**Supplemental materials for "Bidirectional coupling of a long-term integrated assessment model with an hourly power sector model"**

## S1: Model input data

S1-1: Description of model data

The relevant REMIND exogenous input data consists mainly of technological costs, estimated technology learning rate, standing capacities, total VRE and hydro potential, projections of possible future demographic and economic developments. Historical data for the year 2005 is used to calibrate most of the free variables (e.g. primary energy and secondary energy mixes, as well as standing capacities and traded goods). A full list of input data and their sources can be found in (Baumstark et al., 2021). Notably, resource constraints are taken into consideration, such as the limited nature of fossil fuel and biofuel as well as the limited potential for solar, wind and hydro in a given region in terms of total available potential, capacity factor as well as proximity to demand centers.

We obtain the exogenous DIETER hourly time series input data from the Open Power System Data platform, which collects and provides European electricity market data from official sources (Data Platform – Open Power System Data, 2022). Input parameters consist of hourly time series of German electricity demand, as well as the hourly capacity factor of solar PV, onshore and offshore wind power, defined between zero and one. Both are from the historical year 2019.

As researchers designing global energy climate models, we pay special attention to the openness of our models and data. It is becoming increasingly clear that climate impact and also to a large degree climate mitigation research literature suffers from an "attribution gap" (Callaghan et al., 2021; Monteiro, n.d.), where researchers based in the global south contribute much less to the academic literature. This can be due to a number of factors, and one among them is the high initial cost of investment into climate mitigation and energy transition research, including cost for data access or data collection, cost for purchasing firmwares required by the models and cost for institutional access for academic publishing. The models used in our study are either "partially open" in the case of REMIND, where only certain input data are not freely available, or "fully open" in the case of DIETER, where input data and source-code are freely available. In both cases firmware solvers are used to achieve optimal performances, although in the case of DIETER, there exist also open-sourced free solvers such as Gurobi. Both models are implemented in the General Algebraic Modeling System (GAMS).

S1-2: Costs of various selected technologies.

| **Technology** | **Year** | **Overnight capital cost (2005$/kW)** | **O&M fixed cost (2005$/kW)** | **O&M variable cost (2005$/MWh)** | **Learning rate** |
|---|---|---|---|---|---|
| **Solar PV** | 2020 | 564 | 11.3 | 0 | 20.7% |
| | 2045 | 219 | 4.4 | 0 | |

| | | | | | |
|---|---|---|---|---|---|
| **Wind Onshore** | 2020 | 1343 | 26.9 | 0 | 10.8% |
| | 2045 | 1134 | 22.5 | 0 | |
| **Wind Offshore** | 2020 | 4134 | 12.4 | 0 | 10.8% |
| | 2045 | 1946 | 52.3 | 0 | |
| **Lithium-ion battery** | 2020 | 573 | 0.2 | 0.3 | 15% |
| | 2045 | 367 | 0.1 | 0.3 | |
| **Electrolyzers** | 2020 | 1041 | 52 | 0.3 | 15% |
| | 2045 | 428 | 21 | 0.3 | |

**Table S1: Costs of various selected technologies.**

Overnight capital costs are drawn from various sources (IEA, 2016; Lazard, 2019; IEA, 2019, 2020; De Vita et al., 2018; Strefler et al., 2021; IEA PVPS, 2020; Schmidt et al., 2019; Reuß et al., 2017). O&M fixed costs are usually a fixed fraction of the overnight capital cost. The interest rate is endogenously determined in REMIND and is usually around 4% to 5%. Learning rates of technologies are endogenously given in REMIND. Technological learning takes place globally. Due to high learning rates of these alternative energy technologies, the floor costs (i.e. the lower bound on learned costs) are usually reached well before 2045

**S2: Model results**

Price duration curves (PDCs) are obtained by sorting the hourly electricity price time series. They help identify the price distribution in a year of a future decarbonized power market of a high VRE share.

