Multi-Criteria Energy System Optimization: Costs vs. Critical Materials

Karl-Kiên CAO[1], Lilli M. MARTENS[1,2] (*), Eugenio S. ARELLANO RUIZ[1], Steffen J. SCHLOSSER[1], Jan BUSCHMANN[1], Tobias NAEGLER[1]

[1]German Aerospace Center (DLR), Institute of Networked Energy Systems, Curiestr. 4, 70563 Stuttgart, +49 711 6862 459, karl-kien.cao@dlr.de, dlr.de/ve

[2]Hanze University of Applied Science, Zernikeplein 11, 9747 AS Groningen, The Netherlands

Abstract: The question of future energy infrastructure needs is usually studied with modeling approaches that focus on the capability to cover future energy demands while phasing-out conventional power generation at lowest possible cost. However, common planning approaches consider key technologies and thus needed raw materials as available, if needed. We present a modeling approach where assessable limitations of critical raw material are addressed by a novel energy system optimization model. It uses multi-criteria optimization to identify technology mixes for a continental European power system that are pareto-optimal in terms of system costs and system criticality. Compared to the cost minimum, such power systems show shifts from wind to solar power generation. Furthermore, the technology mix is dominated by single sub-technologies, such as wind energy converters without permanent magnets and lithium iron phosphate batteries.

Keywords: Multi-Criteria Optimization, Critical raw materials, Energy System Optimization Modeling

1 Introduction

1.1 Background

The implementation of a climate-neutral energy supply can be realized by numerous commercially available technologies. Optimization models that determine the technology mix bottom-up on the basis of monetary costs are often used to draft corresponding energy system designs. In this step, the demand and availability of the required raw materials, are usually not taken into account although material bottlenecks can hamper the implementation of required infrastructure measures [1].

An established approach to consider raw material demand for climate neutral energy supply is ex-post analyses of given energy system designs or scenarios [2, 3]. In this way, the risk of bottlenecks in the supply of critical raw materials can be assessed. However, there is no feedback loop that adjusts the technology mix according to such bottlenecks. Therefore, including existing criticality indicators of raw materials into the optimization is an obvious step.

To do this, classical modeling approaches used to design of future energy supply systems need to be adapted. This particularly applies to key technologies, such as wind energy converters, photovoltaics and battery storage. Opposed to state-of-the-art modeling setups the technological resolution of the processed data sets needs to be increased. In other words, instead of grouping technologies that utilize the same energy resource into one investment option, sub-technologies have to be distinguished with respect to the raw materials needed for manufacturing. For example, the wind energy converter technology may be split-up into a group with and without permanent magnets.

1.2 Research Question and Contribution

This brings up the leading research questions we aim to answer: How to model climate neutral energy supply systems that incorporate assessments of critical raw materials? What are the impacts on the resulting technology mix?

Hence, the novelty of the work presented is two-fold: i) the model-endogenous consideration of critical raw materials and ii) the extension of a state-of-the-art data set for energy system optimization. Furthermore, we present a method for multi-objective optimization we have implemented into our modeling framework REMix. With that, we determine pareto-optimal future energy systems on the basis of two criteria: costs and criticality.

2 Methodology

2.1 Data processing workflow

To determine the pareto-optimal technology mix according to these criteria, we use technology specific data that describes both costs and criticality associated to an investment into a certain power generation or storage plant. This data serves as input for an instance of the modeling framework REMix [4]. It is parameterized mainly using a consistent data set for a highly renewable European electricity system [5]. In the following, we refer to this REMix model instance as *RE-Europe*[1]. By performing capacity expansion studies with *RE-Europe* using a multi-objective optimization method, we compute the capacities of renewable power generators and storage units at discrete points of a pareto-front.

2.2 Data

We make use of almost all kinds of data provided in the basic data set [5] and convert it into input files for REMix. In particular, this is the network model that describes the transmission grid of continental Europe, the installed capacities of fossil-fired and hydro power plants with the corresponding operational costs, potential data for the expansion of wind turbines and photovoltaics and their hourly capacity factors, and time series of the electricity demand. Greenhouse mitigation is incentivized by an annual budget or costs for CO_2 emissions, which are set to 50 €/t.

