How Far Can Life Cycle Assessment Be Simplified? A Protocol to Generate Simple and Accurate Models for the Assessment of Energy Systems and Its Application to Heat Production from Enhanced Geothermal Systems

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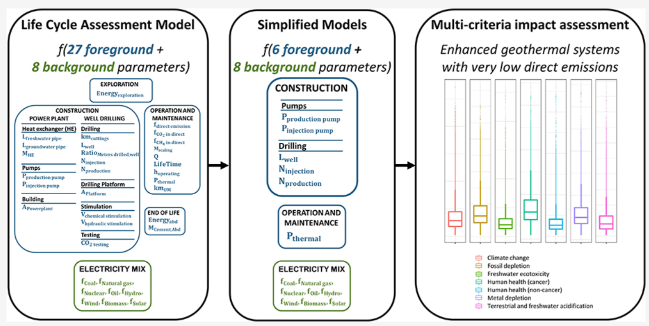
ABSTRACT: Life cycle assessments (LCAs) quantify environmental impacts of systems and support decision-making processes. LCAs are however time-consuming and difficult to conduct for nonexperts, thus calling for simplified approaches for multicriteria environmental assessments. In this paper, a five-step protocol is presented to generate simplified arithmetic equations from a reference parametrized LCA model of an energy system and its application illustrated for an enhanced geothermal system for heat generation with very low direct emissions in continental Europe. The simplified models estimate seven environmental impacts (climate change, freshwater ecotoxicity, human health, minerals and metals, and fossil resources depletion, and acidification) based on six technological parameters: number of injection and production wells, power of the production and injection pump, average well length, thermal power output, and eight background parameters defining the European electricity mix. A global sensitivity analysis identified these parameters as influencing the variance of the environmental impacts the most. Ensuring the representativeness of the reference LCA model and the validity of the simplified models requires thorough assessment. This protocol allows to develop relevant alternatives to detailed LCAs for quick and multicriteria environmental impact assessments of energy systems, showing that LCAs can be simplified to system-specific equations based on few, easily quantified, parameters.



KEYWORDS: *simplified models, global sensitivity analysis, environmental impact, multicriteria, parameterized LCA, geothermal heat, geothermal plant*

1. INTRODUCTION

Renewable energy is expected to be a major contributor to greenhouse gas (GHG) emission reduction in the energy sector within 2030−2050.[1] One source of renewable energy is the thermal resource stored in the Earth's subsurface, the geothermal energy, whose lower global technical potential reaches 117.5 EJ/year,[2] representing 1/5th of the world's energy supply in 2015.[3]

Among the different geothermal technologies, enhanced geothermal systems (EGSs) improve the permeability of an underground reservoir to circulate geothermal fluid and produce heat and/or electricity. The EGS could cover 5% of the global heat demand by 2050,[2,4] supplying not only heat (<100 °C) for residential or district heating systems but also superheated heat (up to 150−200 °C) for industrial applications (petrochemical or agricultural industry), thanks to its wider deployment potential compared to other technologies and the continuous nature of the heat supplied.

In addition, the exploitation of geothermal energy emits less GHG emissions than its fossil fuel counterparts,[5−7] potentially contributing to reducing the 40% of global CO_2 emissions linked to heat production.[8] Such statements rely on life cycle assessment (LCA), a standardized methodology to estimate different potential environmental impacts of a technology or product throughout its entire life cycle.[9] While the standardization of the LCA methodology has broadened its use, conducting an LCA still requires expert knowledge on the process[10] and methodological choices.[11,12] In addition, collecting system-specific data to ensure the LCA accuracy is time-intensive.

At the same time, LCAs are increasingly required by authorities as decision support when planning new energy system developments.[13−15] The need for representative and

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accurate LCAs of different energy pathways counterbalanced with the difficulty of conducting extensive and harmonized LCA calls for novel tools for a wider and easier application of LCA, particularly by non-LCA experts.[10]

Already Curran and Young (1996)[16] advocated for a simplification of LCA methodologies. Recently, Gradin and Björklund (2021)[17] categorized different simplifications methods for LCA from over 500 articles. The simplified parametrized models presented here fit into categories (4) and (7): surrogate data are used to estimate the environmental impacts from specific model components (4) when they contribute only slightly to the overall impacts' spread (7). They even overcome one of the limitations stated in,[17] by using a robust methodology to identify the inventory flows contributing the most to the impact and thus allowing conducting complete multicriteria LCAs without extensive inventory data gathering.

A simplified parametrized model is an arithmetic equation estimating one potential environmental impact of an installation from only few parameters. Its development relies on the identification of key technology-specific parameters. Different techniques exist to choose these key parameters.[18] Here, we apply a global sensitivity analysis (GSA) to identify, from probability distribution functions of all parameters defining the model, the ones driving the spread in the impact the most. A Monte Carlo simulation of the probability distributions of these parameters is performed to vary simultaneously all parameters and quantify with the Sobol' indices their contributions to each environmental impact's variance.[19] The generation of simplified models based on GSA was initiated by Padey et al. (2013)[20] and extended to better account for uncertainty in the inputs' variability.[21] Currently, simplified models exist to estimate the climate change impacts of medium-sized onshore wind turbines in Europe[20] and the EGS for electricity production in central Europe.[22]

GSA finds other application in LCA than the generation of simplified models[23] in the context of prospective LCAs.[24,25] However, overall, only few studies linking Sobol' GSA and LCA exist and even less present simplified models for the estimation of environmental impacts.[23,26−28] In addition, these simplified models estimate only climate change impacts of energy technologies despite the importance of other impacts, such as human health,[29] land use,[30] or resource depletion.[31] The focus on the climate change impact is very likely a result of the increased awareness around this issue since most studies do not reflect on the choice of the impact. Developing simplified models for additional impact categories is therefore essential to ensure a multicriteria assessment of energy producing pathways.

