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Integration of Life Cycle Impact Assessment in Energy System Modelling

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Abstract:

The Paris agreement is the first-ever universally accepted and legally binding agreement on global climate change. It is a bridge between today's and climate-neutrality policies and strategies before the end of the century. However, government and private companies still struggle to develop cost-effective carbon-neutral strategies. Energy system modeling has proved essential in creating strategies to generate carbon-neutral scenarios under minimal costs.
However, cost minimization does not necessarily lead to publicly acceptable solutions nor generate configurations that minimize environmental impacts.
Here we show a methodology to integrate LCIA indicators in an energy system model, assessing the impact of energy system configurations on economic and environmental aspects.
Here we show a methodology to integrate life cycle assessment metrics in an energy system model to account for (i) emissions and impacts beyond the operation of the energy system itself and (ii) identify configurations optimizing both economic and environmental aspects. The model is applied to the case study of Switzerland and shows that with little modifications to the energy system configuration, carbon neutrality can be reached under the cost minimization objective while identifying trade-offs with other environmental issues.
This work allows the generation of MOO of energy systems, minimizing burden shifting of environmental impacts and generating robust solutions for the energy transition, increasing social acceptance towards the biggest challenge of the 21st century.

Keywords:

Energy System, LCA, LCIA, Multiobjective optimization, Renewable Energy

1. Introduction

1.1. Background

With the increasing strength and frequency of climate change events, the urgency to mitigate climate change impact is ever so important as today.
The IPCC reports highlighting the importance of the international coalition to reduce GHG from human activities to limit global warming to 1.5 - 2°C, compared to pre-industrial levels.
As a response, the Paris Agreement, resulting from the COP21 in 2015, required all signers to submit ever more ambitious NDC every five years, listing mid and long-term emissions reduction objectives.
Companies, such as [1] and IRENA, evaluate whether NDCs are on track with the 1.5 - 2°C scenarios and advise countries for improvement.
Interest in energy system modeling has increased due to growing concern for sustainable development and the transition towards renewable energies.
LCA, which studies other environmental impacts, such as ozone layer depletion or particulate matter formation, has also grown exponentially in the past two decades [2].
When planning for a low-carbon energy system, one has to consider other impacts of AoP to monitor potential environmental burden shifting. Thus, this project's methodology aims to integrate LCA and LCIA within Energy System Modelling to monitor and optimize climate change impacts, human health, and ecosystem quality.

1.2. Literature review

In addition to the economic optimization classically used in energy system designs and operations, the focus on Life Cycle Analysis calculation is rapidly gaining momentum. While LCA is mainly applied to small-scale technologies [3–5], more complex systems such as processes [6], plants [7] and buildings [8] were analyzed in recent years. This evolution depicts a will to shift from small-scale towards bigger-scale energy systems. Small-scale systems are optimized on multi-objective functions (OF), integrating economic and environmental impacts. On the contrary, more extensive systems assess LCA indicators, using either post-calculation or solely focusing on the Climate Change indicator, which represents emissions of GHG emissions.

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Therefore, energy system modeling at regional and national levels is currently based on economic optimization, while LCA indicators take a secondary place. [9] assessed the impact of a biomass-based energy system in Europe while optimizing the economic OF and monitoring LCA indicators with post-calculation on the energy system structure. [10] analyzed the electricity demands of the German energy system, focusing on the MOO of economic and Climate Change OFs.
A global energy system model has been developed by [11], generating robust solutions by optimizing the Swiss energy system on economic and environmental aspects by integrating the climate change indicator. [12] went one step further by not only assessing the climate change indicator but integrating the carbon mass flow conservation to the model by Moret.

While LCA optimization is a hot topic in current research, none of the previously cited literature integrates at the same time (i) the generation of a national model with all global energy demands, (ii) the direct optimization of multiple AoP within one model, (iii) and uncertainty.

1.3. Objectives and contribution

This project is based on ES using MILP to define a Swiss energy model through point-average consumption assumption [13]. It is also based on integrating LCA endpoint indicators for environmental impact optimization over three different AoP to compare resulting energy systems with purely economic optimization [14]. The goal is to analyze Switzerland's potential to decarbonize its energy system by 2050 while accounting for other environmental impacts and avoiding shifting the environmental burden.

Several research questions have been identified to tackle this project, which can be divided into three central problems.

- Single-objective optimization of LCA impacts in energy systems modeling
- MOO of LCA impacts in energy systems modeling
- Application of regional LCA modeling to the Swiss energy system

These questions will be treated by answering the following questions:

- How to characterize technologies in LCA?
- How to integrate LCIA in energy systems modeling?
- How to monitor LCA indicators in energy systems modeling and assess the resulting system's performance?
- Does a low-carbon Swiss energy system lead to environmental impact shifting?
- What is the effect of MOO on the energy systems configuration?

