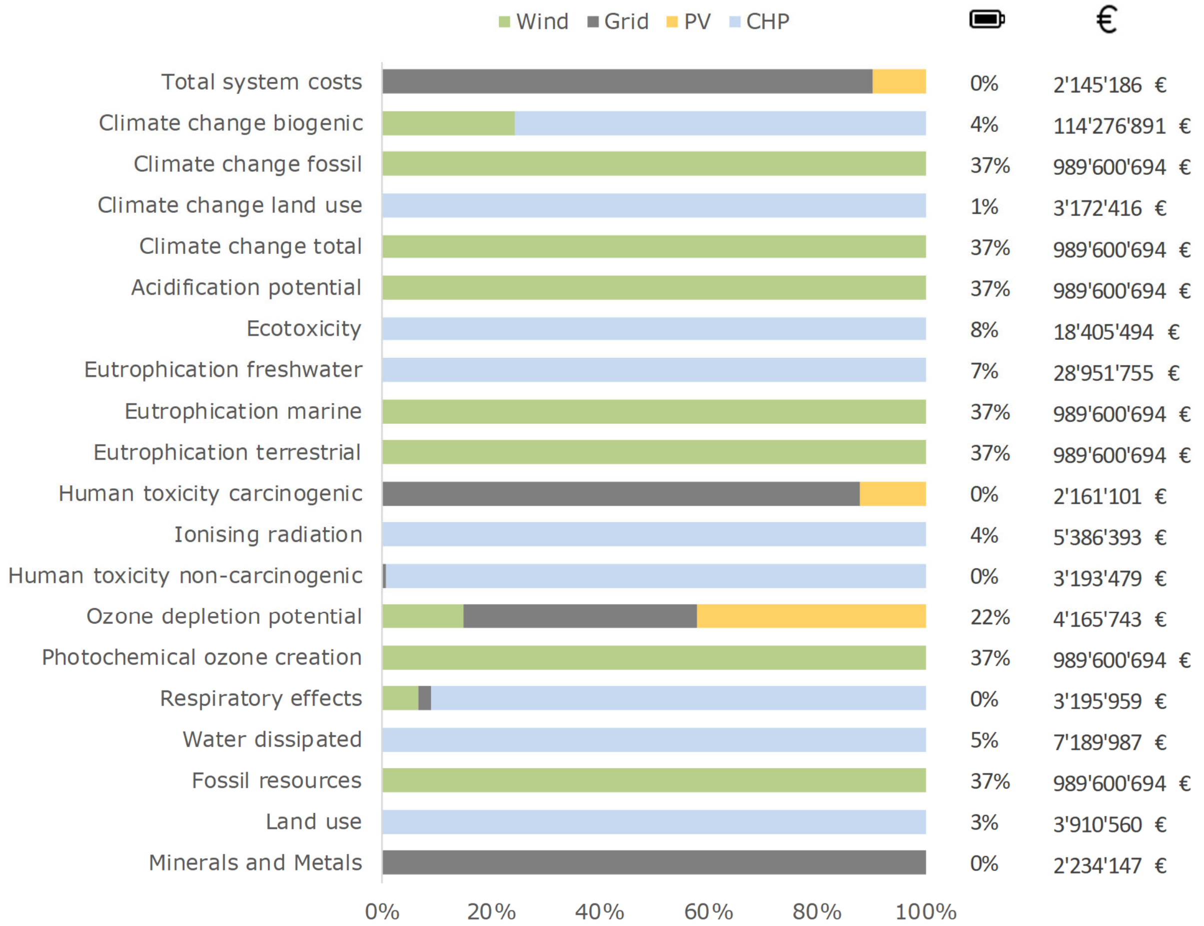

Figure 2 Electricity output in proportion to total production (vertical bars), battery ratio and total system costs for single-criteria optimisation. Battery ratio build as ratio of battery output to total generated electricity.

