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Electricity generation technologies: Comparison of materials use, energy return on investment, jobs creation and CO_2 emissions reduction

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ABSTRACT

Shifting to a low-carbon electricity future requires up-to-date information on the energetic, environmental and socio-economic performance of technologies. Here, we present a novel comprehensive bottom-up process chain framework that is applied to 19 electricity generation technologies, consistently incorporating 12 life-cycle phases from extraction to decommissioning. For each life-cycle phase of each technology the following 4 key metrics were assessed: material consumption, energy return ratios, job requirements and greenhouse gas emissions. We also calculate a novel global electricity to grid average for these metrics and present a metric variability analysis by altering transport distance, load factors, efficiency, and fuel density per technology. This work quantitatively supports model-to-policy frameworks that drive technology selection and investment based on energetic-economic viability, job creation and carbon emission reduction of technologies. The results suggest energetic-economic infeasibility of electricity generation networks with substantial shares of: i) liquefied natural gas transport, ii) long distance transport based hard and brown coal and pipeline natural gas, and iii) low-load factor solar-photovoltaic, concentrated solar power, onshore and offshore wind. Direct sector jobs can be expected to double in renewable-majority scenarios. All combustion-powered technologies without natural (biomass) or artificial carbon capture (fossil fuels) are not compatible with a low carbon electricity generation future.

1. Introduction

Currently, our electricity supply chains are material, fuel, and carbon emission intensive, and thereby alter the greenhouse gas (GHG) balance of the planet (Stocker et al., 2013). Substantial world-wide effort is made to decarbonise our energy system, with the aim of a global GHG emission reduction of at least 80% by 2050 (United Nations, 2016; Rogelj et al., 2016). Emissions in the electricity sector need to be reduced to half of current levels by 2030, and with 85% by 2050 to meet a 2° global warming emission reduction target (OECD/IEA and IRENA, 2017). Several electricity sector technology pathways have been modelled individually to achieve a low-carbon electricity system, with varying outcome and accuracy for different technologies, including: hydro-power, thermal- and PV-solar, onshore and offshore wind, biomass, geothermal, nuclear plants, natural gas, and clean coal with carbon capture and storage (Eom et al., 2015; Heard et al., 2017).

Sound technology policy and investment decision making requires apple-to-apple comparisons of individual pathways on the performance of multiple key technology characteristics (Brandt and Dale, 2011). Model based scenario calculations of GHG emissions and financial cost outcomes at a grid level has become standard practice, yet the evaluation of jobs, material use, fuel use, and overall energy costs to deliver energy, defined as the Energy Return on Investment (EROI), is still missing, with only few studies published with insights at the electricity system level (Kucukvar et al., 2017; Raugei and Leccisi, 2016; Jacobson et al., 2015). If jobs, material inputs and EROI are not taken into account, large gaps can result in our understanding of the feasibility of energy scenarios. This way, the following issues remain unresolved: (1) whether the mineral resources are available to build the new energy system (Graedel, 2011); (2) if the speed of required change will be constrained by skills shortages due to additional employment needs (Gabriel et al., 2016); and (3) whether the energy cost of newly invested energy infrastructure will cannibalise upon discretionary energy available to other sectors (Brandt, 2017).

A key reason why these aspects are not typically calculated is that the underlying datasets and the methodology to calculate them, are still evolving. There is not yet a scientific consensus on how metrics should be calculated, thus a wide variety of methods are used with different system boundaries, uncertainties and key parameters, which reduces the robustness and comparability of published values (Cameron and

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Table 1
Technologies and key parameters used in the analysis.

Technology	Acronym	Load Factor (%) Min/Base/Max	Efficiency (%) Min/Base/Max	Fuel Density (GJ/tonne)	Lifetime (years)	(%) Annual Degradation	Parasitic load (%)
Pulverized hard coal	PH-coal	62%	30%/42%/45%	22.0	40	0.16%	5.3%
IGCC hard coal	IGCC-coal	62%	30%/42%/45%	22.0	40	0.16%	11.0%
Lignite coal plant	L-coal	62%	26%/38%/43%	9.0	40	0.16%	9.0%
CCGT baseload	CCGT-bl	62%	38%/50%/62%	48.0	34	0.20%	1.5%
CCGT load following	CCGT-lf	44%	35%/46%/58%	48.0	34	0.20%	1.5%
SCGT peaker plant	SC-peak	8%	22%/32%/50%	48.0	34	0.10%	1.5%
SC-Heavy Fuel Oil peaker	HFO-peak	24%	27%/29%/47%	42.8	34	0.10%	8.0%
Biomass Municipal Waste	Bio-MSW	53%	10%/20%/27%	9.3	25	0.20%	13.0%
Biomass wood pellets	Bio-WP	62%	14%/32%/39%	17.3	40	0.20%	5.0%
EPR gen. III nuclear	EPRIII-nuclear	40%/74%/95%	30%/33%/50%	5,014,000	40	0.20%	4.2%
Geothermal-hydrothermal	Geo-HT	41%/74%/95%	n.a.	n.a.	30	0.20%	7.9%
Enhanced Geothermal	Geo-EGS	41%/74%/95%	n.a.	n.a.	30	0.20%	46.0%
Onshore Wind	On-Wind	14%/22%/60%	n.a.	n.a.	25	0.40%	3.5%
Offshore Wind	Off-Wind	20%/39%/55%	n.a.	n.a.	25	0.40%	0.7%
Hydro-electric Dam	Hyd-Dam	11%/46.4%/95%	n.a.	n.a.	60	0.20%	6.0%
Hydro-electric ROR	Hyd-RoR	30%/46.4%/90%	n.a.	n.a.	60	0.20%	1.0%
Polysilicon Solar-PV	Sol-PV	13.6%/27.5%/39%	14%/17%/24%	n.a.	25	0.50%	1.0%
Solar-CSP trough	Sol-CSP	15%/27%/35%	n.a.	n.a.	30	0.20%	7.2%
CSP trough w 12 h	Sol-CSP-Salt	30%/55%/70%	n.a.	n.a.	30	0.20%	15.0%