2. Methodology

2.1. Modelling Framework

Integrating LCIA in energy system modeling has been accomplished by Brun et al. [14], adapting the existing MILP EnergyScope framework developed by Moret et al. [11], Li et al. [12] and Schnidrig et al. [13]. *EnergyScope* models a global multi-energy model at a monthly averaged basis under the constraint of mass and energy conservation between demands and resources. The demands are categorized into four sectors (households, services, industry, and transportation) and three energy demand types: (i) electricity at four voltage levels, (ii) heat distinguished between process heat, space, and water heating, and (iii) mobility split in passenger and freight mobility. The resources are either available within the studied region or imported from outside. ES is written as MILP Problem in AMPL and optimizes the configurations, which are determined through the key decision variables $\mathbf{F}$ and $\mathbf{F_t}$, modeling the installation size and the temporal use of the technologies.

2.1.1. Economic objective

The primal OF of EnergyScope has been previously the total cost $\mathbf{C_{tot}}$ (Eq. 1). The total cost is calculated as the sum of the technologies' ($tec \in \mathcal{TEC}$) annualized investment $\mathbf{C_{inv}}$ and maintenance $\mathbf{C_{maint}}$ (Eq. 3) cost affected by $\mathbf{F}$, and the temporary variable as of the resources ($res \in \mathcal{RES}$) operation cost $\mathbf{C_{op}}$ (Eq. 4).

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$$\mathbf{C_{tot}} = \sum_{tec}(\mathbf{C_{inv}}(tec) \cdot \tau(tec) + \mathbf{C_{maint}}(tec)) + \sum_{res}\mathbf{C_{op}}(res) \tag{1}$$

$$\mathbf{C_{inv}}(tec) = c_{inv}(tec) \cdot (\mathbf{F}(tec) - f_{ext}(tec)) \tag{2}$$

$$\mathbf{C_{maint}}(tec) = c_{maint}(tec) \cdot \mathbf{F}(tec) \tag{3}$$

$$\mathbf{C_{op}}(res) = \sum_{t} c_{op}(res) \cdot \mathbf{F_t}(res, t) \cdot t_{op}(t) \tag{4}$$

$$\forall \quad res \in \mathcal{RES},\ tec \in \mathcal{TEC},\ t \in \mathcal{PERIODS},$$

2.1.2. Carbon emissions objective

Li et al. [12] integrated the carbon balance and thus the resulting net emissions secondary objective, measured by the CO_2 equivalent **Emissions**. These emissions are modeled by considering technology-specific layers containing CO_2. The different CO_2 layers are categorized into five classes $c \in \mathcal{C} - \mathcal{LAYERS}$ (captured, sequestrated, stored, emitted to atmosphere). The technology conversion factor η [tCO_2/GWh] is valid for all periods t (Eq. 5) and is either positive or negative, allowing to model net emission limits ϵ (Eq. 6).

$$\mathbf{Emission}(t) = \sum_{tec}\mathbf{F_t}(tec) \cdot t_{op}(t) \cdot \eta(i, c) \quad \forall \quad tec \in \mathcal{TEC}, t \in \mathcal{PERIODS},\ c \in \mathcal{C} - \mathcal{LAYERS} \tag{5}$$

$$\sum_{t}\mathbf{Emission}(t) \leq \epsilon \quad \forall \quad tec \in \mathcal{TEC}, t \in \mathcal{PERIODS} \tag{6}$$

2.1.3. LCIA objectives

The environmental OF variable $\mathbf{LCIA_{tot}(i)}$ is constructed by combining the total cost composition, splitting in a constant (investment) and variable (operation) part and the technology-specific impact of the carbon flow model, where the impact of resources is integrated into the use of technologies: For each indicator i (Eq. 7 & table 3), $\mathbf{LCIA_{tot}(i)}$ is defined as the construction of the technology related to the installation size $\mathbf{F}$ (Eq. 8), and the operation of the technology proportional to its use $\mathbf{F_t}$ (Eq. 9). Finally, the construction impact is divided by the technologies' lifetime n.

$$\mathbf{LCIA_{tot}}(i) = \sum_{tec}(\mathbf{LCIA_{constr}}(i, tec) \cdot \frac{1}{\boldsymbol{n}(i)} + \mathbf{LCIA_{op}}(i, tec)) \tag{7}$$

$$\mathbf{LCIA_{constr}}(i, tec) = lcia_{constr}(i, tec) \cdot \mathbf{F}(tec) \tag{8}$$

$$\mathbf{LCIA_{op}}(i, tec) = lcia_{op}(i, tec) \cdot \sum_{t}\mathbf{F_t}(res, t) \cdot t_{op}(t) \tag{9}$$

$$\forall \quad i \in \mathcal{IND},\ tec \in \mathcal{TEC},\ t \in \mathcal{PERIODS},$$

2.2. Life Cycle Impact Assessment

LCA aims to evaluate the environmental impacts of a product throughout its life cycle. The approach usually considered is the cradle-to-grave, which starts with the extraction of raw materials and ends in the disposal of the product through recycling, landfill, or incineration. The fur stages of LCA consist of [15] (i) Definition of goal and scope phase, (ii) item Life cycle inventory (LCI) phase, (iii) Life cycle impact assessment (LCIA) phase, and (iv) Interpretation phase

2.2.1. Definition of goal and scope

Each technology is characterized separately to integrate an LCIA into the energy system model correctly. Every technology is defined by two products, one related to its construction and one for its operation, modeling the cradle-to-grave approach. Their functional units depend on the end-use categories the technology belongs to, where their units are reported in table 1.