The aim of this paper is to revise and generalize the methodology initiated by Padey et al.[20] to develop a protocol to generate simplified models for a multicriteria environmental assessment of energy systems and to apply it to quantify potential environmental impacts of heat production by EGSs. The name "protocol" is hereby understood as a set of steps to follow to generate simplified models for the environmental assessment of energy systems.[32]

2. METHODS

The protocol to generate simplified models estimating the potential environmental impacts of energy systems is based on a global sensitivity analysis (GSA) and combines long-lived experience with previous developments.[20] This protocol consists of (1) definition of the scope of the study, (2) modeling of the reference LCA model and validation with the literature, (3) identification of the key input variable parameters, (4) generation of one simplified model per impact category and validation with the literature, and (5) description of the applicability domain of the simplified models with an optional iterative adjustment of the scope of the study (Figure 1). Its application relies on a Python library, *lca_algebraic*

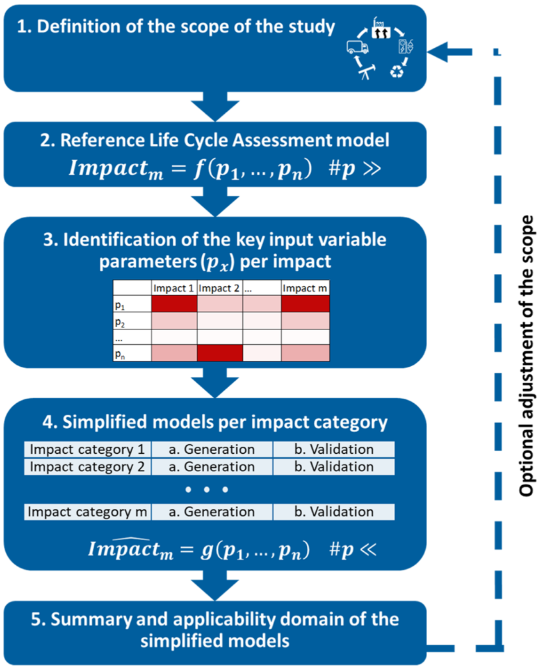

Figure 1. Graphical representation of the protocol used to generate the simplified models estimating the potential environmental impacts of an energy system. $Impact_m$ represents any impact category chosen to be assessed by a simplified model, p_1 to p_n are the parameters required to assess the chosen impact, #p is the number of parameters which is smaller for the simplified model compared to the reference life cycle assessment model, $Impact_m = f(p_1 \dots p_n)$ describes the equation of the reference LCA model to estimate the impact category $Impact_m$, and $\widehat{Impact}_m = g(p_1 \dots p_n)$ is the equation of the simplified model to estimate the impact category $Impact_m$.

v0.12,[33] developed within the INCER-ACV project (ADEME, grant no.1705C0045) as a layer above Brightway2,[34] which ensures fast computation of all the statistical analyses presented in the protocol.

2.1. Definition of the Scope of the Study. The technological, geographical, and temporal features of the type of energy system for which the simplified models should be developed are characterized. To ease the development of the reference LCA model, we recommend to identify a representative energy generating installation (REI) of the energy system, either an existing installation or a hypothetical one with average values obtained from a set of the existing installations. In addition, the LCA methodological aspects, such as the functional unit, background data, and impact categories, should be set. Whenever possible, we recommend to align these choices to the guidelines potentially available to frame LCAs of the studied energy system (e.g., geothermal energy,[12] solar energy,[11] fuel cells,[35] etc.).

2.2. Reference LCA Model. A reference LCA model describing the energy system under investigation (step (1)) is defined by modeling the inventory flow using parameters with probability distribution functions. Its environmental profile is then generated from Monte Carlo simulations from the set of input variable parameters (p_n in Figure 1). This environmental profile is finally compared to the available literature to ensure the representativeness of the reference LCA model, which conditions the applicability of the simplified models.

The reference LCA model is a parametrization of the chosen energy system: parameters describe each part of it. Such parameterized LCA models are very valuable as they enable a comprehensive LCA modeling based on variable technological, temporal, and geographical parameters. They exist for wind turbines,[36] photovoltaics,[37] or electric vehicles.[38] We recommend to parameterize the energy system based on the REI (step 1) but the inventory flows should still be general enough to adequately represent the energy system. They can rely on scaling relationships[39] or regressions between observed inventory flows and parameters.[40] Equation 1 displays an example of such a scaling relationship, where the mass of a heat exchanger is assumed to scale to the known mass of a heat exchanger according to the ratio of the flows, all representing parameters, p_n, in Figure 1. This type of equations has been used in Section 3 to apply the protocol to EGSs for heat generation. More details on other equations available are provided in Supporting Information, S2.

$$M_{\mathrm{HE,new}} = \frac{Q}{\mathrm{Flow_{known}}} \times M_{\mathrm{HE,RGS}} \tag{1}$$

$M_{\mathrm{HE,RGS}}$ is the mass of the known heat exchanger [kg], $\mathrm{Flow_{known}}$ is the known flow, and Q is the variable describing the flow rate in the considered heat exchanger [t/h], all three representing parameters, p_n, in Figure 1.

Fixed and variable parameters can describe the inventory flows and further characterize the applicability domain of the reference LCA and simplified models. The distinction between variable and fixed parameters is driven by the definition of the scope of the study and their potential influence on the environmental impact's variability. The latter depends on their value range for the studied installation type and their contribution to the environmental impacts: while the transport of small equipment pieces might occur over several kilometers, large value range, its influence on the environmental impacts remains small, thus setting it as a fixed parameter. The whole protocol follows an iterative process, and changing a parameter from a variable to a fixed parameter is possible if its influence on the results' variability appears small.

The fixed parameters are representative values of the studied energy system and might not always be defined explicitly. The variable parameters are defined over a value range with a probability distribution function (pdf). The choice of the pdf should rely on expert's opinions, knowledge from the literature, or observations. In the latter case, the pdf represents the best fit to the observations. Triangular, normal, or beta distributions are examples of pdfs. In case no information is available, we recommend a uniform distribution to ensure equal probability of all values in the set range. Furthermore, some variable parameters might best be defined by a discrete distribution, such as the powering of the drilling rig with either diesel or electricity. Great care should be given to guarantee that the variable parameters are uncorrelated before applying the GSA in Step 3.

2.3. Identification of the Key Input Variable Parameters. A GSA is conducted on the variable parameters to identify the ones with the highest contribution to the variance of the impact categories considered as the ones with the highest first-order Sobol' indices (S_1).[41] The Sobol' method is based on a variance decomposition approach: the first-order Sobol' indices represent the contribution of an individual parameter to the variance, while the second- to ith-order Sobol' indices represent the contribution of a group of 2 to i interacting parameters to the total variance and require a larger number of Monte Carlo (MC) iterations to ensure their robustness. The sum of the S_1 can be lower than 1, indicating that interactions between parameters explain some of the variance.[41] However, to our knowledge, the contribution to variance due to interactions is minor, so that the S_1 is sufficient to analyze the contribution to variance with GSA. In practice, the Sobol' indices are computed from a sufficient number of MC simulations conducted from realizations of the variable parameters, as displayed in eq 2. The number of MC simulations is sufficient when the statistics and S_1 remain stable.

$$S_1 = \frac{\mathrm{Var}[E(\mathrm{Impact_m}|p_n)]}{\mathrm{Var}(\mathrm{Impact_m})} \tag{2}$$

where $\mathrm{Var}[E(\mathrm{Impact_m}|p_n)]$ describes the variance of one impact category ($\mathrm{Impact_m}$) due to one parameter (p_n) and $\mathrm{Var}(\mathrm{Impact_m})$ describes the total variance of this impact category.