Van Der Zwaan, 2015; Jones et al., 2017; Turconi et al., 2013a; Hellweg and Mila i Canals, 2014). Another challenge is the rapid change of parameters in the life-cycle inventory data for particular technologies (Su and Zhang, 2016; Koppelaar, 2016), such as the Energy Return Ratio of solar-PV (Louwen et al., 2016; Ferroni and Hopkirk, 2016; Ferroni et al., 2017; Raugei et al., 2017), GHG emissions of liquefied natural gas (LNG) (Balcombe et al., 2016), job requirements in solar and wind energy supply chains (Cameron and Van Der Zwaan, 2015), and energy inputs and emissions in biomass power generation (Thornley et al., 2015; Thakur et al., 2014; Muench and Guenther, 2013).

Since electricity technology supply chains involve many processes, especially when accounting for downstream material extraction, concentrating and manufacturing, it is imperative to carry out analyses in a standardised, comprehensive, accurate and transparent manner. Poor research practices in the absence of a common standard include: i) incomplete reporting of key parameter assumptions (Koppelaar, 2016), ii) lack of transparently employed technology boundaries (Turconi et al., 2013a), iii) comparisons of metrics based on power plant capacity as opposed to generated electricity (Cameron and Van Der Zwaan, 2015; Lambert and Silva, 2012), and iv) the absence of variability and uncertainty analysis stemming from variation in physical and technology conditions to explore study result differences (Jones et al., 2017).

Consequently, comparisons for single technologies across study results, let alone comparisons between technologies and on their performance, cannot be reliably carried out (Raugei et al., 2017, 2015). Despite these obvious shortcomings, a number of meta-analyses have been published without compensating for differences in system boundaries (Murphy and Hall, 2010; Hall et al., 2014; Murphy et al., 2016). Yet since system boundaries and key parameters in underlying studies are often not accurately reported guesstimates need to be introduced, which introduces the risk of 'apple-to-pear' comparisons (Bauer et al., 2015; Turconi et al., 2013b).

To address these shortcomings and related model-to-policy needs, we developed a detailed bottom-up methodology which is comprehensive in its life-cycle scope, and can be utilised to calculate key performance metrics. Our framework consists of 12 cradle-to-grave life-cycle phases, describing processes and resource flows from raw material extraction to decommissioning, using 4 metrics to assess material, energy, and labour inputs as well as GHG emissions per functional unit of a petajoule (PJ) of electricity output into the local grid at the power plant. These 4 metrics and the life-cycle framework have been uniformly applied on 19 electricity generation technologies, yielding a robust and reliable technology comparison. In addition, this enables us to calculate a novel global average benchmark for each metric. The value can be used for comparison of individual electricity generation technologies, and to compare global electricity sector transition scenarios. Such a comparison helps to understand if a technology or scenario would reduce or increase the value of a respective metric over time if implemented in the energy system. The added granularity allows decision makers, which are using a global scenario perspective, to better rank scenarios and technology options for the overall feasibility of the global energy transition.

Our analysis is based on standardised life-cycle material and energy process methodologies (Brandt and Dale, 2011; Murphy et al., 2016), and incorporate specific data reporting recommendations from previous studies for electricity generation technologies (Turconi et al., 2013a). All calculations are carried out on a bottom-up engineering (physical) basis, also referred to as process chain analysis (PCA), as opposed to using financial values to estimate physical inputs, which can result in aggregation bias (Majeau-Bettez et al., 2016; Weisz and Duchin, 2006). The impact of min-max parameter variability on results was also analysed for transport distances, load factors, power plant efficiency and fuel density. Geographic and supply chain differences are thereby captured by approximation to provide a more accurate understanding of how local technology factors between countries impact results. The presented results do not show values at individual country level but give an approximation. Specific country values are not the scope of this paper, as it would also require study and reporting on grid-level supply-demand analysis and scenario creation for each country (Raugei and Leccisi, 2016), which demands an individual study in its own right, and for which the results presented here are a pre-requisite.

2. Methods

2.1. Technologies, boundaries and metrics

Nineteen electricity generation technologies were selected for the analysis, listed in Table 1, along the technology acronyms used in the article. To capture solar-PV irradiation differences three variants were calculated based on north-Chile, south-Spain, and the United Kingdom, using solar load factors 39.0%, 27.6%, and 13.6% based on 2-axis tracker geo-localized renewable energy data (Pfenninger and Staffell, 2016, 2017). Pipeline and liquefied natural gas (LNG) tanker variants for natural gas power plants were also modelled.

Composite technology estimates were made for the global electricity