

Energy Planning Toward Absolute Environmental Sustainability: Key Decisions and Actionable Insights Through Interpretable Machine Learning

Nicolas Ghuys^a, Diederik Coppitters^{a*}, Anne van den Oever^b, Maarten Messagie^b, Francesco Contino^a and Hervé Jeanmart^a

^a Institute of Mechanics, Materials and Civil Engineering (IMMC), Université catholique de Louvain (UCLouvain), Place du Levant, 2, 1348 Louvain-la-Neuve, Belgium

^b EVERGI research group, MOBI Research Centre, ETEC Department, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium

* Corresponding Author: diederik.coppitters@uclouvain.be.

ABSTRACT

Energy planning models traditionally support the energy transition by focusing on cost-optimized solutions that limit greenhouse gas emissions. However, this narrow focus risks burden-shifting, where reducing emissions increases other environmental pressures, such as freshwater use, solving one problem while creating others. Therefore, we integrated Planetary Boundary-based Life Cycle Assessment (PB-LCA) into energy planning to identify solutions that respect absolute environmental sustainability limits. However, integrating PB-LCA into energy planning introduces challenges, such as adopting distributive justice principles, interpreting trade-offs across PB indicator impacts, and managing subjective weighting in the objective function. To address these, we employed weight screening and interpretable machine learning to extract key decisions and actionable insights from the numerous quantitative solutions generated. Preliminary results for a single weighting scenario show that the transition scenario exceeds several PB thresholds, particularly for ecosystem quality and mineral resource depletion, underscoring the need for a balanced weighting scheme. Next, we will apply screening and machine learning to pinpoint key decisions and provide actionable insights for achieving absolute environmental sustainability.

Keywords: energy planning, life cycle assessment, absolute environmental sustainability assessment, multi-criteria decision making, interpretable machine learning.

INTRODUCTION

Energy planning models serve as tools to support the energy transition, charting cost-effective pathways that meet carbon reduction targets. A limitation of these models lies in the narrow focus on carbon reduction which leads to burden-shifting, where emission reductions inadvertently increase other environmental pressures, like freshwater use. To address this, Life Cycle Assessment (LCA) methods have been integrated into energy models, revealing burden-shifting but providing only relative insights compared to a reference system. A shift toward Absolute Environmental Sustainability Assessment has recently emerged, linking LCA with the Planetary Boundary framework (PB-LCA). However,

integrating PB-LCA into energy planning poses significant challenges [1]. For instance, considering PBs as hard constraints relies on normative distributive justice theories to convert PBs into regional and sectorial thresholds. Alternatively, multi-objective optimization of the PB impacts introduces hard-to-interpret trade-offs, and aggregating impacts into a single objective raises concerns over the weighting scheme.

In this work, we integrated PB-LCA into energy planning. To address the challenges related to decision making under normative distributive justice theories and multiple criteria, we leveraged interpretable machine learning techniques [2]. This allows deriving key decisions and actionable insights from the many quantitative solutions generated.

METHOD

We adopted Energyscope TD [3], a Linear Programming (LP) tool for whole-energy system planning, applied to Belgium. To assess the environmental impact of 24 resources and 111 technologies available, we developed a prospective database using premise [4], aligned with the REMIND-SSP2-1150 scenario for 2020–2050. The impact indicators from EF 3.0 were adopted and scaled by the global carrying capacities, to reflect the share of the global safe operating space occupied by the optimized energy system [5]. The total cost and environmental indicators were combined into a weighted objective function. To avoid fixed subjective weighting, we sampled numerous weighting schemes.

For postprocessing, we applied downscaling methods to determine regional limits for the energy transition (e.g., utilitarian). From the solution set obtained via weight screening, solutions meeting absolute environmental sustainability were identified for each sharing principle. Additionally, we used decision trees [2] and rule lists to identify "must-have" technologies (common choices across solutions) and key decisions (e.g., low bioenergy adoption implies full electrification of low-temperature heating) to reach interpretable insights from the numerous quantitative solutions.

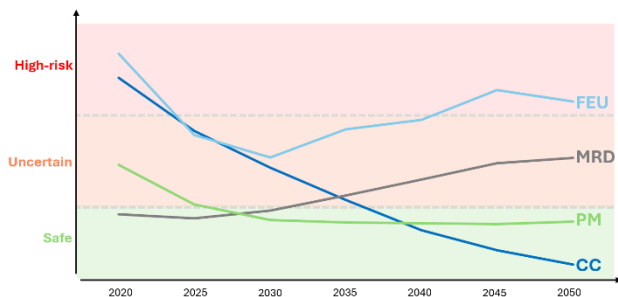


Figure 1. The main environmental impacts for a GWP trajectory reaching zero impact by 2050. CC = Climate change, PM = Particulate Matter, MRD = Mineral Resource Depletion, FEU = Freshwater eutrophication.

PRELIMINARY RESULTS

As a preliminary result, we optimized the energy transition for total cost while constraining the GWP limit to decrease linearly from current emissions to zero by 2050 (Figure 1). The impact on other PB indicators was evaluated a posteriori but not integrated into the objective function at this stage. The results show a reduction in the climate change indicator, reaching a safe operating space by 2040, driven by the phase-out of fossil fuels and increased deployment of renewables and electrification in heating and mobility. Conversely, burden-shifting is observed in Mineral Resource Depletion, which evolves from a safe level in 2020 to an uncertain state from 2030

onwards, driven by the growing reliance on batteries and electric mobility.

PERSPECTIVES

Preliminary results illustrate that while limiting GWP reduces climate-related impacts, it shifts burdens to other indicators. This highlights the need for weight screening and key decision analysis to balance PB reduction targets. Next, all indicators will be integrated into the objective and weight screening will be applied. From the numerous solutions generated, actionable insights will be extracted to guide decision-making.

ACKNOWLEDGEMENTS

N.G. acknowledges the support of the European Union's Horizon 2020 research and innovation programme under grant agreement 101075660 - FEDECOM. D.C. acknowledges the support of the Fonds de la Recherche Scientifique - FNRS [CR 40016260].

REFERENCES

1. Weidner T, Galán-Martín Á, Ryberg MW, et al. Energy systems modeling and optimization for absolute environmental sustainability: current landscape and opportunities. *Comput Chem Eng* 164:107883 (2022)
2. Limpens G, Moret S, Jeanmart H, et al. EnergyScope TD: a novel open-source model for regional energy systems. *Appl Energy* 255:113729 (2019)
3. Baader FJ, Moret S, Wiesemann W, et al. Streamlining energy transition scenarios to key policy decisions. *arXiv preprint arXiv:2311.06625* (2023)
4. Sacchi R, Terlouw T, Siala K, et al. PProspective EnvironMental Impact asSEment (premise): a streamlined approach to producing databases for prospective life cycle assessment using integrated assessment models. *Renew Sustain Energy Rev* 160:112311 (2022)
5. Sala S, Crenna E, Secchi M, et al. Environmental sustainability of European production and consumption assessed against planetary boundaries. *J Environ Manag* 269:110686 (2020)

© 2025 by the authors. Licensed to EUROSIS-ETI acting on behalf of [KU Leuven/BioTeC+](#). This is an open access article under the creative commons CC-BY-SA licensing terms. Credit must be given to creator and adaptations must be shared under the same terms. See <https://creativecommons.org/licenses/by-sa/4.0/>