Besides the S_1 being high, the choice of the key variable parameters for the generation of the simplified model is a trade-off between covering at least 75−80% variance for the considered impact indicator,[22,42] choosing easily determined parameters, and keeping their number low, aiming for 70% less variable parameters compared to their initial number. Applying GSA to each impact category may lead to a different hierarchy or different sets of key variable parameters. The user can then either select a common set of key variable parameters or different ones per impact category and thus per simplified model.

2.4. Generation of One Simplified Model per Impact Category and Validation with the Literature. The key variable parameters identified in step (3) for each impact category are the basis of the simplified models. These models are derived by setting the other nonkey variable parameters to the median of the stochastic simulation, rounding float values, replacing background activities with their impact values, and removing sum terms contributing to less than 1% to the impact. The choice of the median follows current practices.[20] The estimates of the simplified models ($\widehat{\mathrm{Impact}}_{\mathrm{m},i}$) are then compared to the ones of the reference LCA model ($\mathrm{Impact}_{\mathrm{m},i}$) with the statistical coefficient R^2 (eq 3).

$$R^2 = 1 - \frac{\sum_{i=1}^{u} (\mathrm{Impact}_{\mathrm{m},i} - \widehat{\mathrm{Impact}}_{\mathrm{m},i})^2}{\sum_{i=1}^{u} (\mathrm{Impact}_{\mathrm{m},i} - \overline{\mathrm{Impact}}_{\mathrm{m}})^2} \tag{3}$$

where u represents the number of realizations of the stochastic simulations, $\mathrm{Impact}_{\mathrm{m},i}$ represents the value obtained for the impact category $\mathrm{Impact_m}$ with the reference LCA model, $\widehat{\mathrm{Impact}}_{\mathrm{m},i}$ represents the value obtained for the impact category $\mathrm{Impact_m}$ with the simplified model, and $\overline{\mathrm{Impact}}_{\mathrm{m}}$ represents the mean of all obtained values for the impact category $\mathrm{Impact_m}$ with the reference LCA model.

The value for the reference LCA model ($\mathrm{Impact}_{\mathrm{m},i}$) is obtained from a complex equation describing the environ-

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Table 1. Variable Parameters ($p_1...p_n$, n = 35) Used for the Reference LCA Model with the Minimum and Maximum Values[a]

phase	variable parameter name	p_n	default	min	max	unit
electricity mix	share of coal	f_{coal}	0.04	0	1	
electricity mix	share of natural gas	f_{NG}	0.05	0	1	
electricity mix	share of nuclear	$f_{nuclear}$	0.76	0	1	
electricity mix	share of oil	f_{oil}	0.01	0	1	
electricity mix	share of hydropower	f_{hydro}	0.11	0	1	
electricity mix	share of wind power	f_{wind}	0.02	0	1	
electricity mix	share of biomass	$f_{biomass}$	0.01	0	1	
electricity mix	share of solar power	f_{solar}	0	0	1	
power plant	area of the power plant	$A_{powerplant}$	692	400	1200	m^2
power plant	length freshwater pipe	$L_{fw,pipe}$	160	100	300	M
power plant	length geothermal fluid pipe	$L_{gw,pipe}$	200	100	300	M
power plant	mass REI heat exchanger	$M_{HE,RGS}$	92,280	23,070	92,280	Kg
power plant	power production pump	P_{prod}	500	200	1,200	kW
power plant	power injection pump	P_{inj}	0	0	500	kW
exploration	energy for exploration	$E_{exploration}$	282,000	282,000	965,000	MJ
well testing	CO_2 released	$M_{CO_2,testing}$	312,000	0	312,000	Kg
transport	distance for the cuttings	$km_{cuttings}$	50	50	500	km
transport	transport of staff during operation and maintenance	km_{OM}	30	10	50	km
end of life	mass cement for well abandonment	$M_{cement,Abd}$	47,000	25,000	50,000	Kg
end of life	energy for well abandonment	E_{Abd}	1,450,800	772,000	1,500,000	MJ
stimulation	volume stimulated fluid (chemical)	$V_{Chemsti}$	40	40	250	m^3
stimulation	volume hydraulic stimulation	$V_{hydrsti}$	4,200	1,000	5,000	m^3
general	flow rate	Q	306	140	350	t/h
general	operating hours	OH	8,000	5,000	8,500	H
general	lifetime	LT	30	20	40	y
general	thermal power output	P_{th}	22.5	10	40	MW
OM	CH_4 content in gas released	f_{CH_4}	0	0	0	
OM	CO2 content in gas released	f_{CO_2}	0	0	0	
OM	fraction of direct emissions	f_{direct}	0	0	0	
OM	mass scaling	$M_{scaling}$	300	200	500	kg
drilling	area drilling platform	$A_{platform}$	20,000	6500	20,000	m^2
drilling	length well	L_W	2,888	1,300	5,500	M
drilling	ratio meters drilled and well length	$Ratio_{MD,well}$	1.13	1	2	
drilling	number injection wells	N_{in}	1	1	2	
drilling	number production wells	N_{prod}	1	1	2	

[a]They were all assigned a uniform distribution, except for the shares in the electricity mix, which were assigned a beta distribution (Supporting Information, S1). The default value corresponds to the REI.

mental impacts of the studied system based on all parameters defined in step (2). The parameters driving the results' spread the most are then identified to generate equations to estimate the environmental impacts from which $\widehat{\text{Impact}_{m,i}}$ is derived.

The validation of the simplified model consists of (a) identifying in the chosen literature the values of the key variable parameters identified in step 3, (b) running the simplified models with the specific key variable parameter values, and (c) comparing the simplified models' results to the ones published.

2.5. Description of the Applicability Domain of the Simplified Models with an Optional Iterative Adjustment of the Scope of the Study. In this last step, the simplified models developed are summarized and their applicability domain is stated. Beforehand, potentially ill-defined parameters are corrected and the scope is adjusted: variable parameters can be requalified as fixed parameters and the range of the variable parameters adjusted to adapt the models' applicability domain. This iterative process ensures the generality of the model while guaranteeing a good representativeness of the chosen energy system.