4.2 Results optimising multi criteria

For the multi-criteria optimisation, CHP operated by natural gas is favoured in the *JRCII* scenario which considers environmental impact categories only (Figure 3). The same applies for the *5050* scenario which combines *JRCII* and *Total system costs* weighted equally. The results for both scenarios are equal, hence the effect of the normalised cost implementation seems to be marginal compared to the environmental impacts. Both scenarios roughly coincide with the minimisations for *Climate change (land use)*, *Ecotoxicity*, *Eutrophication freshwater*, *Ionising radiation*, *Human toxicity non-carcinogenic*, *Respiratory Effects*, *Water dissipated* and *Land use*. Battery storage is avoided in these sccenarios and total system costs are in the low-field, although around 54 % higher than the sole cost optimisation scenario.

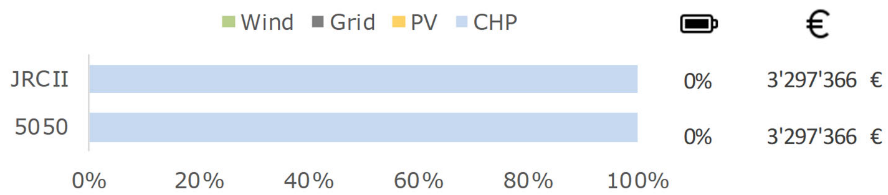

Figure 3 Electricity output in proportion to total production (vertical bars), battery ratio and total system costs for multi-criteria optimisation. Battery ratio buildas ratio of battery output to total generated electricity.

4.3 Sensitivity analysis

Sensitivity analysis shows the robustness of the results and uncovers critical assumptions and influenctial parameters. From the results we observe that in most scenarios the expansion of PV is avoided. PV technology was object of fast-growing changes and its efficiency increased by 5 % in the last 10 years (Fraunhofer ISE, 2019b). Therefore we assume a 5 % stepwise decrease of the impact assessment results of PV to investigate effects of possible changes in electricity production from PV production. Not before the impact of the PV is reduced to 45 %, compared to the actual data, the model starts to expand PV and the share of PV electricity generation is about 5 %. By a reduction to 30 % of the original impact, wind is excluded and solely PV used.

Both PV and wind power effectivness depend highly on the weather conditions which refer to the location chosen. Therefore we analyse two additional locations, Norden in Germany which represents an area with high wind levels and Tarifa in southern Spain to additionaly investigate higher wind levels and higher solar insolation rates. In Norden the optimisation for total system costs leads to a 2 % lower result. PV power partly is replaced by wind power, however the electricity demand is still supplied to 85 % by grid power. From an environmental perspective the choice of a more wind-intense location leads to increased wind power shares and two additional impact categories change to a wind power supply (*Land use*, *Ionising radiation*). In the Norden case 12 out of 18 impact categories propose solely wind power or a partly share. Results for Tarifa show a reduction of total system costs of 9 %. Furthermore, the optimisation of impact categories already applying PV increase the PV share by partly replacing wind power. No use of PV occurs for the optimisation of impact categories which have not used PV before. It has to be kept in mind that Tarifa, being near the coast also has higher wind occurrence than the original location of this study and therefore both factors influence the cost reduction.

The results show that the optimum in many impact categories leads to a steep cost increase partly because of the high costs of battery storage. As battery storage is a relative new technology, a cost decrease in the common years is expected. We therefore assume a cost decrease for battery storages to test when the storage plus renewable would be cost-efficient compared to grid electricity. The lowering of variable and investment costs to 4 % of the actual value leads to a switch to more electricity from PV than from the grid.

5 Discussion

The developed tool *LAEND* allows a linear optimisation of a residential energy system by both total system costs and by LCIA categories - either singularly or combined if normalisation and weighting procedures are applied. Therfore the results provided by *LAEND* enable a more sophisticated identification of goal conflicts in the optimisation of energy systems, especially when implementing renewables and battery storage. Critical uncertainties and assumptions are tested in a sensitivity analysis. However, meeting the aim of the study is accompanied by limitations given by the methodology and the assumptions made.

In general, models represent a very simplified reflection of real-world system behaviour and hence the results of the models are only valid within the opted system boundaries and the specific input data depending on the applied location, the efficiency factors and the costs. For our ESM, constraints such as emission limits from national goals have not been applied yet because they are not provided for all of the LCA assessed environmental interventions.