2.2.2. Life cycle inventory

The LCI was computed using a matrix approach instead of a sequential one. The matrix method easily integrates feedback loops in product systems and avoids the explicit computation of scaling factors when the final demand vector f is known (Table 2).
The technology matrix A defines the exchanges between products. Its columns represent products, processes,

Table 1: Functional unit of the ES technologies' operation and construction products, depending on the end use category it belongs to.

End use categories	Unit of the technologies	
	Operation	Construction
Electricity	GWh	GW
Heat (low and high temperature)	GWh	GW
Mobility freight	Mtkm	$\frac{\text{Mtkm}}{h}$
Mobility passenger	Mpkm	$\frac{\text{Mpkm}}{h}$

or services, with each row representing its respective input or output. A is square, and its columns are linearly independent; thus, it is invertible. The matrix F defines the elementary flows for each process related to direct emissions. Both matrices are defined inside the Ecoinvent database [16]. The final demand f was defined as an all-ones vector; thus, the LCI represents each specific technology's total emissions per functional unit (table 1). The scaling factor vector s and the life cycle inventory vector g are defined as follows:

$$s = A^{-1} \cdot f \tag{10}$$

$$g = \text{LCI} = F \cdot s = F \cdot \left(A^{-1} \cdot f\right) \tag{11}$$

Table 2: Notation used in the life cycle inventory phase of the LCA

Notation	Name
A	Leontief technology matrix
F	Matrix of elementary flows
f	Final demand
s	Scaling factor
g	Life cycle inventory

2.2.3. Life cycle impact assessment

Seventeen mid-point indicators are categorized as endpoint levels into three main AoP for the LCIA: HH, EQ, and CC. Twenty-three endpoint indicators were considered in the matrix IW^+, based on the impact assessment method IMPACT world+ [17] (table 3). IW+ is multiplied by the LCI g to get the impact result matrix R:

$$R = \text{IW}^+ \cdot g \tag{12}$$

2.2.4. Technology characterization

EnergyScope was run on a national scale on economic optimization to identify which technologies to characterize in LCIA, allowing to make a trade-off between characterization time and methodology development.
Data collection was then performed, mainly with the Ecoinvent 3.8 database. The tools used to create the Leontief matrix A and the elementary flow matrix F directly from the database were given by [18]. The initial Leontief matrix directly resulting from the ecoinvent database was modified as follows :

$$A_{ES}^{nxn} = \mathbf{I}^{nxn} - A_{ecoinvent}^{nxn} \tag{13}$$

n represents the total number of products in the database, and $\mathbf{I}^{nxn}$ is an identity matrix of size n to align with the convention used in ES. Namely, negative values represent input flows or products, and positive values represent output flows or products, with an all-one diagonal to yield an invertible matrix.
In EnergyScope, conversion technologies are characterized by their construction and operation impacts. A similar decomposition of impacts was used for the LCIA. First, the products representing a technology's construction and operation were identified using data collection. In LCA, the impact of a technology's operation intrinsically considers the impact of its construction. Hence, to avoid the impacts of double counting, the construction of a technology needed to be discarded from matrix A. Then, new columns and rows are added to the matrix A to create a new matrix A', illustrated in figure 1. The size of the new technology matrix and the number of operation products will increase A' characterized by n' for a final dimension of $A'^{(n+n')x(n+n')}$.

New columns are added to the emission flows matrix $F^{(fxn)}$, where f is the number of emissions flows in the database for matrix multiplication compatibility. The new columns correspond to the emission flows related to P'_{op}, which are the same as the flows of the original product P_{op}, creating the new matrix $F'^{(fx(n+n'))}$.

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Table 3: Table summarizing mid- and endpoint indicators, with the respective ones used for their integration in ES and the AoP they belong to according to IMPACT World +.
The unit of the endpoint indicators is expressed in $kgCO_2$-eq for Climate Change (CC). The impact of Ecosystem Quality (EQ) is given in PDF·m^2·year, representing the Potentially Disappeared Fraction of species on a one m^2 surface during a year. Finally, the impact on Human Health (HH) is expressed in DALY, the Disability Adjusted Life-Years, representing the loss of the equivalent of one year in perfect health.

Midpoint level indicator	Endpoint level indicator	Abbreviation	AoP
Climate change	Climate change, short term	CCST	CC
Freshwater acidification	Freshwater acidification	FWA	EQ
Freshwater ecotoxicity	Freshwater ecotoxicity, short term	FWEXS	EQ
Freshwater eutrophication	Freshwater eutrophication	FWEU	EQ
Human toxicity cancer	Human toxicity cancer, long term	HTXCL	HH
	Human toxicity cancer, short term	HTXCS	HH
Human toxicity non-cancer	Human toxicity non-cancer, long term	HTXNCL	HH
	Human toxicity non-cancer, short term	HTXNCS	HH
Ionizing radiation	Ionizing radiation, ecosystem quality	IREQ	EQ
	Ionizing radiation, human health	IRHH	HH
Land occupation	Land occupation, biodiversity	LOBDV	EQ
Land transformation	Land transformation, biodiversity	LTBDV	EQ
Marine acidification	Marine acidification, long term	MAL	EQ
	Marine acidification, short term	MAS	EQ
Marine eutrophication	Marine eutrophication	MEU	EQ
Ozone layer depletion	Ozone layer depletion	OLD	HH
Particulate matter formation	Particulate matter formation	PMF	HH
Photochemical oxidant formation	Photochemical oxidant formation	PCOX	HH
Terrestrial acidification	Terrestrial acidification	TRA	EQ
Thermally polluted water	Thermally polluted water	TPW	EQ
Water availability	Water availability, freshwater ecosystem	WAVFWES	EQ
	Water availability, human health	WAVHH	HH
	Water availability, terrestrial ecosystem	WAVTES	EQ