3. APPLICATION TO EGSS FOR HEAT GENERATION

The following section depicts the application of the protocol to estimate the environmental impacts of EGSs for heat production with very low direct emissions in continental Europe.

3.1. Definition of the Scope of the Study for EGS Heat Production Systems. The energy system considered entails EGSs for heat production with very low direct emissions built on the European mainland with the technologies available today. The geothermal heat plant of Rittershoffen, a typical EGS for heat generation, was used as REI. This geothermal plant, with an installed capacity of 27.5 MWth, supplies heat to the industrial processes of a starch plant in Beinheim (France) with 100 MWth total thermal needs. It provides, since June 2016, on average, 22.5 MWth and 180 GWh/year of heat to this starch plant.[43] Regular exchanges with the operator during the GEOENVI project ensured a good representativity of the derived model.

The functional unit of this analysis was 1 kWh of produced heat. The background data necessary for the inventory were taken from ecoinvent cutoff v3.6.[44] The results were generated

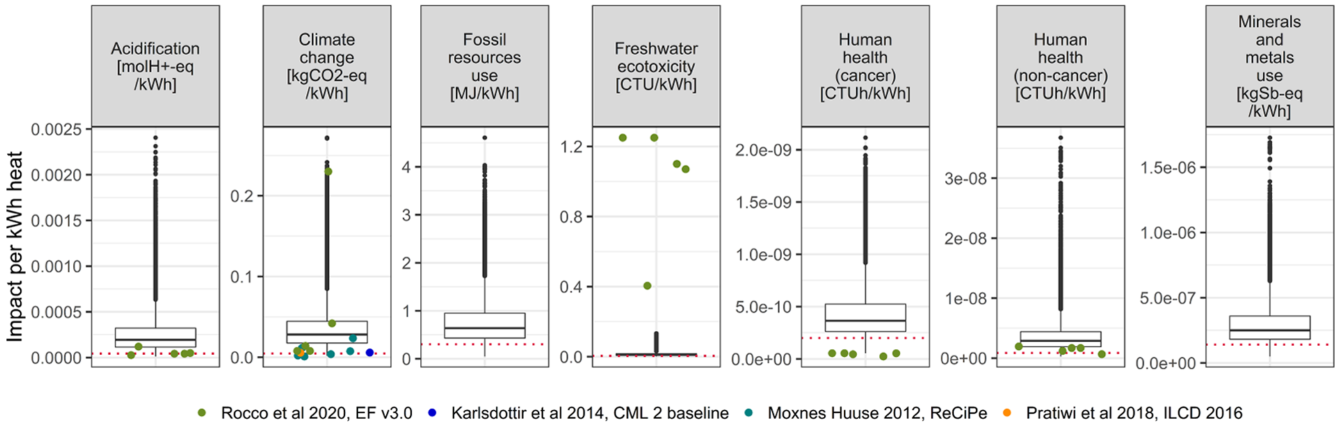

Figure 2. Comparison of the reference LCA model outcomes ($Impact_{m,i}$) (ILCD 2018) to the LCA results reported by Huuse and Moxnes, 2012;[50] Karlsdottir et al., 2014;[49] Pratiwi et al., 2018[43] (only for climate change); and Rocco et al., 2020.[40] In the boxplots, the lower and upper hinges correspond to the 25th and 75th percentiles, while the whiskers extend from the hinge to the value no further than 1.5 * interquartile range from the hinge. The red dashed line represents the outcome of the reference LCA model using default values corresponding to the Rittershoffen geothermal heat plant.

for the ILCD 2018 impact categories of total climate change (referred to as climate change), freshwater ecotoxicity, carcinogenic and noncarcinogenic human health effects (referred to as human health (cancer) and human health (noncancer)), minerals and metal use, fossil resources use, and freshwater and terrestrial acidification (referred to as acidification).[45,46] These impact categories represent $Impact_m$ in Figure 1. The ILCD 2018 impact assessment method was chosen over the Environmental Footprint method because the latter was not available in the Python programming environment used in this paper. The protocol can however easily be reapplied to different impact assessment methods once available.

3.2. Reference LCA Model for EGS Heat Production Systems. The reference LCA model, based on the REI of Rittershoffen, included the construction, operation and maintenance, and end of life phases. The construction included the exploration, well drilling, and power plant construction. The operation and maintenance accounted for the utility and electricity consumptions, equipment replacements, and direct gas emissions. Finally, the end of life describes the well abandonment and waste treatment.

The reference LCA model relied on 35 variable parameters, p_n in Figure 1, listed in Table 1, and 47 fixed parameters (Supporting Information SI, S2). Among the 35 variable parameters, eight were background parameters describing the shares of the eight electricity sources defining the tailormade European electricity mix used to power the equipment during the operation phase. The electricity consumption during the operation and maintenance phase of a heat generating power plant contributes, namely, between 20[43] and 90%[40] to the climate change impact category if a French or European electricity mix is used. Modeling a tailormade electricity mix thus enlarges the applicability domain of the simplified models to installations connected to any current and future power grid supplying electricity in Europe. The beta distributions assigned to the shares of each electricity source, namely, rely on observed (2000, 2005, and 2010) and forecasted (2030, 2040, and 2050) shares for the 28 EU countries[47,48] (Supporting Information, S1). We made sure that the sum of the electricity technologies always amounts to 1.

The other variable parameters are foreground parameters, specific to the geothermal category, defined by uniform distributions because more precise data were lacking. The transport of the materials was assumed to occur over 500 km with a 16−32 metric ton lorry of category EURO4. It was not included as a variable parameter because it was assumed to be similar across installations over continental Europe. The modeling of the inventory of the core modules of the reference LCA model relies on scaling relationships to the REI, regression equations,[40] and representative values for the geothermal installation type based on the parameters listed in Table 1 and further detailed in Supporting Information, S2.

The 35 variable parameters included in the reference LCA model are summarized in Table 1 together with the default value from the REI.

Snippets of codes illustrating the modeling of certain elements with *lca_algebraic* are shown in Supporting Information, S3.