The LCA methodology includes uncertainties in the data sources, dataset choices, specifities of the datasets, assumptions made and the methodologocial choices. Because of the application of the ecoinvent database as well as literature data, the study relies on the data quality and furthermore on the inherent allocation procedures of the datasets (Weidema *et al.*, 2013). The validity and topicality of the data is not always ensured, for example the PV data is from the year 2012. From the methodological site, linear scaling of datasets and impacts is common practice in LCA. However linear scaling has not necessarily to correspond with real-world behaviour of systems, which goes beyond the methodological limits of LCA. Moreover the LCA was conducted without taking into account future changes which can alter the LCIA especially due to a different future electricity mix or improved efficiencies. Uncertainties of Life Cycle Impact Asessment methods such as USEtox, which build the underlying methodology of the toxicity impact categories, are discussed in recent literature (Nordborg *et al.*, 2017). Furthermore most LCIA methods do not distinguish between local or global environmental interventions. Therfore they are not able to assess impacts in the context of the local specifities which can have a major influence in energy system assessments. Another source of uncertainties is the use of the single score approach by normalisation and weighting of the individual impact categories based on global impact factors.

The results of the single-criteria optimisation clearly show the discrepancy of total system costs and environmental goals. While cost-optimal systems rely on electricity from the grid and CHP, the impacts in the categories *Climate change (fossil & total)*, *Acidification Potential*, *Eutrophication (marine & terrestrial)*, *Photochemical ozone creation*, *Fossil resources* can be reduced by the implementation of wind power and battery storage. But wind power and battery storage lead to a tremendous cost increase, and even at wind-intense locations it is challenging to compete with electricity from the grid. The results also show that CHP operated with natural gas on the one hand has a higher output in the category *Climate Change (fossil & total)* but on the other hand is able to minimise the values for *Ecotoxicity*, *Eutrophication freshwater*, *Ionising radiation*, *Human toxicity non-carcinogenic*, *Respiratory effects*, *Water dissipated* and *Land use*. All in all it can also be derived that except for *Total system costs* and *Minerals and Metals* electricity from the grid has disadvantages in all other impact categories compared to a self-sufficient energy system considering the simplified model of a residential area. Also the assessment of PV is connected to mining activities which show a negative influence on the environmental impacts. It has to be taken into account that PV data is from 2012 and the actual impacts of such a fast-changing technologies could be different - an assessment with recent data therefore could turn the results. Nevertheless, in the current state a share of PV is beneficial not only for the minimisation of *Total system costs*, but also for the categories *Human toxicity carcinogenic* and *Ozone depletion potential*. Due to the avoidance of constraints in the model also marginal variations in the costs or the environmental interventions can lead to a complete switch to other technologies, which is known as Penny Switching Effect (Lopion *et al.*, 2019).

To enhance communication and decision-support, results for two combined scenarios are calculated: *JRCII* covering the environmental categories and *5050* adding total system costs to the environmental categories. They both show conflicting results compared to other midpoints and do not completely reflect the results of the individual environmental indicators. Eventhough communicability improves by the aggregation they do not replace the individual assessment of the midpoint impact categories. Moreover it can dissolve individual peaks and impede the adaption to specific environmental pressures.

6 Conclusions and Outlook

Under the assumptions made and the limitations given, we conclude that total system costs are not a sufficient objective for the optimisation of residential electricity systems. Environmental pressures caused by the energy sector and the already existent exceedance of environmental planetary boundaries call for a multi-criteria analysis considering environmental impacts. But also environmental single score indicators, calculated from normalised and weighted midpoint indicators, have to be used with caution as they do not necessarily represent the trend or majority of the individual midpoint indicators. Conflicts between environmental indicators such as climate change and land or resource use are diluted by single score indicators. It is shown that electricity from the grid with a 10 % share of PV is cost-effective but not optimal from an environmental perspective. Wind power, battery storage and CHP show advantages in most of the environmental impact assessment categories, but do lead to an increase in the total system costs. Thus we conclude that environmental indicators at midpoint level need to be integrated into energy system models to allow a decision-making based on environmental sustainability determinants. In contrast to that, cost optimisation will lead to optimised systems which do not correspond to sustainability goals.