Since we have to extend the technological detail of the model, we introduce the sub-technologies as shown in

Table 1. Other technologies are kept as provided with the basic data set. Although techno-economic data for power generation technologies is well documented in the literature, such

[1] Available at https://gitlab.com/dlr-ve/esy/remix/projects/re-europe

data becomes rare, if it needs to be specific for the sub-technology level. Therefore, we limit the number of considered sub-technologies and make the following assumptions for wind energy converters: We only distinguish two sub-technologies whereas those equipped with a permanent magnet are considered with a surplus of 7% compared to the specific investment costs of wind energy converters without permanent magnet.

Table 1: Sub-technologies considered for multi-criteria generation expansion planning

	Considered sub-technologies	**Investment cost**		**Ref.**
			Investment cost	
Battery storage	lithium iron phosphate batteries (LFP)	58 €/kW	187 €/kWh	[11]
	nickel manganese cobalt (NMC)	58 €/kW	193 €/kWh	[11]
	lead acid (LA)	106 €/kW	190 €/kWh	[11]
	vandadium redox-flow (VRF)	106 €/kW	231 €/kWh	[11]
			Cost surcharge	
Wind Energy Converters (onshore)	with permanent magnet (PMSG)	1359 €/kW	7 %	[12]
	without permanent magnet (EESG)	1270 €/kW		[13]
			Efficiency	
Photovoltaics	Passivated Emitter and Rear Cell (PERC)	771 €/kW	22 %	[14]
	Silicon Heterojunction (SHJ)	694 €/kW	24 %	[14]

Concerning the criticality, we derived mass-weighted criticality scores per functional unit for each sub-technology $c_{subtech}$. This criticality score is derived from raw material proportions used for manufacturing [1] and based on state-of-the-art methods used to assess the criticality of raw materials [6]. It can be approximated as the sum of the criticality scores c_i of the materials i in a functional unit multiplied by specific weights w_i [7]:

$$c_{subtech} = \sum_i c_i \cdot w_i \qquad \textit{Equation 1}$$

In the context of this evaluation, we limit the concept of “criticality” to the likelihood of supply disruption due to the geopolitical supply structure. For the material-level criticality indicator w_i, we use the Supply Disruption Probability indicator published by the European Union [8], and the masses of the materials in a functional unit as the weights[2].

[2] Note that the material-level Supply Disruption Probability indicator by the European Union comprises a substitution index. For the purpose of this analysis, the substitution index was omitted in order to derive a technology-level criticality indicator which does not account for any substitution options.

The reason for defining the criticality score in this way is to determine a total system criticality c by simply summing up the technology specific criticalities. It is defined as

$$c = \sum_{tech} P_{subtech} \cdot c_{subtech} \qquad \text{Equation 2}$$

$$subtech = \{LFP, NMC, LA, VRF, EESG, PMSG\ , PERC, SHJ\}$$

where P_{tech} represents the model-endogenously determined power generation capacity.

2.3 Model and optimization approach

To create the *RE-Europe* model instance the data set from [5] is converted into the required input files for REMix. The corresponding conversion scripts are published open source in [9]. In its basic configuration *RE-Europe* minimizes the total costs for one target year scenario, where all sub-technologies $subtech$ are subject to capacity expansion. To keep computing times and memory demands manageable, the spatial resolution of *RE-Europe* is reduced to country-level, where only cross-border transmission capacities constrain spatial load-balancing. The cost-minimal solution serves as the basis for sub-sequent optimization runs where the total criticality is minimized. However, these runs are constrained by upper bounds on the system costs variable. Therefore, we define pareto points for cost increases of 0.4%, 0.8%, 1.2%, 1.6% and 2% of the minimal system costs observed with the basic model.

3 Exemplary results

The resulting pareto-front with our multi-criteria optimization approach is shown in Figure 1. We observe a typical curve shape where the greatest gains in terms of criticality reduction can be achieved at pareto point 1. Note that the system criticality is dimensionless and not normalized.