The outcomes of the reference LCA model were compared to results for heat producing geothermal plants: the Hellisheidi plant in Iceland,[49] the Rittershoffen geothermal heat plant (results from a previous study),[30] a heat power plant located in Norway modeling different types of electricity mix and electrical and diesel drilling,[50] and from averaged results issued from the aggregation of different geothermal heat plant clusters.[40] This comparison gives a first sense check, in the absence of LCA results matching the methodological assumptions and technological details, even if these studies rely on different impact assessment techniques, ecoinvent database versions, and system boundaries. The confidence in our reference LCA model was further increased by comparing the deterministic outcomes of the reference LCA model when using default values of the REI (Rittershoffen) to the results obtained in Pratiwi et al. (2018).[43]

3.3. Identification of the Key Input Variable Parameters for EGS Heat Production Systems. In this third step, a GSA based on 360,000 iterations was conducted on the 35 variable parameters with the function *incer_stochastic_dashboard* () of *lca_algebraic* (Table 1) to identify, using the S_1, the ones with the highest contribution to the variance of the different impact categories.[41]

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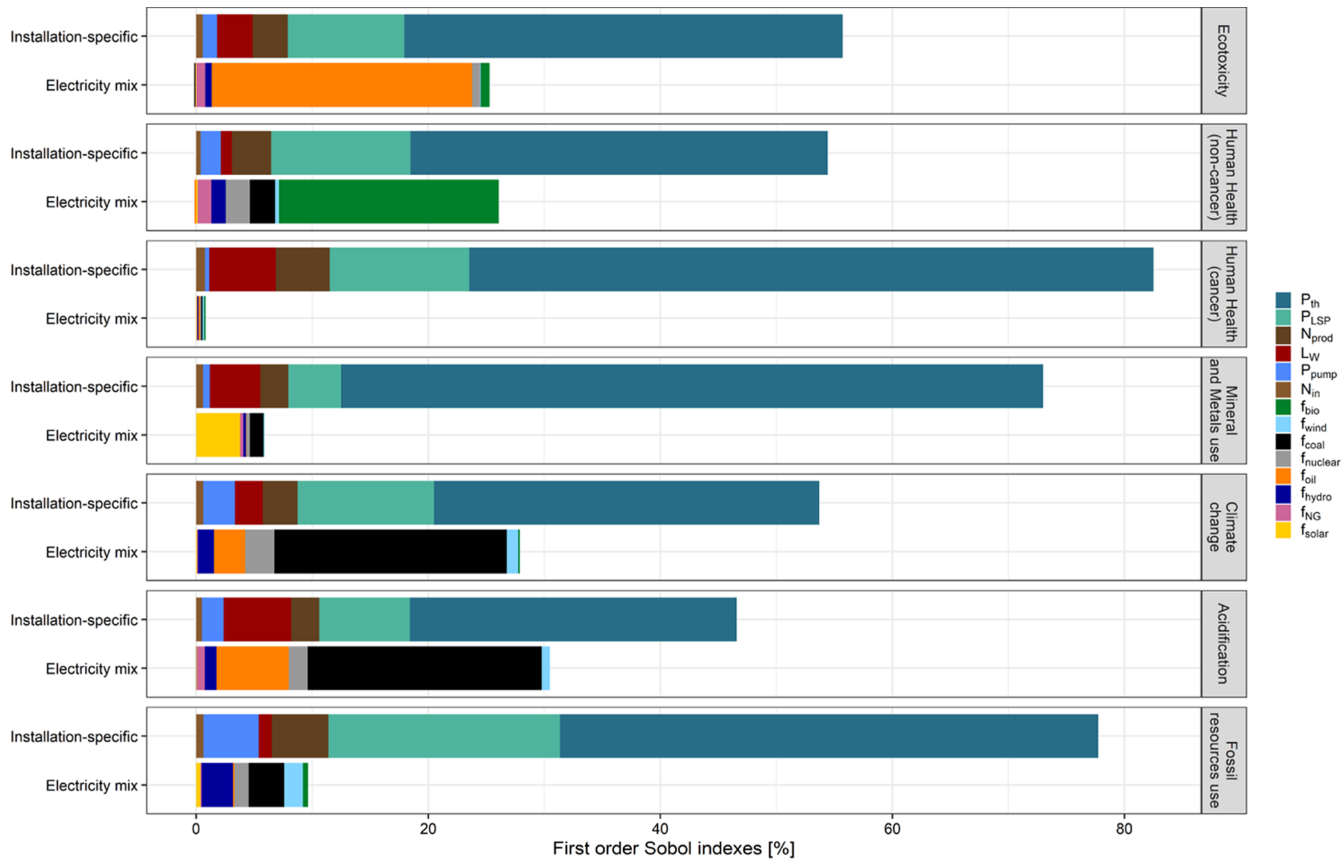

Figure 3. First-order Sobol' indices (S_1) [%] for the key input variable parameters (p_1...p_n in Figure 1) classified as variable parameters specific to the electricity mix (background) and the installation-specific variable parameters (foreground) shown for all seven impact categories. The first-order Sobol' indices have been presented separately for background and foreground parameters for the sake of visualization, and they are summed to compute the total variance contribution.

3.4. Generation of the Simplified Models for EGS Heat Production Systems. Once the simplified models were generated using the *simplifiedModel()* function of *lca_algebraic*, their performance was tested against one publication corresponding to their applicability domain, formalized in step (5).[43]

4. RESULTS

The Monte Carlo simulation results are presented here, together with the main contributors to the impacts and the simplified models' generation.

4.1. Environmental Impacts of an EGS for Heat Production with Very Low Direct Emissions. Figure 2 shows the MC results of the seven ILCD 2018 impact categories for the reference LCA model of the EGS for heat generation with very low direct emissions after varying the 35 variable parameters over the ranges defined in Table 1. The corresponding values can be found in Supporting Information, S4. The coefficient of variation, meaning the ratio of the standard deviation to the mean value, of the impacts modeled with the reference LCA model ranges from around 53% for minerals and metals use and human health (noncancer), up to 78% for acidification. Applying the reference LCA model to the default values corresponding to the REI led to environmental impacts in the lower range of the MC estimates.

The results reported by the publications representing the same geothermal category are generally in the lower range of the reference LCA model results[40,43,49,50] (Figure 2). The freshwater ecotoxicity impact category is one exception: the impacts estimated by the reference LCA model are 10 times lower than the reported ones.[40] This relates to the different impact assessment methods used (Discussion) (Figure 2). None of the published LCAs of the same geothermal category estimated impacts on the fossil resources use and minerals and metals use.