Due to the conflicts identified with the single score indicators, we recommend the further integration of *a priori* multi-criteria optimisation methodologies. Moreover we see the necessity to calculate the entire impact assessment independently from the individual optimisation objective for single criterion optimisation. This would enhance the possibility to show distances from optimal values and thus give further assistance to the decision maker. Thereout also distance-to-minima scenarios could deliver a more sophisticated normalisation factor for the midpoint impact indicator results. The inclusion of constraints such as national emission limits or targets, e.g. according to the ecological scarcity method, is necessary in future assessments to avoid Penny Switching Effects. A consequential approach for future LCA data has to be implemented in order to reflect future changes in power mix, production efficiencies etc. Additionally uncertainties and limitations in LCA datasets and LCIA methodologies have to be investigated to include a risk assessment into the decision supporting procedure of the combined ESM and LCA approach.

The energy model used for this study representing a residential energy system is very basic. The implementation of a wider range of technologies as well as sector coupling by the inclusion of heat and mobility are a future subject to research. From the perspective of a sustainability assessment also the extention of the indicator set to the social dimension, particularly in view of the compliance with the Sustainable Develeopment Goals, is proposed.

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8 References

Arvesen, A., Luderer, G., Pehl, M., Bodirsky, B.L. and Hertwich, E.G. (2018), “Deriving life cycle assessment coefficients for application in integrated assessment modelling”, *Environmental Modelling & Software*, Vol. 99, pp. 111–125.

ASUE (2014), *BHKW-Kenndaten 2014/2015: Module, Anbieter, Kosten*, energieDRUCK, Berlin.

Atilgan, B. and Azapagic, A. (2016), “An integrated life cycle sustainability assessment of electricity generation in Turkey”, *Energy Policy*, Vol. 93, pp. 168–186.

Azapagic, A. and Clift, R. (1999), “The application of life cycle assessment to process optimisation”, *Computers & Chemical Engineering*, Vol. 23 No. 10, pp. 1509–1526.

Azapagic, A., Stamford, L., Youds, L. and Barteczko-Hibbert, C. (2016), “Towards sustainable production and consumption: A novel DEcision-Support Framework IntegRating Economic, Environmental and Social Sustainability (DESIRES)”, *Computers & Chemical Engineering*, Vol. 91, pp. 93–103.

Bauer, C. (2010), “Ökobilanz von Lithium-Ionen Batterien”, *Paul Scherrer Institut, Labor für Energiesystem-Analysen (LEA), Villingen, Switzerland*.

Baumann, M., Peters, J. and Weil, M. (2018), “Ökologische und ökonomische Performance stationärer Li-ion-Batteriespeicher”, *Technische Universität Graz*, No. 15. Symposium Energieinnovation, 14. bis 16. Februar 2018,

Baumann, M., Peters, J.F., Weil, M. and Grunwald, A. (2017), “CO2 Footprint and Life-Cycle Costs of Electrochemical Energy Storage for Stationary Grid Applications”, *Energy Technology*, Vol. 5 No. 7, pp. 1071–1083.

Biggar, D.R. and Hesamzadeh, M.R. (2014), *The economics of electricity markets*, John Wiley & Sons.

BMWi, B.M.U. (2010), “Energiekonzept für eine umweltschonende, zuverlässige und bezahlbare Energieversorgung”, *Bundesministerium für Wirtschaft und Technologie (BMWi), Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit (BMU), Berlin*.

Brown, T., Hörsch, J. and Schlachtberger, D. (2018), “PyPSA: Python for Power System Analysis”, *Journal of Open Research Software*, Vol. 6 No. 3, p. 12.

Bruijn, H., Duin, R., Huijbregts, M.A.J., Guinee, J.B., Gorree, M., Heijungs, R., Huppes, G., Kleijn, R., Koning, A., Oers, L. and Wegener Sleeswijk, A. (Eds.) (2004), *Handbook on Life Cycle Assessment: Operational Guide to the ISO Standards, Eco-Efficiency in Industry and Science*, Vol. 7, Kluwer Academic Publishers, Dordrecht.

Bundesnetzagentur (2014), *Biogas- Monitoringbericht 2014: Bericht der Bundesnetzagentur über die Auswirkungen der Sonderregelungen für die Einspeisung von Biogas in das Erdgasnetz*, Bonn.

Bundesnetzagentur (2017), *Monitoringbericht 2017*, Bonn.

Carapellucci, R. and Giordano, L. (2012), “Modeling and optimization of an energy generation island based on renewable technologies and hydrogen storage systems”, *International journal of hydrogen energy*, Vol. 37 No. 3, pp. 2081–2093.