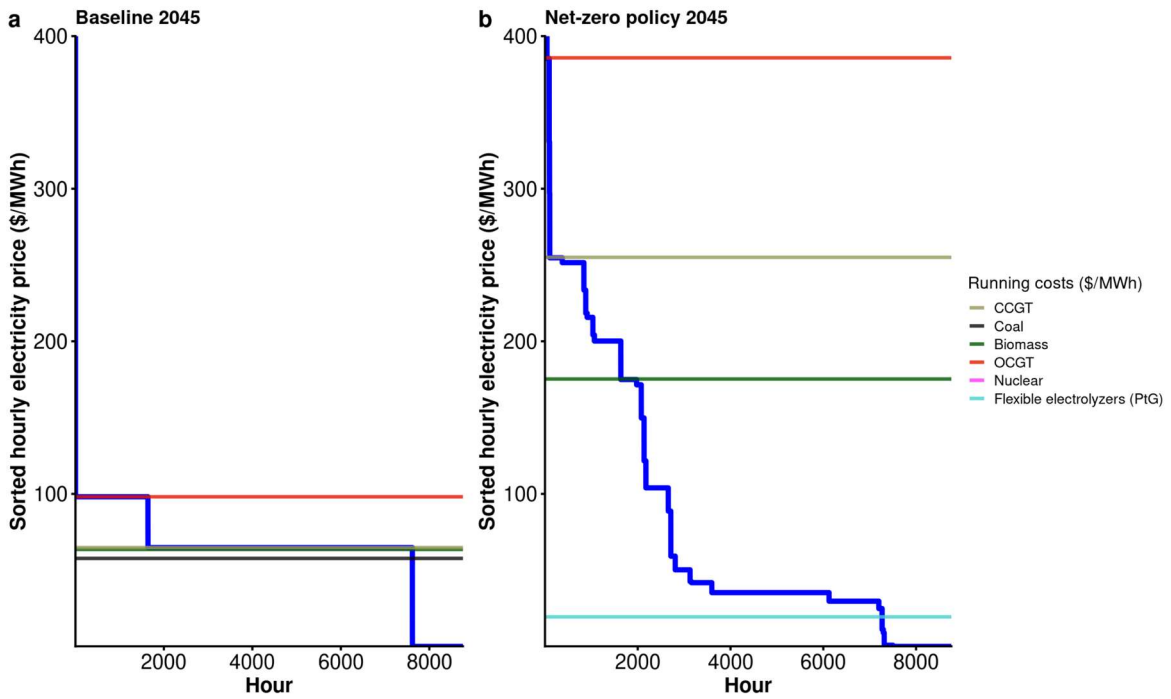


**Figure S1: Side-by-side comparison of PDCs (thick dark blue lines) between (a) baseline without storage or flexible demand, and (b) net-zero by 2045 scenario with storage and flexible demand. Horizontal lines are color coded for the running cost of various generation or flexible demand-side technologies.**

Under baseline without storage or flexible demand (Fig. S1a), because variable generations have close-to-zero running costs, the hourly prices where these generations can meet all of inflexible demand are zero. Without storage, as the generation shares of renewables increases, the number of zero-price hours increases but only to a degree, since for the remaining times of the year in Germany the renewable generation cannot fully meet the demand, leaving CCGT and biomass to set the price of the hours for the majority of the year, at a moderately low level around $65/MWh.

In the Net-zero scenario with storage and flexible demand (Fig. S1b), the shape of PDC is drastically changed. The implementation of storage decreases the number of zero-price hours, and lowers the average annual prices. For around two thirds of the year, the price is at a low level below $50/MWh. However, the distribution of prices under such high shares of renewables looks drastically different – for around 2000 hours, the prices are higher than $100/MWh, and for several hundred hours (around a month) the prices are above $200/MWh. The remaining dispatchable generation such as CCGT with carbon capture and storage (CCS) and biomass act as price-setting in fewer hours, but at much higher prices due to the low capacity factors of these plants (around 200~300$/MWh). For a few hours of the year OCGT is price-setting at close to 400$/MWh. Notably, electrolysis runs on a rather low annual average electricity price (lower than 30$/MWh) due to its complete flexibilization.

