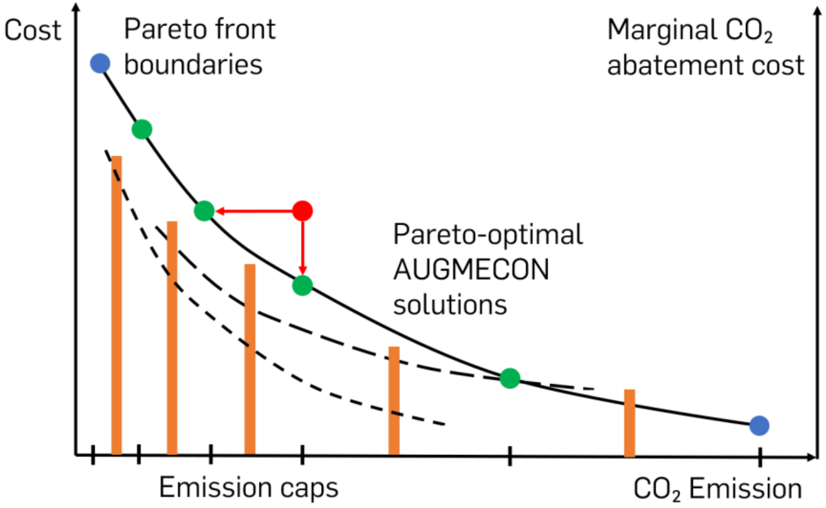

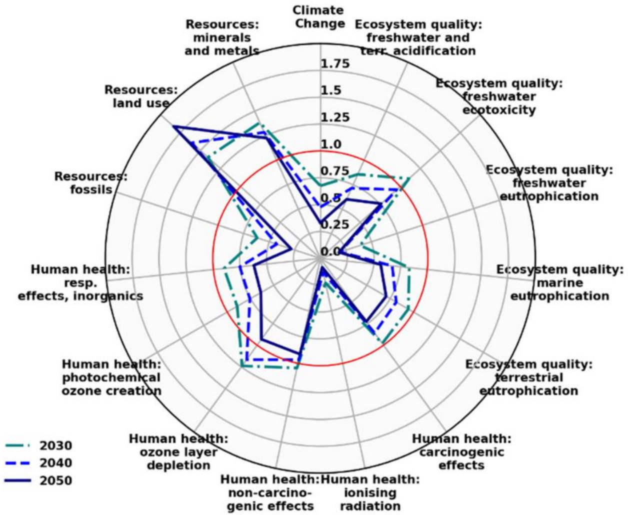

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IMPLEMENTING THE AUGMENTED EPSILON-CONSTRAINT METHOD FOR MULTI-OBJECTIVE OPTIMISATION OF ENERGY SYSTEMS

Chair of Energy Systems & Energy Economics

Jonas Finke, Valentin Bertsch # 02.09.2021 # OR 2021 Bern # jonas.finke@rub.de

Agenda

- Introduction
- Implementation
- Case Study
- Conclusion & Outlook

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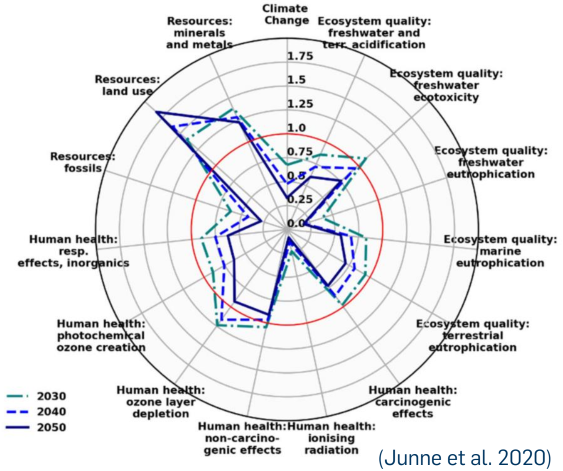
Introduction

Why Energy System Modelling?

- Energy sector transformation to mitigate climate change
- Structural changes
  - Intermittent renewables increase flexiblility requirements (temporal, spatial and sectoral)
  - Increased number of stakeholders
- Energy system models provide insights and support complex decisions

Why Multiple Objectives?

- Conflicting interests have to be balanced
- Environmental sustainability is multi-criteria concept in itself
- Feasible and “interest-optimal” scenarios to support decisions

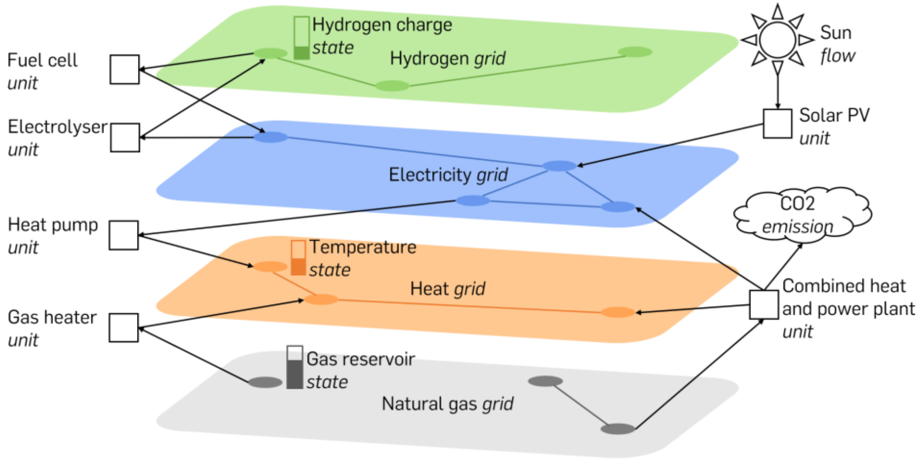


(Junne et al. 2020)

Bertsch and Fichtner, *A participatory multi-criteria approach for power generation and transmission planning*, Annals of Operations Research 2016.
Junne et al., *Environmental Sustainability Assessment of Multi-Sectoral Energy Transformation Pathways: Methodological Approach and Case Study for Germany*, Sustainability 2020.