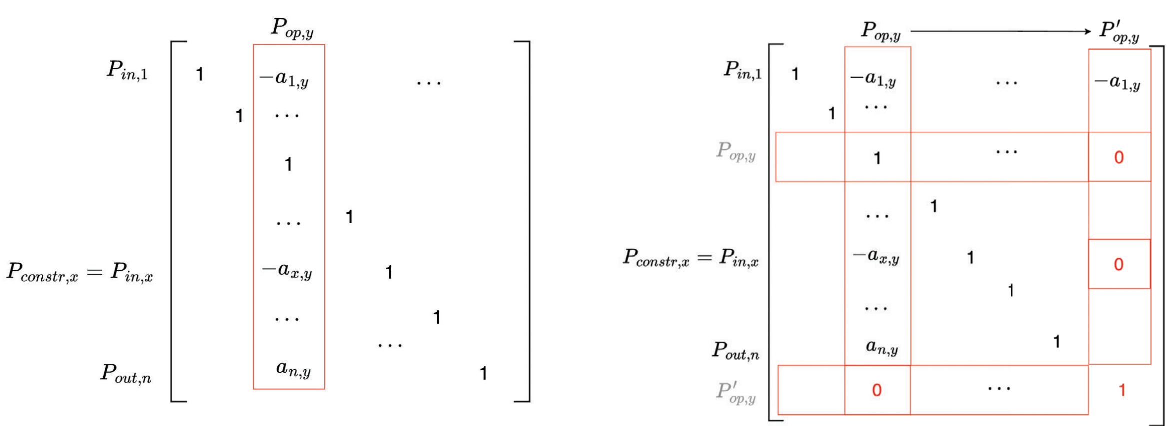

Figure 1: On the left-hand side : Initial technology matrix A^{nxn}. On the right-hand side: New technology matrix $A'^{(n+n')x(n+n')}$. n represents the total number of products in the database, and n' represents the number of conversion technologies characterized.
Example for a single technology: P_{op} represents the ecoinvent product for operating a certain technology. P_{constr} is the ecoinvent product related to the construction of the same technology. The matrix A' contains an additional column and row, with P'_{op} representing the operation of the technology while disregarding its construction, allowing later to compute the isolated impact of the operation

To assess the impact on the selected region, provincial data was selected. The following best resolution was used when unavailable: national, continental, or global. This methodology was applied to the technologies installed on economic optimization.

2.2.5. LCIA Integration in Energy System Modelling

After adding the technologies' operation products, they discarded their relations with their respective construction products (defined as P'_{op}) in the technology matrix A. Their respective LCI was computed by multiplying the new elementary flow matrix F' by the new technology matrix A'.

The subsequent step of the LCIA was to convert the emissions to their functional units (table 1.)
Most construction technologies are characterized by "units." Therefore, to convert the input-output and emissions flow to the ES functional unit, the capacity was defined as :

$$\text{Capacity} = \frac{GW^1}{\text{unit} \cdot \mathbf{c}_{p(i)} \cdot time_{tot} \cdot n_i} \tag{14}$$

[1] : [GW[] is only for electricity and heat, but [Mtkm] for freight mobility and [Mpkm] for passenger mobility.

Each technology LCI was multiplied by the impact matrix $IW+$, as in equation 12. This resulted in the impact matrix R as defined for the construction and operation per technology and region.

2.2.6. Assumptions

Regarding mobility, ecoinvent car products are defined per km. For unit conversion, 1.6 people per car are estimated for Switzerland, according to [19].

Technology maintenance and transportation impact are mainly accounted for within the operation. However, it is not always explicitly detailed. Therefore, the choice was not to isolate the technologies' maintenance and transport impacts but to keep them as part of the operational impact.

2.3. MOO

MOO (MOO) is a field of multi-criteria decision-making that deals with mathematical optimization problems in which multiple OFs must be optimized simultaneously. MOO has proven to be a valuable tool in energy planning, where the decision-maker has to select between two or more competing objectives. For example, EnergyScope traditionally optimized one OF only [11, 12, 20] or proceeded to bi-objective optimization with environomic Pareto curves generation in specific cases [19]. MOO consists of finding a single solution that fulfills the arbitrary preferences of the human decision-maker, locating a sample collection of Pareto optimum solutions, and quantifying the trade-offs involved in achieving various goals.