The outcomes of the reference LCA model with the default values corresponding to the REI were compared to the ones of a published LCA model of the Rittershoffen EGS heat plant.[43] The direct deterministic comparison, assuming electricity shares of the French ecoinvent electricity mix, a 25 years' lifetime, and using the same ILCD version (ILCD 2016 instead of ILCD2018) led to absolute differences between 6 and 57% (Supporting Information, S5). Adjusting the amount of diesel used for drilling, the electricity required during maintenance, and the electricity mix used to model the operation and maintenance phase to the values and processes of the published model[43] reduced the absolute differences in the outcome for all impact categories to 0.2−7%, except for freshwater ecotoxicity (57% difference) and human health (cancer) impact (21% difference) (Supporting Information, S5).

We analyzed the contributions of life cycle stages and processes to the impact category results using the default values of the variable parameters. The exploration phase had a negligible (<1%) influence on the outcome, while the plant construction phase and the operation and maintenance phase

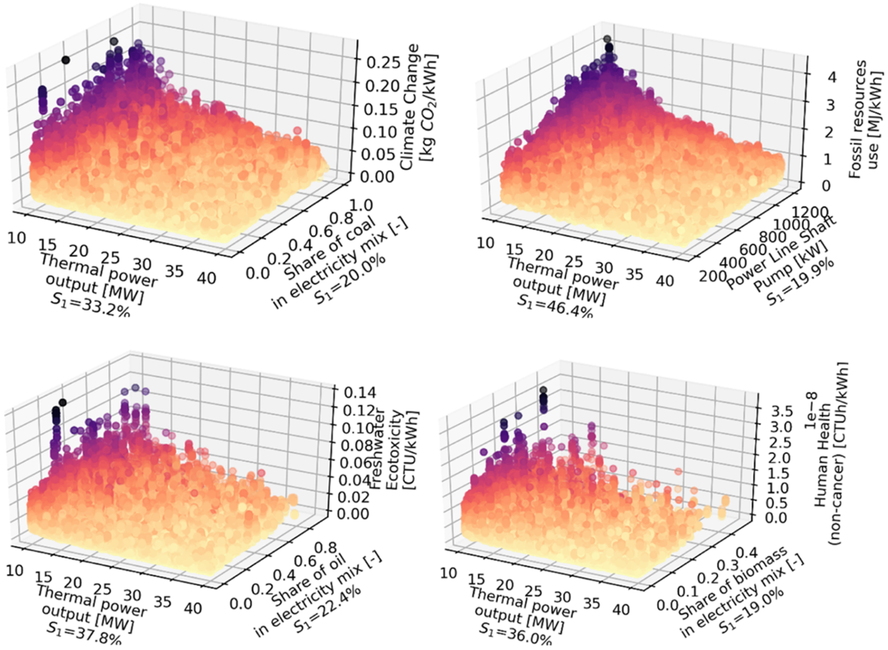

Figure 4. 3D plots displaying how the climate change, fossil depletion, ecotoxicity, and human health (noncancer) impact categories results ($Impact_m$ in Figure 1) vary according to the two variable parameters ($p_1 ... p_n$ in Figure 1) with the highest first-order Sobol' indices. For each impact category, the first-order Sobol' index (S_1) is also listed on the graph per parameter.

explained more than 60% of the impacts for all impact categories. The plant construction phase entails the actual building and the equipment needed for the heat transfer such as the heat exchangers. The end of life, driven essentially by the landfilling of cuttings and scalings, contributed between 5 and 7% to the freshwater ecotoxicity and human health impacts. Metals influenced up to more than 40% of the freshwater ecotoxicity, human health cancer and noncancer, and the acidification. The chemicals used throughout the life cycle of the installation contributed to less than 10% of the total impacts, except for minerals and metals use (18.7%) (Supporting Information, S6).

4.2. Identification of the Key Input Variable Parameters. The key input variable parameters and their S_1 are shown in Figure 3, while the S_1 for all variable parameters are reported in Supporting Information, S7.

The following six foreground variable parameters, explaining between 46.6 and 83.7% of the total variance of the seven impact categories, were used in all seven simplified models:

- power output, P_{th},
- power of the production pump (line shaft pump), P_{prod},
- power of the injection pump, P_{inj},
- number of production and injection wells, N_{prod} and N_{in}, and
- well lengths, L_W

The operating hours and installation's lifetime explained between 3 and 5% of the variance for the human health (cancer) and the minerals and metals use but were not kept for the definition of the simplified models.

In addition to these foreground variable parameters, the eight background variable parameters related to the electricity mix explained more than 25% of the total variance for freshwater ecotoxicity, human health (noncancer), climate change, and acidification and between 1 and 7% for the other three impact categories. They were still included in all simplified models to have a single set of variable parameters explaining 78−92% of the total variance.

Figure 4 displays how the climate change, fossil resources use, freshwater ecotoxicity, and human health (noncancer) impacts vary depending on the two variable parameters with the highest S_1. In all cases, the higher the thermal power output, the lower the impact. The climate change impact increases with higher share of coal-based electricity in the tailormade electricity mix, like the freshwater ecotoxicity and human health (noncancer) impacts increase with increasing fraction of oil-based and biomass-based electricity, respectively. The fossil resources use increases with higher power of the line shaft pump. The figures for the other three impact categories can be found in Supporting Information, S8.

4.3. Simplified Models of EGSs for Heat Generation with Very Low Direct Emissions. The generated simplified models based on the six foreground and eight background parameters identified in step (3) showed a good overlap with the estimates of the reference LCA model with R^2 values ranging from 85.1% for minerals and metals resource depletion up to 99.1% for fossil resources depletion. The comparisons between the predictions of the simplified model and the reference LCA model are provided in Supporting Information, S9. The simplified models estimating each impact from the 14 variable parameters chosen are displayed in eqs 4 to 10. The impact categories represent $Impact_m$ in Figure 1, and the symbols refer to the parameters ($p_1 ... p_n$) listed in Table 1.