Ciroth, A. (2007), “ICT for environment in life cycle applications openLCA — A new open source software for life cycle assessment”, *The International Journal of Life Cycle Assessment*, Vol. 12 No. 4, p. 209.

Deutscher Wetter Dienst (DWD) (2018), “Climate Data Center”, available at: https://cdc.dwd.de/portal/201809260905/index.html (accessed 25 November 2018).

Di Noi, C., Ciroth, A. and Srocka, M. (2017), “openLCA 1.7 Comprehensive User Manual”, available at: https://www.openlca.org/wp-content/uploads/2017/11/openLCA1.7_UserManual.pdf (accessed 14 May 2019).

Dorfner, J., Schönleber, K., Dorfner, M. and Herzog S. (2017), “tum-ens/urbs: v0.7”, *Zenodo*.

Doukas, H., Flamos, A. and Lieu, J. (2019), *Understanding Risks and Uncertainties in Energy and Climate Policy*, Springer International Publishing, Cham.

European Commission (2010), *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy 2020 A strategy for competitive, sustainable and secure energy*, Brussels, available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1409650806265&uri=CELEX:52010DC0639 (accessed 6 May 2019).

European Commission (2017), “Photovoltaic Geographical Information System (PVGIS)”, available at: http://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#PVP.

European Parliament and Council of the European Union (2009), *Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC*, available at: http://www.nezeh.eu/assets/media/fckuploads/file/Legislation/RED_23April2009.pdf (accessed 22 November 2018).

Fazio, S., Castellani, V., Sala, S., Schau, E.M., Secchi, M., Zampori, L. and Diaconu, E. (2018), *Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment method.: New models and differences with ILCD*, JRC109369.

Fraunhofer ISE (2019a), “Energy Charts”, available at: https://www.energy-charts.de (accessed 13 May 2019).

Fraunhofer ISE (2019b), *Photovoltaics report*, Freiburg, available at: http://www. ise. fraunhofer. de/en/downloads-englisch/pdf-files-englisch/photovoltaics-report-slides. pdf/view, rapport publié en (accessed 25 May 2019).

García-Gusano, D., Iribarren, D., Martín-Gamboa, M., Dufour, J., Espegren, K. and Lind, A. (2016), “Integration of life-cycle indicators into energy optimisation models: the case study of power generation in Norway”, *Journal of Cleaner Production*, Vol. 112, pp. 2693–2696.

Goedkoop, M., Heijungs, R., Huijbregts, M., Schryver, A. de, Struijs, J. and van Zelm, R. (2013), *ReCiPe 2008: A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level*, First edition (revised).

Goedkoop, M.J. and Spriensma, R. (2000), *The Eco-indicator 99: a damage oriented method for Life Cycle Impact Assessment Methodology Report,* Second edition, Amersfoort, available at: http://teclim.ufba.br/jsf/indicadores/holan%20ecoindicator%2099.pdf (accessed 22 November 2018).

Greendelta (2018), “openLCA”, available at: http://www.openlca.org/ (accessed 20 February 2019).

Gurobi (2013), *Gurobi 5.5 Performance Benchmarks*, available at: http://sat-ag.com/Benchmarks%205.1b.pdf (accessed 14 May 2019).

Hauschild, M., Goedkoop, M., Guinée, J., Heijungs, R., Huijbregts, M., Jollie, O., Margini, M. and Schryver, A. de (2011), *Joint Research Centre. Institute for Environment and Sustainability. Recommendations for Life Cycle Impact Assessment in the European context: Institute for*

Environment and Sustainability: International Reference Life Cycle Data System (ILCD) Handbook-Recommendations for Life Cycle Impact Assessment in the European context, Publications Office of the European Union, Luxembourg.

Hauschild, M.Z., Goedkoop, M., Guinée, J., Heijungs, R., Huijbregts, M., Jolliet, O., Margni, M., Schryver, A. de, Humbert, S. and Laurent, A. (2013), "Identifying best existing practice for characterization modeling in life cycle impact assessment", *The International Journal of Life Cycle Assessment*, Vol. 18 No. 3, pp. 683–697.