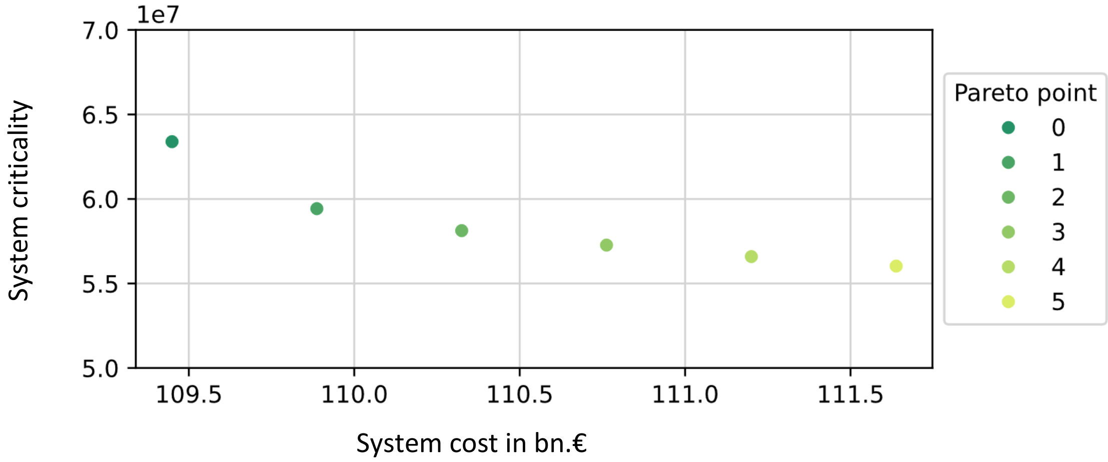

Figure 1: Pareto points with system cost increases of 0.4% (pareto point 1), 0.8% (2), 1.2% (3), 1.6% (4) and 2% (5).

3.1 Storage sub-technologies in a fully renewable system

Figure 2 shows exemplary results of our proof-of-concept with storage expansion planning for battery sub-technologies only[3]. It depicts the technology switch between two battery sub-technologies in terms of annual power generation at minimal system cost and pareto point 5. At an individual country level, we observe partial substitutions of lithium iron phosphate batteries by redox-flow batteries. Further results are as expected: If only the criticality of storage technologies is considered, the total amount of installed units decreases and the missing flexibility is compensated by expensive but slack generation. In other words, situations where demand is not fully served become more.