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Climate change

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[0.0588f_{biomass} + 1.28f_{coal} + 0.434f_{NG} \\ + 0.917f_{oil} + 0.0624f_{solar}] + 5.06 \times 10^{-9}[3.28 \times 10^{3}N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}790.0 \times 10^{0.000397\cdot L_W + 2.04} + 276.0L_W \\ + 28.2{L_W}^{1.05} + 58.5{L_W}^{1.22} + 25.9{L_W}^{1.23}\end{gathered}\right) \\ + 7.27 \times 10^{6}]\end{gathered}}{P_{th}} \quad (4)$$

Fossil resources use

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[0.689f_{biomass} + 15.4f_{coal} + 7.81f_{NG} + 13.4f_{nuclear} \\ + 11.1f_{oil} + 0.915f_{solar} + 0.204f_{wind}] + 5.01 \times 10^{-9}[4.7 \times 10^{4}N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}1.05 \times 10^{4}\cdot 10^{0.000401\cdot L_W + 2.04} + 3.86 \times 10^{3}L_W \\ + 461.0{L_W}^{1.05} + 839.0{L_W}^{1.22} + 128.0{L_W}^{1.23}\end{gathered}\right) \\ + 5.21 \times 10^{7}]\end{gathered}}{P_{th}} \quad (5)$$

Minerals and metals use

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[7.07 \times 10^{-7}f_{biomass} + 2.56 \times 10^{-6}f_{coal} \\ + 1.92 \times 10^{-7}f_{hydro} + 1.03 \times 10^{-7}f_{NG} + 5.01 \times 10^{-7}f_{oil} + 8.54 \times 10^{-6}f_{solar} \\ + 1.6 \times 10^{-6}f_{wind}] + 5.06 \times 10^{-9}[11.3N_{in} + 0.105N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}0.000727 \times 10^{0.000402\cdot L_W + 2.04} + 0.0237L_W + 0.000756{L_W}^{1.05} \\ + 0.00097{L_W}^{1.22} + 0.00014{L_W}^{1.23}\end{gathered}\right) \\ + 414.0]\end{gathered}}{P_{th}} \quad (6)$$

Fresh water ecotoxicity

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[0.309f_{biomass} + 0.0891f_{coal} + 0.0114f_{NG} + 0.0251f_{nuclear} \\ + 0.671f_{oil} + 0.0937f_{solar} + 0.0374f_{wind}] + 5.13 \times 10^{-9}[8.09 \times 10^{5}N_{in} + 7.92 \times 10^{3}N_{prod} \times P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}131.0 \times 10^{0.000395\cdot L_W + 2.04} + 328.0L_W \\ + 202.0{L_W}^{1.05} + 66.4{L_W}^{1.22} + 2.76{L_W}^{1.23}\end{gathered}\right) \\ + 5.53 \times 10^{6}]\end{gathered}}{P_{th}} \quad (7)$$

Acidification

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[0.00211f_{biomass} + 0.00949f_{coal} + 0.000241f_{NG} \\ + 0.00888f_{oil} + 0.000511f_{solar}] + 5.01 \times 10^{-9}[6.42 \times 10^{3}N_{in} + 26.0N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}11.2 \times 10^{0.000398\cdot L_W + 2.04} + 1.82L_W \\ + 0.256{L_W}^{1.22} + 0.0661{L_W}^{1.23}\end{gathered}\right) \\ + 6.17 \times 10^{4}]\end{gathered}}{P_{th}} \quad (8)$$

Human health (non-cancer)

$$= \frac{\begin{gathered}0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot[3.37 \times 10^{-7}f_{biomass} + 6.23 \times 10^{-8}f_{coal} + 2.68 \times 10^{-9}f_{NG} + 3.97 \times 10^{-9}f_{nuclear} \\ + 2.14 \times 10^{-8}f_{oil} + 2.94 \times 10^{-8}f_{solar} + 7.09 \times 10^{-9}f_{wind}] + 4.94 \times 10^{-9}[0.192N_{in} + 0.00144N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot\left(\begin{gathered}1.74 \times 10^{-5}\cdot 10^{0.000395\cdot L_W + 2.04} + 4.04 \times 10^{-5}L_W + 3.52 \times 10^{-5}{L_W}^{1.05} \\ + 1.18 \times 10^{-5}{L_W}^{1.22} + 1.31 \times 10^{-6}{L_W}^{1.23}\end{gathered}\right) \\ + 1.21]\end{gathered}}{P_{th}} \quad (9)$$

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Human health (cancer)

$$= \frac{\begin{array}{l} 0.00113(N_{in}\cdot P_{inj} + N_{prod}\cdot P_{prod})\cdot \\ \quad [3.37\times 10^{-9} f_{biomass} + 2.01\times 10^{-9} f_{coal} \\ \quad + 3.83\times 10^{-10} f_{hydro} \\ + 5.28\times 10^{-10} f_{NG} + 5.95\times 10^{-10} f_{nuclear} \\ \quad + 2.08\times 10^{-9} f_{oil} + 2.21\times 10^{-9} f_{solar} \\ + 2.21\times 10^{-9} f_{wind}] + 5.05\times 10^{-9}[0.0509 N_{in} \\ \quad + 0.000497 N_{prod}\cdot P_{prod} \\ + (N_{in} + N_{prod})\cdot \\ \left(\begin{array}{l} 1.2\times 10^{-6}\cdot 10^{0.000398\cdot L_W + 2.04} \\ \quad + 9.68\times 10^{-6} L_W \\ + 9.78\times 10^{-6} L_W{}^{1.05} + 4.13\times 10^{-6} \\ \quad L_W{}^{1.22} + 6.42\times 10^{-8} L_W{}^{1.23} \end{array}\right) \\ \quad + 0.232] \end{array}}{P_{th}} \tag{10}$$

The simplified model applied for the configuration described by Pratiwi et al.[43] resulted in 4.0 and 4.8 g of CO_2-eq/kWh for the Alsacian and French electricity mixes, respectively, compared to a mean estimate of 5.6 g of CO_2-eq/kWh (min: 4.7, max: 7.1 g CO_2-eq/kWh) (Supporting Information, S9). The French and Alsacian electricity mixes were used here to accurately represent the electricity mix supplied to the EGS considered.

5. DISCUSSION

5.1. Representativeness of the Reference LCA Model.

The comparison of published LCA results for heat generating power plants with the reference LCA model's outcomes was only possible for climate change, freshwater ecotoxicity, human health, and acidification. It showed a relatively good overlap of published and generated results except for freshwater ecotoxicity. Here, the published results were more than 10 times larger than the reference LCA model results.[40] A more conservative approach to estimate the freshwater ecotoxicity impacts is, namely, used in EF v3.0 compared to ILCD 2018. In the ILCD 2018 method, the concentration potentially hazardous for 50% of the ecosystem is the basis for the effect assessment, while it is the concentration potentially hazardous to 20% of the population for the EF v3.0. The latter is therefore lower and more conservative than the former.[51] This stresses the importance of the methodology behind each LCA result.