**S3: Coupled run when brown-field constraint is not present in DIETER**

Removing standing capacity constraint in coupled DIETER reveals the distortion in DIETER from REMIND, had there been no brown-field constraints. Removing this constraint reduces the degree of convergence not just in near-term but also in more “green-field” periods such as in the 2050s and 2060s. In order to demonstrate this,

we have conducted an additional experiment, where all the setup of soft-coupling remains the same as before in Sec. 4, except that the "brown-field" constraints in DIETER are removed (Fig. S2).

There are some obvious mismatches in the coupling here if most of the quantities are not being exchanged. The first mismatch is for the 2020-2030 period, especially, brown-field and near-term constraints are implemented in REMIND, but these constraints are not identical in DIETER. The best estimate from DIETER of the mix is based purely on a rather low CO2 price, where by this information alone it seems to vastly underestimate existing wind generation. The second one is the total absence of hydroelectric generation after 2030. This is likely due to the long life-time of these plants (~100 years), which already exist in Germany. In REMIND, the brown-field constraints mean that the model gets the plants "for free". In DIETER, not seeing this "free standing capacity", does not see an economic case for hydro due to its high cost compared to other generators (see Fig. 7(a)), leading to distortions also in the medium and long-term of the cost-value structure. The slightly higher electricity price of REMIND in the medium to long term encourages more solar deployment, because its lower cost is on average more competitive. This is in line with what we observed in Fig. 4-5 where REMIND tends to have higher solar shares than DIETER.