This work has realized the MOO by integrating the LCIA OFs $I \in \mathcal{LCIA} - \mathcal{I} \subset \mathcal{OF}$ as constraints under the economic optimization (Eq. 15), defining the technology size $\mathbf{F}$ and use $\mathbf{F_t}$. The weighting (Eq. 16) allows processing through the multidimensional Pareto-Curve in between the extreme points identified at mono-objective optimization, where $\omega(j) = 1$ and $\omega(i) = 0,\ \forall i \in \mathcal{OF} \setminus \{j\}$.

$$\min_{\mathbf{F},\mathbf{F_t}} \mathbf{C_{tot}} \tag{15}$$

$$\text{s.t.} \quad \mathbf{f_{obj}}(i) \leq \omega(i) \cdot f_{obj}^{\max}(I) + (1 - \omega(i)) \cdot f_{obj}^{\min}(I) \tag{16}$$

$$\forall \quad i \in \mathcal{OF} = \mathcal{COST} \cup \mathcal{LCIA}$$

To account for the solution space of the MOO, a Monte-Carlo approach [21] on the weights ω is applied. The decision variables define the modeled solution space under varying weighting parameters $\omega(i)$ (Eq. 17). The probability of appearance of $\omega(i)$ follows a uniform distribution U(0, 1) (Eq. 18).

$$\mathbf{F}(i), \mathbf{F_t}(i) : \quad f((\mathbf{F}(i), \mathbf{F_t}(i)), \omega(i)) \tag{17}$$

$$\text{s.t.} \quad \omega(i) = P(\tilde{\omega}, \text{U}(0,1)) \tag{18}$$

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3. Results

3.1. Case study

The methodology above is applied to the case study of Switzerland, aiming at following the energy strategy *Energieperspektiven 2050+* (EP50+) [22]. EP50+ analyzes the development of an energy system compatible with the long-term climate goal of net zero greenhouse gas emissions in 2050 while ensuring a secure energy supply without nuclear power. While EP50+ defined several variants of this scenario, differing in terms of a different mix of technologies and a different speed of expansion of renewable energies in the power sector, we consider within this study only the demands estimation, the potentials of energy vectors, and the constraints of carbon-neutrality and no nuclear power.

Demands

EP50+ decomposed the final energy demand evolution by sector in 5 years interval [22]. Taking the energy demand of 2019 [23] being split into the energy categories, allows us to extrapolate the specific energy demand by category to the sectoral energy demand estimation for 2050 (Tab. 4).

Table 4: Annual final energy demand per sector and energy type 2050.

		Households	Services	Industry	Mobility
Electricity LV	[GWh]	9818	9154	0	0
Electricity MV	[GWh]	0	1407	3173	0
Electricity HV	[GWh]	0	0	5350	0
Electricity EHV	[GWh]	0	0	0	0
Heat HT	[GWh]	0	183	5855	0
Heat LT SH	[GWh]	31849	6994	1965	0
Heat LT HW	[GWh]	6322	1605	393	0
Freight	[Mtkm]	0	0	0	21106
Passenger	[Mpkm]	0	0	0	74590

Potentials

We model an independent energy system, limiting the imports of any energetic vector to zero to achieve the goal of security of supply. Therefore all primary energy needs to originate from the studied region, defined by the potentials (Tab. 5). Furthermore, contrary to EP50+, we model the technical potential of the resources, as economic potential is subject to arbitrary and uncertain estimation of future renewable energy markets.

Table 5: Annual resources and renewable energy technologies potential.
The values in brackets for the hydropower technologies correspond to the potential with reinforcement.

Resources	**Waste Fossil**	**Waste Biomass**	**Wood**	**Wet biomass**	**Hydro Storage**
[GWh]	10833	8917	15278	12472	8900
Technologies	**Geothermal**	**Hydro Dam**	**Hydro River**	**PV**	**Wind**
[GW]	4.8	8.08 (8.52)	3.8 (4.65)	67	20
[GWh]	42.08	17.48	19.726	66.4	40.3

3.2. Mono-Objective Optimization

In the first step, every single OF is optimized individually, allowing to determine the maximum value f_{obj}^{min} and f_{obj}^{max} necessary for the normalization in the MOO. The tracking of the OF values on individual optimization is represented in Figure 2. For each optimization, the other OF values are at their maximum value, indicating significant differences in configurations and operations.

By digging into the energy system configurations of the respective individual optimizations via the cost composition (Figure 3), only the cost minimization is distinguished in a major way from the other configurations. The LCIA indicators minimization leads to higher investment costs at an almost equal level, similar to the observation in Figure 2). From the point of view of investments, the main difference is the deployment of massive quantities of PV, reaching the potential of PV (50 GW) in addition to geothermal electricity generation, while the wind share is reduced.

The discrepancy between wind and PV leads to a higher dephasing between the generation of electricity in Summer and consumption and winter, which affects the necessity of installing seasonal storage in the form of

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Figure 2: OFs values comparison for mono-objective optimizations. Each sub-figure corresponds to an individual optimization. The height of the segments corresponds to the OF's relative variation to the 2020 reference scenarios OFs values [%].

natural gas between 7800 GWh-12 450 GWh. Hydro Dams are used in pumping and storing at their respective maximum capacity of 8900 GWh, leading to a combined maximum seasonal storage potential of up to 21 350 GWh.
The switching towards methane storage furthermore affects the service sector; on one side, while biomass still is converted in gaseous energy carriers, the excess electricity is converted into hydrogen via fuel cell technologies, such as SOEC, PEM, or Alkaline Electrolysis for a cumulative electrolysis capacity of 0.6 GW - 2.8 GW.
The additional gas production is transported in the existing methane infrastructure, while only minor investments in the construction of local Hydrogen infrastructure have to be made (0.8 GW-1.4 GW). Therefore, minimizing LCA indicators tends to limit the reinforcement of energy transportation infrastructure to a minimum.