We investigated the representativeness of the reference LCA model further by comparing its outcomes using default values of the REI (Rittershoffen) to published LCA results.[43] Despite several adaptation steps, such as the use of measured inventory flows instead of equations, differences remained between both models mostly because of the inclusion of the waste treatment in the reference LCA and the differences in the copper manufacturing modeling between the ecoinvent versions used. Putting these differences in the perspective of the reported impact ranges supports a good representativeness of our reference LCA model.

A final check of the reference LCA model was possible by analyzing the parameters contributing to the environmental impacts, setting the reference LCA model's variable to the REI's values. For example, the construction phase, covering the plant construction phase and equipment and the well drilling, contributed to nearly 50% of the total climate change impacts, while the end of life phase did not, as reported by Eberle et al.[52] too. The construction phase, mostly because of the steel requirement, contributed largely (>50%) to all impact categories except climate change and fossil resources use. For these impact categories, the operation and maintenance phase was more influencing because of the electricity requirement, as observed elsewhere.[40,43]

The environmental impacts' comparisons with the literature, the close collaboration with experts from the geothermal energy sector, and the alignment, as far as possible, to the guidelines to conduct LCA of geothermal systems[12] gave confidence in the developed reference LCA model. The rare LCA results published so far matching our methodological and technological assumptions made it however difficult to establish precisely the level of confidence in the model and should be further addressed in future work.

5.2. Applicability Domain of the Simplified Models.

The simplified models rely on six foreground and eight background variable parameters. The six foreground variable parameters are well known to any heat plant operator. The same set of six installation-specific variable parameters was used for all simplified models to ease their application and because all influenced the variability of the impact categories. The good overlap between the estimates of the reference LCA model and the simplified models for the seven impact categories supported our choice of this unique set of variable parameters. The eight background parameters represent the shares of electricity sources: typical values for the European electricity mixes are provided in Supporting Information, S11. The inclusion of a tailormade electricity mix offers a large flexibility and an extended applicability of the simplified models to any continental Europe, an essential feature given the influence of the electricity requirement of the operation and maintenance phase on the outcome of LCA of heat-producing geothermal installations.[40,43]

Applying the simplified model for climate change to the REI led to 10% lower impacts than that reported using the same shares of electricity (Alsacian mix).[43] When compared to the model of the REI, the deterministic climate change impacts of the reference LCA model were also lower than those reported (Supporting Information, S5). The main explanations lie in the underestimation of the energy required for drilling from the regression equations,[40] the lower electricity requirement modeled for the operation and maintenance phase, and the use of a tailormade electricity mix which represents a simplification of the ecoinvent mixes.

The applicability domain of the presented simplified models, derived after some adjustments of the variable parameters' boundaries, can be summarized as follows:

- enhanced geothermal systems for heat generation,
- with very low direct emissions during operation (0.001–0.02 mass fraction of the flow rate),
- located in continental Europe,
- using a diesel-powered drilling rig based on currently common drilling techniques, and

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- connected to the power grid supplying any current or prospective EU electricity mix

In addition, the variable parameters' ranges (Table 1) and the fixed parameters (Supporting Information, S2) should be carefully reviewed before using the simplified models. These models should only be applied when the scope of the study matches the context for which they were obtained. The user should also keep in mind that these simplified models characterize the environmental impacts according to the ILCD 2018 method.

6. CONCLUSIONS AND OUTLOOK

We presented a protocol to generate simplified models for energy systems with the use of a representative energy-generating installation and allowing a multicriteria environmental assessment of the studied system. The protocol has been tested on several energy systems[20,22,53] and could be applied to different impact assessment methods, as long as they are available in *Brightway2*. Some modeling steps could be adapted in the future: (1) the identification of the key parameters could rely on higher-order Sobol' indices in case of many interactions between parameters, (2) the nonkey variable parameters in the simplified models could be set to mean instead of median values or regression equations instead of the ones based on the reference LCA model's structure could be used,[42] and (3) different techniques to derive the simplified models could be investigated such as, for example, fitting a regression model based on the key parameters to the values estimated by the reference LCA model. The current method does not use machine-learning algorithms or regression techniques, potentially promising for the modeling of life cycle inventories[54] or life cycle impact assessment[55]

Besides the protocol, the simplified models presented here are also an important outcome as they estimate the environmental impacts of any EGS for heat generation with very low direct emissions matching the specified applicability domain. They rely on a small number of easily quantified parameters and prevent their user from collecting other variable parameters, which might be more difficult to determine such as the energy required for well abandonment. The presented simplified models are a good alternative to detailed LCAs, but their representativeness needs to be further investigated before they can be applied widely. This was currently not possible because of the limited number of LCA results, so far, for heat generating power plants, the tendency to report only climate change impacts, and the lack of uniformity in the impact assessment methods used in the published LCAs. This investigation could further contribute to extend the scope of the model to hydrothermal heat plants in general. The chemical and hydraulic stimulation influenced only slightly (<0.2%) the different impact categories, but a more thorough assessment is necessary to ensure the applicability of the simplified models to hydrothermal heat plants (Supporting Information, S10). Also, as more information on the EGS becomes available, the choice of uniform distributions for the variable parameters could be refined. The choice of distributions can namely influence the importance of the variable parameters during the sensitivity analysis and therefore also the definition of the simplified models.[21] Finally, the tailormade electricity mix could be refined to include more electricity sources such as geothermal, wave and tidal, and concentrated solar energy or account for regional specificities. Still, the inclusion of this tailormade electricity mix in the simplified model represents a major advantage in the characterization of the environmental impacts of geothermal heat plants (Supporting Information, S1).

In conclusion, we showed that complete parameterized LCAs of energy systems can be greatly simplified with few and easily quantified parameters explaining at least 75−80% of the variance of the environmental impacts. This protocol ensures that these simplified equations represent a multicriteria assessment of the system and proposes strategies for an application across energy sectors. When applied within their applicability domain, these tools can help industrial stakeholders and policy-makers to identify improvement opportunities in a continuously evolving energy transition context.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.0c06751.

> Description of the tailormade electricity mix, modeling of the reference LCA model, snippets of the code showing the use of the *lca_algebraic* library to model the reference LCA model, environmental impacts of the reference LCA model, comparison of the reference LCA model to the published LCA results, contributions of life cycle stages and processes to the reference LCA model outcome set to default values, first-order Sobol' indices, impact category results as a function of the two parameters with the highest S_1, generated simplified models, contribution of the chemical and hydraulic stimulation, and observed and prospective electricity mixes for the EU28 countries (PDF)

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