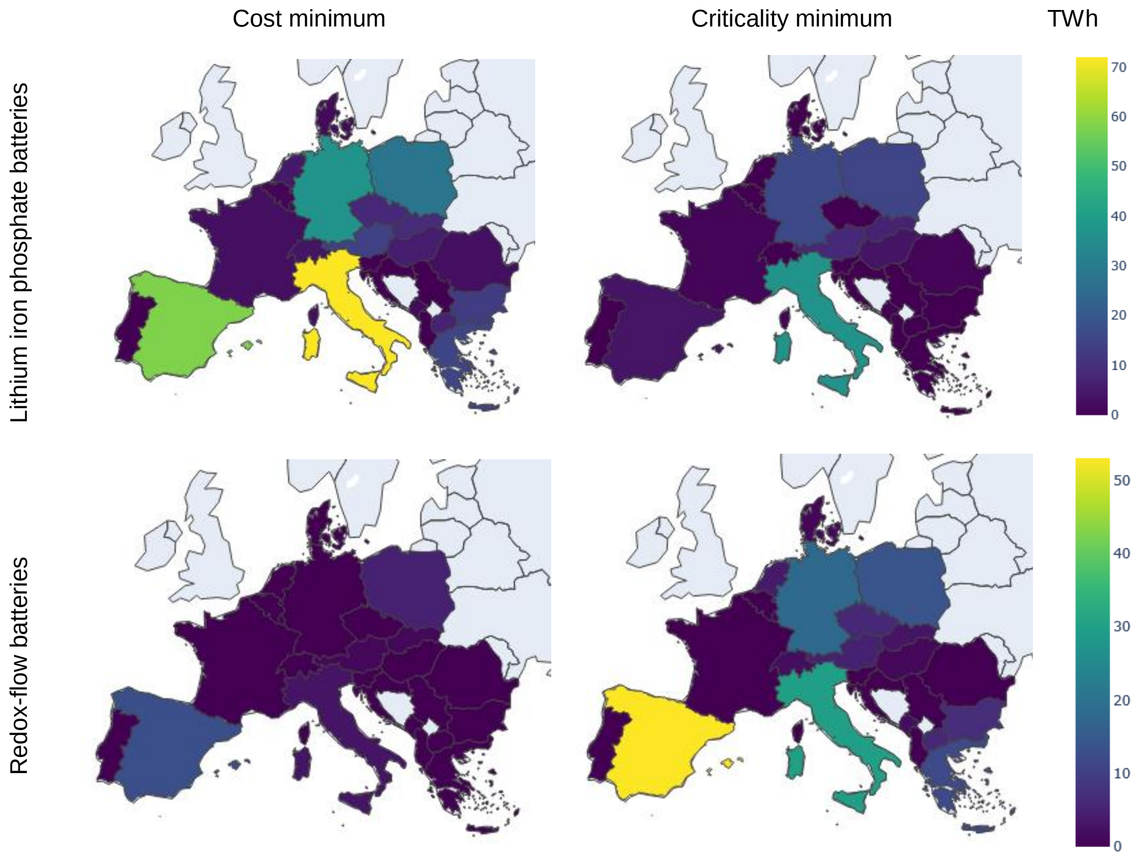

Figure 2: Power generation from lithium iron phosphate batteries (top) and redox-flow batteries (bottom) for energy systems with minimal system cost (left) and minimal criticality for an allowed cost increase of 2% opposed to the cost optimum (right).

3.2 Complete power system with renewable sub-technologies

For Figure 3, the model additionally includes the all sub-technologies for power generation from wind and solar according to Table 1. There is a clear shift in electricity generation from 955 to 798 TWh/a of wind energy to 686 to 813 TWh/a photovoltaics generation. This change is not only taking place in relation to the sub-technologies, but also spatially, as the southern locations (e.g. Spain +28 TWh/a and Italy +26 TWh/a) have significantly better potential for

[3] To enforce the expansion of battery storage RE-Europe is simplified to a fully renewable system where battery storage represents the only option to balance variable renewable power generation.

photovoltaics than Germany, which is dominant in wind energy (46 TWh/a less wind energy production at pareto point 5).

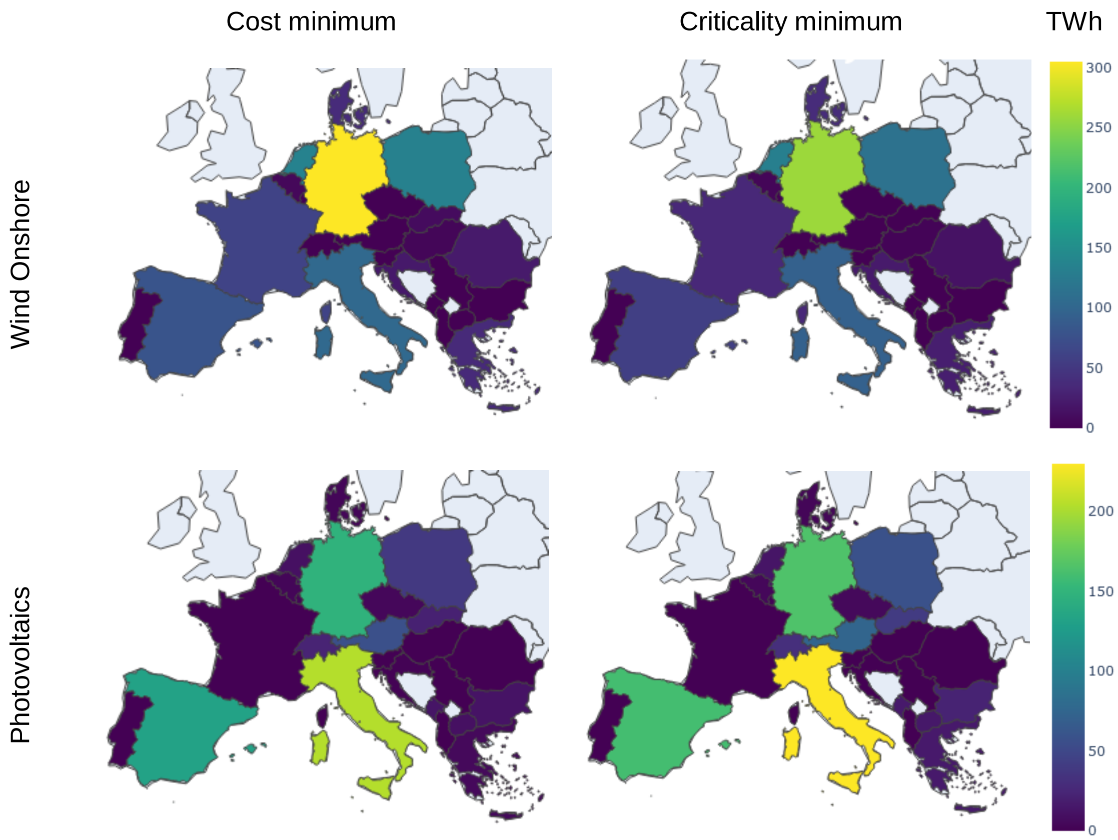

Figure 3: Power generation from Wind Onshore (top) and Photovoltaic (bottom) for energy systems with minimal system cost (left) and minimal criticality for an allowed cost increase of 2% opposed to the cost optimum (right)