The LCA indicators can be split into indirect (construction) and direct (operation) emissions (Figure 4), where we can identify the highest contributor sectors to the respective OFs. While cost minimization leads to a highly operation-intensive energy system environmental impact, the LCIA OF configurations have a lower impact on the operation side of the technologies and minimize the technologies' constructions individually while reaching the maximum value in the other indicators construction.
The sectors of mobility, hydropower, and electricity generation dominate the LCA indicators. The mobility sector mainly affects the operation, as technologies using methane release CO_2 in operation, which is not captured

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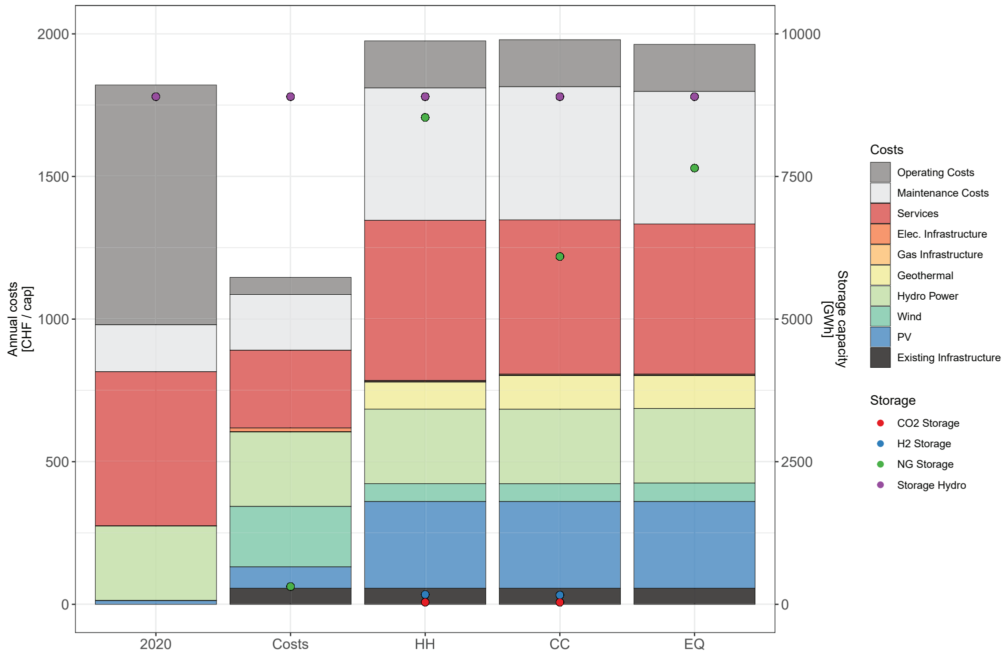

Figure 3: Total costs energy systems composition for mono-objective optimizations. The secondary axis displays the installed storage capacity. Case study Switzerland 2050 independent and CO_2-neutral, without nuclear power.

yet. Methane-powered vehicles are used for road freight transport in the cost minimization, while lower shares of methane-powered fuel cell vehicles in public transport are used in the LCA minimizations.
The hydro dam construction impact significantly impacts the EQ indicator while minimizing CC due to deploying new hydro dams. Differences in the operation between the optimizations can be explained by a different operation strategy of the hydro dams in the cost minimization scenario.
The electricity generation impact is visible on the construction side, where the impacts are shifted to minimize the respective indicator in the optimization. In this category, the concurrence between the installation of new hydro dams for CC minimization, installation of Hydrothermal gasification CHP in the HH minimization, and combined cycle gas turbines for the EQ minimization is visible, as the respective technologies have a minor impact on the specific indicator and similar impacts in the other ones.

3.3. MOO

Running the multi-objective optimization (Equation 17) 500 times results in 500 different configurations. The comparison between those configurations has been made by generating the Pearson correlation coefficient matrix of the technologies and the OFs. Figure 5 represents the main renewable energy resources installation capacities. In the upper half, clear correlations between technologies and between OFs are visible. The biggest correlation is between the OF cost and PV $r = 0.94$, indicating that further installing PV leads to higher total costs, or vice-versa; the more money is available, the more PV is installed. A high negative correlation is visible between geothermal power and wind ($r = -1$), as geothermal power is only installed as a backup to the missing wind. Lower correlations are visible between PV and EQ ($r = -0.61$) and between PV and HH ($r = -0.53$). This negative correlation can be interpreted as the lower the indicator; the more PV must be installed.
Meaningful correlations $r \geq 0.5$ between OFs can only be observed between costs and EQ ($r = -0.56$) and HH ($r = -0.55$), respectively, showing a negative correlation between the environmental indicators and the costs. The weak correlation between costs and climate change can be explained by the analyzed case study, modeling a carbon-neutral energy system, where CO_2 emissions highly contribute to the CC indicator.