Hilpert, S., Kaldemeyer, C., Krien, U., Günther, S., Wingenbach, C. and Plessmann, G. (2018), "The Open Energy Modelling Framework (oemof)-A new approach to facilitate open science in energy system modelling", *Energy strategy reviews*, Vol. 22, pp. 16–25.

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M. and Roehrl, A. (2011), "OSeMOSYS: The Open Source Energy Modeling System", *Energy Policy*, Vol. 39 No. 10, pp. 5850–5870.

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M.D.M., Hollander, A., Zijp, M. and van Zelm, R. (2016), *ReCiPe 2016: A harmonized life cycle impact assessment method at midpoint and endpoint level. Report I: Characterization*.

Huppes, G. and van Oers, L. (2011), "Evaluation of weighting methods for measuring the EU-27 overall environmental impact", *JRC Scientific and Technical Reports, Publications Office of the European Union, 75pp*.

Huppmann, D., Gidden, M., Fricko, O., Kolp, P., Orthofer, C., Pimmer, M., Kushin, N., Vinca, A., Mastrucci, A. and Riahi, K. (2019), "The MESSAGEix Integrated Assessment Model and the ix modeling platform (ixmp): An open framework for integrated and cross-cutting analysis of energy, climate, the environment, and sustainable development", *Environmental Modelling & Software*, Vol. 112, pp. 143–156.

Hwang, C.-L. and Masud, A.S.M. (1979), "Methods for multiple objective decision making", in *Multiple Objective Decision Making—Methods and Applications*, Springer, pp. 21–283.

Icons8 (2018), "Free Icons", available at: https://icons8.com/icons (accessed 14 May 2019).

ifu (2016), *Umberto NXT Universal (v7.1): User Manual,* 2.85th ed., Hamburg.

IMF (2019), "World Economic Outlook (April 2019)", available at: https://www.imf.org/external/datamapper/datasets/WEO (accessed 13 May 2019).

International Standard Organisation (2006), *Environmental management – Life cycle assessment – Principles and framework (ISO 14040:2006)*, Beuth Verlag, Berlin.

International Standard Organisation (2009), *Environmental management – Life cycle assessment – Requirements and guidelines (ISO 14044:2006)*, Beuth Verlag, Berlin.

IPCC (2014), *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, USA.

IRENA (2018), *Renewable Power Generation Costs in 2017*, Abu Dhabi.

Itsubo, N. and Inaba, A. (2005), "LIME2, Life-cycle impact assessment method based on endpoint modelling: summary", *Japan Environmental Management Association for Industry*.

Jones, D.F., Mirrazavi, S.K. and Tamiz, M. (2002), "Multi-objective meta-heuristics: An overview of the current state-of-the-art", *European journal of operational research*, Vol. 137 No. 1, pp. 1–9.

Klöpffer, W. and Grahl, B. (2014), *Life cycle assessment (LCA): a guide to best practice*, John Wiley & Sons.

Lazar, L. and Tietze, I. (2019), "External Costs as Indicator for the Environmental Performance of Power Systems", in *Progress in Life Cycle Assessment 2018*, Springer, pp. 89–102.

Lopion, P., Markewitz, P., Stolten, D. and Robinius, M. (2019), “Cost Uncertainties in Energy System Optimisation Models: A Quadratic Programming Approach for Avoiding Penny Switching Effects”, *Preprints*, No. 2019050211.

Luglietti, R., Rosa, P., Terzi, S. and Taisch, M. (2016), “Life cycle assessment tool in product development: Environmental requirements in decision making process”, *Procedia CIRP*, Vol. 40, pp. 202–208.

McKenna, R., Bertsch, V., Mainzer, K. and Fichtner, W. (2018), “Combining local preferences with multi-criteria decision analysis and linear optimization to develop feasible energy concepts in small communities”, *European journal of operational research*, Vol. 268 No. 3, pp. 1092–1110.

Means, P. and Guggemos, A. (2015), “Framework for life cycle assessment (LCA) based environmental decision making during the conceptual design phase for commercial buildings”, *Procedia engineering*, Vol. 118, pp. 802–812.

Meindl, B. and Templ, M. (2012), “Analysis of commercial and free and open source solvers for linear optimization problems”, *Eurostat and Statistics Netherlands within the project ESSnet on common tools and harmonised methodology for SDC in the ESS*, Vol. 20.