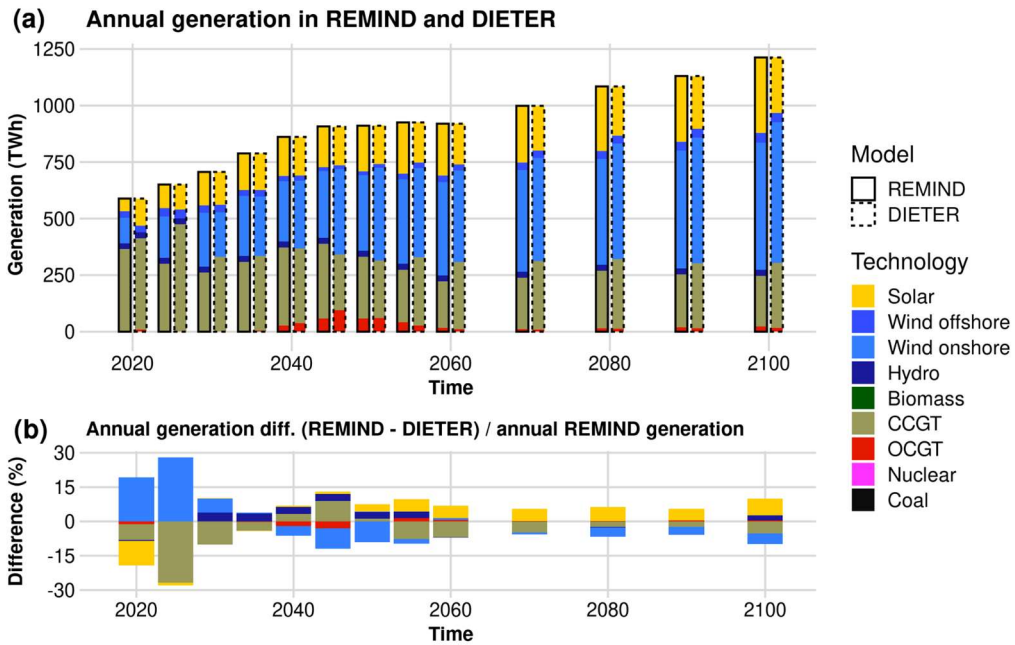


**Figure S2: Generation mix at final iteration of a coupled run where standing capacity constraint (c8) in DIETER is removed. No additional change in configuration from the baseline run presented in Sec. 4 is implemented. (a) Side-by-side comparison of the two models' generation portfolio at the end of the coupled run. (b) The difference between the two models as a share of total generation. Due to the large discrepancies in early years, the convergence criteria is removed from the algorithm, such that the coupled run halts as soon as REMIND internal Nash iterations converge. (Wind offshore capacity is still fixed, so excluded from this experiment.)**

## References


Data Platform – Open Power System Data: https://data.open-power-system-data.org/renewable_power_plants/2017-02-16, last access: 22 January 2022.

Baumstark, L., Bauer, N., Benke, F., Bertram, C., Bi, S., Gong, C. C., Dietrich, J. P., Dirnaichner, A.,

Giannousakis, A., Hilaire, J., Klein, D., Koch, J., Leimbach, M., Levesque, A., Madeddu, S., Malik, A., Merfort, A., Merfort, L., Odenweller, A., Pehl, M., Pietzcker, R. C., Piontek, F., Rauner, S., Rodrigues, R., Rottoli, M., Schreyer, F., Schultes, A., Soergel, B., Soergel, D., Strefler, J., Ueckerdt, F., Kriegler, E., and Luderer, G.: REMIND2.1: Transformation and innovation dynamics of the energy-economic system within climate and sustainability limits, Geosci. Model Dev. Discuss., 1–50, https://doi.org/10.5194/gmd-2021-85, 2021.
Callaghan, M., Schleussner, C.-F., Nath, S., Lejeune, Q., Knutson, T. R., Reichstein, M., Hansen, G., Theokritoff, E., Andrijevic, M., Brecha, R. J., Hegarty, M., Jones, C., Lee, K., Lucas, A., van Maanen, N., Menke, I., Pfleiderer, P., Yesil, B., and Minx, J. C.: Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies, Nat. Clim. Change, 11, 966–972, https://doi.org/10.1038/s41558-021-01168-6, 2021.
De Vita, A., Kielichowska, I., Mandatowa, P., Capros, P., Dimopoulou, E., Evangelopoulou, S., Fotiou, T., Kannavou, M., Siskos, P., Zazias, G., De Vos, L., Dadkhah, A., and Dekelver, G.: Technology pathways in decarbonisation scenarios, ASSET project, 2018.
IEA: World Energy Outlook 2016, International Energy Agency, Paris, France, 2016.
IEA: Offshore Wind Outlook 2019, IEA, Paris, 2019.
IEA: World Energy Outlook 2020, IEA, Paris, 2020.
IEA PVPS: TRENDS IN PHOTOVOLTAIC APPLICATIONS, International Energy Agency, Paris, 2020.
Lazard: Lazard's Levelized cost of energy analysis-version 13.0, 2019.
Monteiro, S.: Sustainable Solutions for the Global South in a Post-Pandemic World, 84, n.d.
Reuß, M., Grube, T., Robinius, M., Preuster, P., Wasserscheid, P., and Stolten, D.: Seasonal storage and alternative carriers: A flexible hydrogen supply chain model, Appl. Energy, 200, 290–302, https://doi.org/10.1016/j.apenergy.2017.05.050, 2017.
Schmidt, O., Melchior, S., Hawkes, A., and Staffell, I.: Projecting the Future Levelized Cost of Electricity Storage Technologies, Joule, 3, 81–100, https://doi.org/10.1016/j.joule.2018.12.008, 2019.
Strefler, J., Kriegler, E., Bauer, N., Luderer, G., Pietzcker, R. C., Giannousakis, A., and Edenhofer, O.: Alternative carbon price trajectories can avoid excessive carbon removal, Nat. Commun., 12, https://doi.org/10.1038/s41467-021-22211-2, 2021.