The lower half represents the scatter plot of the different solutions. Observing the Pareto-front between the environmental indicators is possible when taking the total cost column. The points outside the Pareto-front are due to low weighting on the cost indicator. The strong correlation between cost and PV can be observed, as the points almost perfectly line up on $E^{PV}[\mathrm{GW}] = \frac{20}{3}[\frac{\mathrm{GW}}{\mathrm{GCHF}}] \cdot C^{tot}[\mathrm{GCHF}] - 91.7[\mathrm{GW}]$ between 15 GW-35 GW.

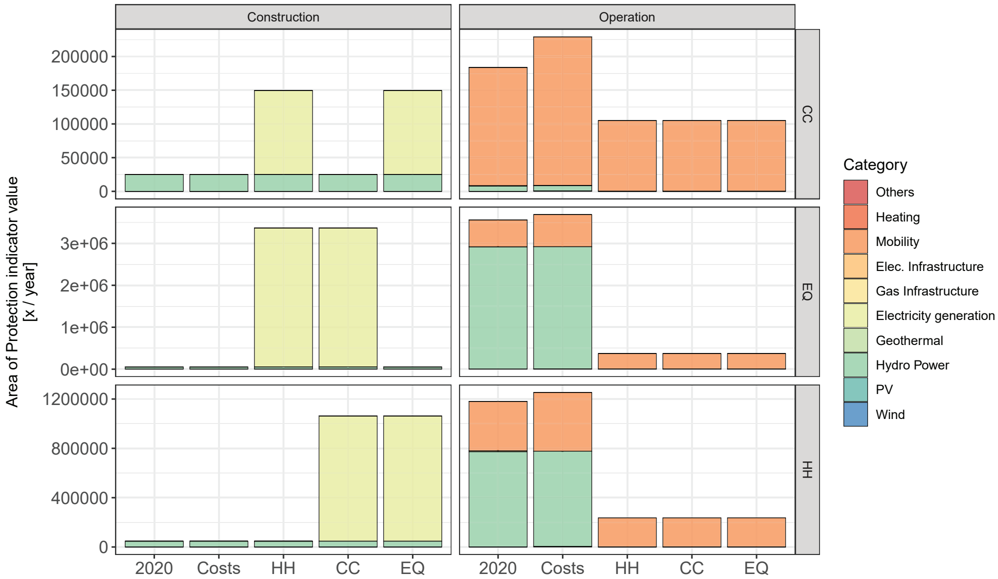

Figure 4: LCIA impacts composition for mono-objective optimizations. The secondary axis displays the installed storage capacity. Case study Switzerland 2050 independent and CO_2-neutral, without nuclear power.

Observing the other scatter point patterns in the LCA indicator columns allows us to identify the reason for the low correlation: The point distributions fill out the observed area in a well-distributed pattern, generated by the Monte Carlo method (Eq. 18).
Comparing the effect of the primary renewable resources, we can observe that PV is generating a Pareto-curve for all OFs; generating an upper border for PV, which is validated with the positive correlation, a lower horizontal border with CC and concave lower borders for the EQ and HH indicators.
Wind (20 GW) and geothermal (0 GW) are almost constant throughout the scenarios, except for only three outliers can be identified, installing 16 GW (-4 GW) of wind, which is compensated by 0.8 GW of geothermal power. This low variation also explains the low correlation validity ρ between those two technologies and the other indicators.

4. Conclusion

This work generated an LCIA database of technologies within a global energy system by characterizing over 200 technologies. This database allowed us to assess the impact of the energy system on environmental indicators by integrating their impact directly into the optimization rather than post-calculating it. The integration was achieved by splitting the LCIA impact into direct (operation) and indirect (construction) emissions related to the installation and use of the technologies within the global energy system MILP model EnergyScope.

The results have been generated by applying the framework to the case study of a CO_2 neutral and energy-independent Swiss energy system 2050. The individual optimizations show different configurations, where the economic and environmental burden is shifted to the other indicators depending on the objective. Independent of the scenario, the deployment of high shares of renewable energy in the form of PV, wind, hydropower, and biomass gasification is observed. The scenarios are distinguishing, in the end, uses sector, where different mobility types for long-distance public and freight mobility are selected: While cost-optimization prefers to reinforce the electric distribution grid, environmental aspects limit the reinforcement to a maximization of the use of existing infrastructure, leading to the gasification of the mobility sector.