Meyer, D.E. and Upadhyayula, V.K.K. (2014), “The use of life cycle tools to support decision making for sustainable nanotechnologies”, *Clean technologies and environmental policy*, Vol. 16 No. 4, pp. 757–772.

Mutel, C. (2016), “Brightway 2. Advanced life cycle assessment framework”, available at: https://brightwaylca.org/.

naturstrom (2019), “naturstrom biogas: Umweltschonden heizen und kochen”, available at: https://www.naturstrom.de/privatkunden/gas/ (accessed 13 May 2019).

Nordborg, M., Arvidsson, R., Finnveden, G., Cederberg, C., Sörme, L., Palm, V., Stamyr, K. and Molander, S. (2017), “Updated indicators of Swedish national human toxicity and ecotoxicity footprints using USEtox 2.01”, *Environmental Impact Assessment Review*, Vol. 62, pp. 110–114.

oemof (2018), “oemof.solph package”, available at: https://oemof.readthedocs.io/en/v0.2.3/api/oemof.solph.html (accessed 13 May 2019).

Onat, N.C., Kucukvar, M., Tatari, O. and Zheng, Q.P. (2016), “Combined application of multi-criteria optimization and life-cycle sustainability assessment for optimal distribution of alternative passenger cars in US”, *Journal of Cleaner Production*, Vol. 112, pp. 291–307.

Pauliuk, S., Arvesen, A., Stadler, K. and Hertwich, E.G. (2017), “Industrial ecology in integrated assessment models”, *Nature Climate Change*, Vol. 7 No. 1, pp. 13–20.

Peters, J.F., Baumann, M., Zimmermann, B., Braun, J. and Weil, M. (2017), “The environmental impact of Li-Ion batteries and the role of key parameters – A review”, *Renewable and Sustainable Energy Reviews*, Vol. 67, pp. 491–506.

Peters, J.F. and Weil, M. (2018), “Providing a common base for life cycle assessments of Li-Ion batteries”, *Journal of Cleaner Production*, Vol. 171, pp. 704–713.

Pfenninger, S. and Keirstead, J. (2015), “Renewables, nuclear, or fossil fuels? Scenarios for Great Britain’s power system considering costs, emissions and energy security”, *Applied Energy*, Vol. 152, pp. 83–93.

Polarstern (2019), “Polarstern-Energie”, available at: https://www.polarstern-energie.de (accessed 13 May 2019).

PyPi (2019), “olca-ipc 0.0.7”, available at: https://pypi.org/project/olca-ipc/ (accessed 13 May 2019).

Rauner, S. and Budzinski, M. (2017), “Holistic energy system modeling combining multi-objective optimization and life cycle assessment”, *Environmental Research Letters*, Vol. 12 No. 12, p. 124005.

Ren, H., Lu, Y., Wu, Q., Yang, X. and Zhou, A. (2018), “Multi-objective optimization of a hybrid distributed energy system using NSGA-II algorithm”, *Frontiers in Energy*, Vol. 12 No. 4, pp. 518–528.

Richstein, J.C. (2019), “openmod - open energy modelling initiative”, available at: http://www.openmod-initiative.org (accessed 14 May 2019).

Ringkjøb, H.-K., Haugan, P.M. and Solbrekke, I.M. (2018), “A review of modelling tools for energy and electricity systems with large shares of variable renewables”, *Renewable and Sustainable Energy Reviews*, Vol. 96, pp. 440–459.

Sala, S., Crenna, E., Secchi, M. and Pant, R. (2017), “Global normalisation factors for the Environmental Footprint and Life Cycle Assessment”.

Schiffer, H.-W. (2019), *Energiemarkt Deutschland*, Springer Fachmedien Wiesbaden, Wiesbaden.

Steen, B. (1999), *A systematic approach to environmental priority strategies in product development (EPS): Version 2000 - General system characteristics*, Gothenburg, available at: https://www.ivl.se/download/18.7e136029152c7d48c202bba/1465979612076/CPM%20report%201999_4.pdf (accessed 25 November 2018).

Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., Vries, W. de, Wit, C.A. de, Folke, C., Gerten, D., Heinke, J., Mace, G.M., Persson, L.M., Ramanathan, V., Reyers, B. and Sörlin, S. (2015), “Sustainability. Planetary boundaries: guiding human development on a changing planet”, *Science (New York, N.Y.)*, Vol. 347 No. 6223, p. 1259855.