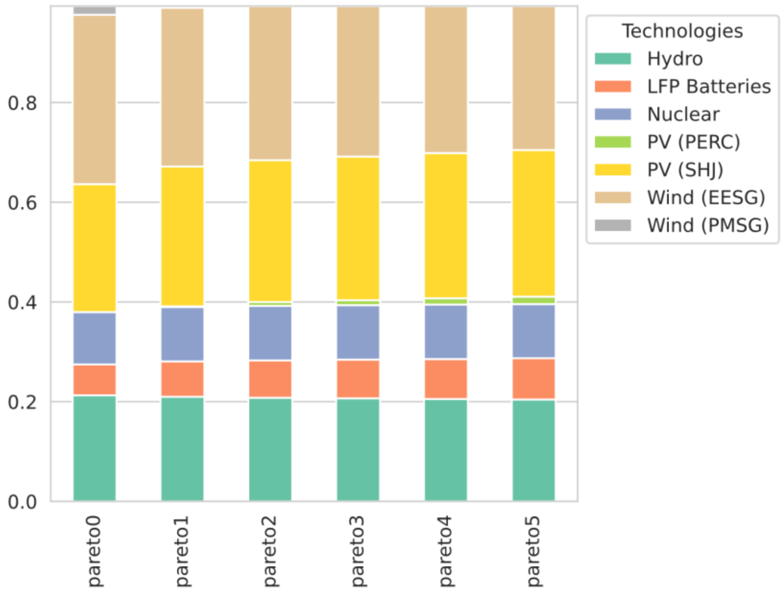

Figure 4: Power generation share of technologies (with >1% share at the cost optimum, pareto0) for five pareto points.

At the sub-technology level, we observe different effects. All technologies are cleary dominated by one technology. This mainly applies to battery storage, where only LFP achieves a share of >1% in the technology mix shown in Figure 4. Solar and wind power generation are dominated by Silicon Heterojunction (SHJ) modules and generators without permanent magnets, respectively. However, at the cost minimum a small share of wind energy converters with permanent magnets is present. Opposed to that, for photovoltaics, the share of Passivated Emitter and Rear Cells (PERC) slightly increases with decreasing system criticality levels.

4 Conclusions

Critical raw materials may hamper the transition towards a climate-neutral energy system. In this study, we presented a novel approach to construct future energy systems that take into account this aspect. For this, we used a multi-objective optimization approach to determine pareto-optimal European power systems based on criticality assessments for battery storage, wind energy converters and photovoltaic technologies. An open-source model instance of the modeling framework REMix - *RE-Europe* - has been created to gain a deeper understanding of the desired energy system designs. In our analyses, we observed two effects: On the one hand, a technology shift from wind to solar power generation, if system criticality is to be minimized. On the other hand, technology classes were dominated by single sub-technologies, such as wind energy converters without permanent magnets and lithium iron phosphate batteries. This indicates that the need for further adaptions of our methodology, e.g., the incorporation of an objective that reflects market risks.

If we extent the model to consider market risks, the multi-criteria optimization will thus be done for three dimensions. This comes at the cost of additional computational effort. Therefore, we consider the implementation of performance enhancement approaches, such as the parallel computation of pareto points. This is particularly possible, if independent grid points can be solved as individual optimization problems. However, we plan to compare pareto-optimal systems determined with further approaches, such as random weighting or sandwiching [10].

Apart of the typical limitations that come with the chosen optimization approach for a single target year, using a set of fixed input parameters, we see space for improvements on the data side, particularly concerning the determination of suitable criticality scores. There are many conceivable aggregation approaches still to be investigated. Nevertheless, with this work we presented a proof-of-concept for identifying energy system designs that are robust against constrained access to critical raw materials.

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