The correlations between the main renewable technologies and the OFs are strongly dominated by economic optimization, drawing Pareto-fronts. The quantity of PV installed depends on the weight put on the environmental indicators, where the economic optimum is located at 16 GW. In contrast, more substantial weights on the LCA indicators lead to more deployed PV and higher costs. Wind and Geothermal energy stay constant, with some outlier exceptions ($< 0.6\%$), which needs further investigation with more runs. While low correla-

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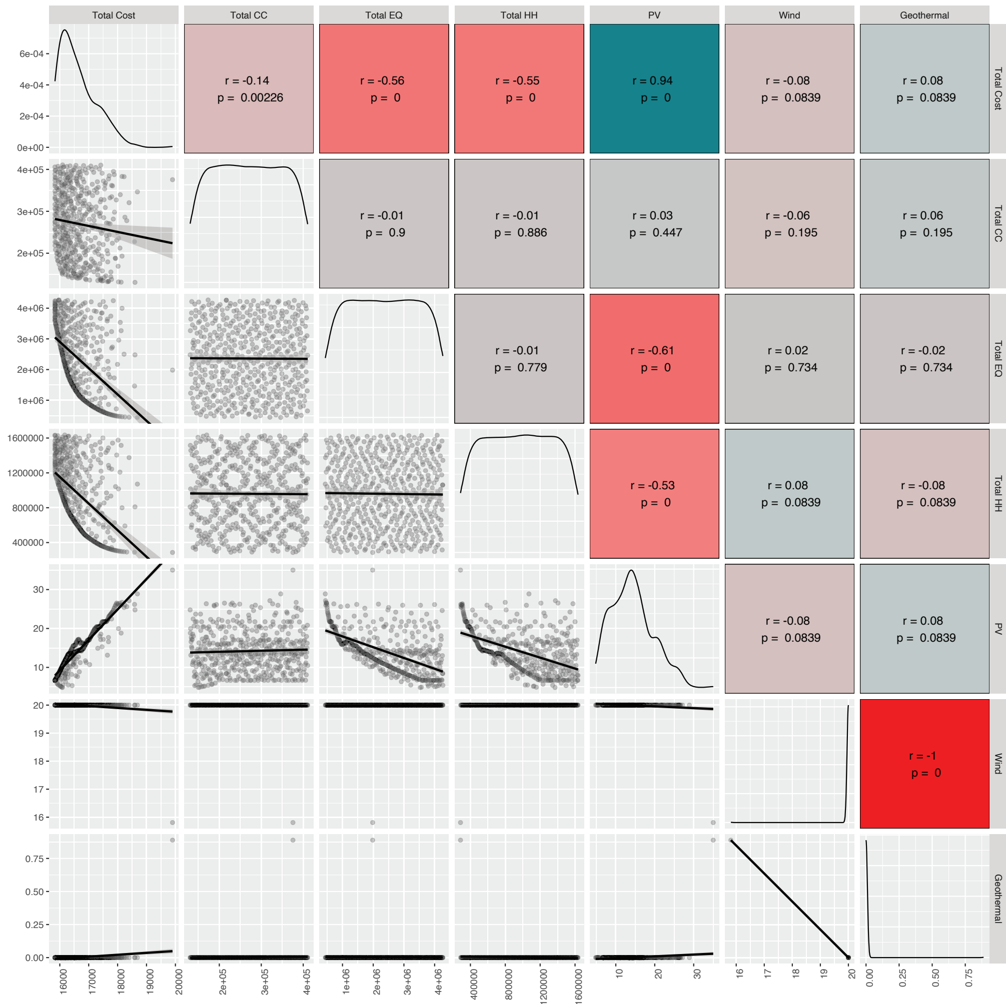

Figure 5: Pearson correlation coefficient matrix. The upper triangle depicts the correlation factor *r* with the color gradient and the significance *p* with the transparency. The diagonal depicts the distribution of the appearance of the individual variables. The lower triangle represents the observation distribution with the corresponding trend line and confidence interval.

tions between the LCA indicators are observed, the negative correlation between environmental impact and additional costs could be assessed, except for the climate change indicator, which is intrinsically integrated into the case study for carbon neutrality, where the carbon emissions are highly affecting the CC indicator.

While already general conclusions on the effect of economic and environmental indicators through the deployment of renewable technologies have been drawn, further work needs to be done in (i) separating the effect of double-counting in impact analysis by assessing the impact of midpoints, including resource depletion, endpoints and areas of protection, (ii) validating the multi-objective approach on economic optimization under parametrized environmental variables to generate the LCA-indicators Pareto-fronts, (iii) identifying the most-optimal solutions by applying multi-criteria decision methods, (iv) dig deeper in correlations between all technologies and the different indicators, and (v) identify typical energy system configurations by applying suitable clustering methods.
Further improving the methodology is necessary to (vi) remove the double-counting of energy system internal flows throughout scopes II and III. While, for example, electricity has been removed from the operational phase of using a heat pump, the construction phase still uses electricity based on the current energy system. The identification of those flows will allow the definition of a prospective LCA database coupled with the energy system.

Based on this paper's database and modeling framework, points (i)-(v) are subject to a future publication in preparation. Point (vi) is subject to a research project over several years in collaboration with CIRAIG.

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Glossary

AoP	Area of Protection
CC	Climate change
EP50+	Energieperspektiven 2050+ [22]
EQ	Ecosystem quality
ES	EnergyScope
GHG	Greenhouse gas emissions
GWP	Global Warming Potential
HH	Human Health
IRENA	International Renewable Energy Agency
LCA	Life cycle analysis
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
MILP	Mixed Integer Linear Programming
MOO	MOO
NDC	Nationally Determined Contributions
OF	OF
PV	Photovoltaic
WAVH	Water availability impact on human health

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