Strantzali, E. and Aravossis, K. (2016), “Decision making in renewable energy investments: a review”, *Renewable and Sustainable Energy Reviews*, Vol. 55, pp. 885–898.

Tjaden, T., Bergner, J., Weniger, J. and Quaschning, V. (2015), “Representative electrical load profiles of residential buildings in Germany with a temporal resolution of one second”, *ResearchGate: Berlin, Germany*.

Umweltbundesamt (2018a), “National Trend Tables for the German Atmospheric Emission Reporting 1990 - 2016 Final version 14.02.2018 (v1.0)”, available at: https://www.umweltbundesamt.de/themen/luft/emissionen-von-luftschadstoffen (accessed 7 August 2018).

Umweltbundesamt (2018b), “National Trend Tables for the German Atmospheric Emission Reporting 1990 - 2016 Version for the EU-Submission 15.01.2018”, available at: https://www.umweltbundesamt.de/themen/klima-energie/treibhausgas-emissionen (accessed 7 August 2018).

United Nations (2018), *The Sustainable Development Goals Report*, New York, available at: https://unstats.un.org/sdgs/files/report/2018/TheSustainableDevelopmentGoalsReport2018-EN.pdf.

United States Environmental Protection Agency, *Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis: Assessment and Standards Division*, Washington, DC, available at: https://nepis.epa.gov/Exe/ZyPDF.cgi/P1006DXP.PDF?Dockey=P1006DXP.PDF.

Vattenfall (2019), “Die Strompreis-Zusammensetzung”, available at: https://www.vattenfall.de/infowelt-energie-strompreis (accessed 13 May 2019).

Verivox (2019), “Verivox - Verbraucherpreisindex Gas”, available at: https://www.verivox.de/verbraucherpreisindex-gas/ (accessed 13 May 2019).

Weber, S., Peters, J.F., Baumann, M. and Weil, M. (2018), “Life Cycle Assessment of a Vanadium Redox Flow Battery”, *Environmental Science & Technology*, Vol. 52 No. 18, pp. 10864–10873.

Weidema, B.P., Bauer, C., Hischier, R., Mutel C, Nemecek, T., Reinhard, J., Vadenbo, C.O. and Wernet, G. (2013), *Overview and Methodology: Data quality guideline for the ecoinvent database version 3: Ecoinvent Report 1 (v3)*, The ecoinvent Centre, St. Gallen.

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E. and Weidema, B. (2016), “The ecoinvent database version 3 (part I): overview and methodology”, *The International Journal of Life Cycle Assessment*, Vol. 21 No. 9, pp. 1218–1230.

Wikner, E. and Thiringer, T. (2018), “Extending Battery Lifetime by Avoiding High SOC”, *Applied Sciences*, Vol. 8 No. 10, p. 1825.

Wirth, H. (2019), *Aktuelle Fakten zur Photovoltaik in Deutschland,* Fassung vom 18.03.2019, Freiburg.

Wood, A.J., Wollenberg, B.F. and Sheblé, G.B. (2013), *Power generation, operation, and control*, John Wiley & Sons.

Yilmaz, O., Anctil, A. and Karanfil, T. (2015), “LCA as a decision support tool for evaluation of best available techniques (BATs) for cleaner production of iron casting”, *Journal of Cleaner Production*, Vol. 105, pp. 337–347.

Yue, D., Pandya, S. and You, F. (2016), “Integrating Hybrid Life Cycle Assessment with Multiobjective Optimization: A Modeling Framework”, *Environmental Science & Technology*, Vol. 50 No. 3, pp. 1501–1509.

Zackrisson, M., Avellán, L. and Orlenius, J. (2010), “Life cycle assessment of lithium-ion batteries for plug-in hybrid electric vehicles–Critical issues”, *Journal of Cleaner Production*, Vol. 18 No. 15, pp. 1519–1529.

Zhang, Y., Liang, K., Li, J., Zhao, C. and Qu, D. (2016), “LCA as a decision support tool for evaluating cleaner production schemes in iron making industry”, *Environmental Progress & Sustainable Energy*, Vol. 35 No. 1, pp. 195–203.