Energy System Optimisation Framework Backbone

- Network Model
  - Highly adaptable structure
  - Various energy carriers and sectors
  - Flexible spatial and temporal resolution
  - High technological detail
  - Stochastic modelling
- Optimisation
  - Investment and operational planning
  - Cost minimisation
  - Various constraints
- Open Source



$$v^{\text{obj}}_{\text{BB}} = \sum_{f,t} p^{\text{probability}}_{f,t} \cdot \left(v^{\text{vomCost}}_{f,t} + v^{\text{fuelCost}}_{f,t} + v^{\text{startupCost}}_{f,t} + v^{\text{shutdownCost}}_{f,t} + v^{\text{rampCost}}_{f,t} + v^{\text{stateCost}}_{f,t} + v^{\text{penalties}}_{f,t} \right) + v^{\text{fomCost}} + v^{\text{unitInvestCost}} + v^{\text{lineInvestCost}}$$

Helistö et al., *Backbone – An Adaptable Energy Systems Modelling Framework*, Energies 2019. See also https://gitlab.vtt.fi/backbone/backbone.

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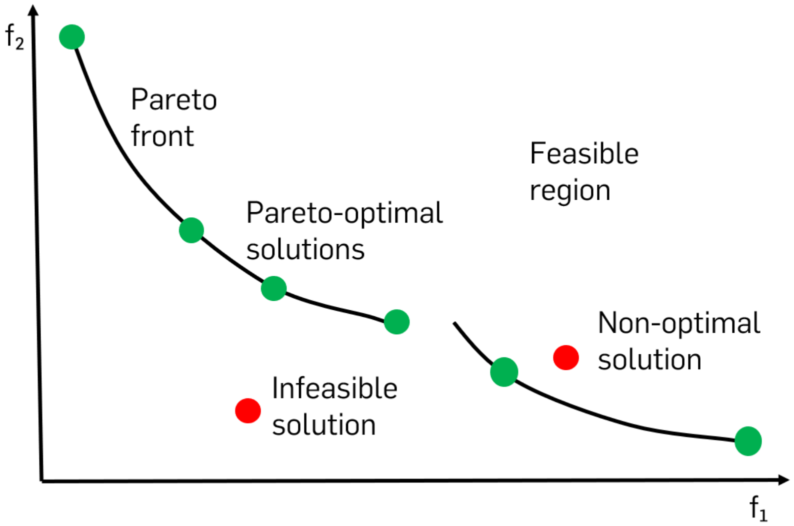
Multi-Objective Optimisation – General Principles

- Consider simultaneous optimisation of multiple real objective functions
- Notion of optimum: set of Pareto-optimal solutions, the so called *Pareto-front*
- A solution is called *Pareto-optimal* if improvements of one objective necessarily lead to deterioration of another



- Preferences are key to making decisions between optimal alternatives
  - express preferences before (*a priori*) or after optimisation (*a posteriori*)
  - express preferences and optimise iteratively (interactive)

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Augmented Epsilon-Constraint Method (AUGMECON)

- Advantages
  - Each solution is Pareto-optimal
  - Suited for a posteriori and interactive methods
  - No convexity or continuity required
- Method
  - Reformulate all but one objective to constraints
  - Introduce slack variable for each constraint

$$\min_{x \in V} \quad \{f_1(x), f_2(x), \ldots, f_k(x)\} \qquad \longrightarrow \qquad \min_{x \in V} \quad \left(f_j(x) + c \sum_{i \in K} s_i \right) \quad \text{s.t.} \quad f_i(x) + s_i = \varepsilon_i \ \forall \ i \in K \setminus \{j\}$$

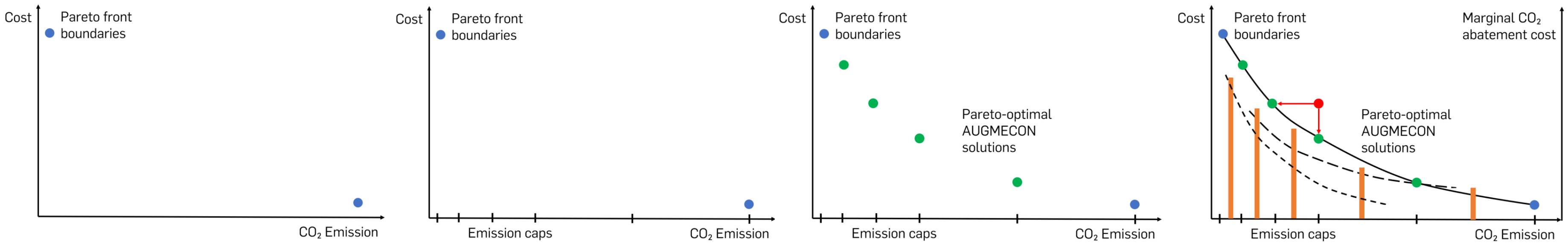
- Further developments improve performance for 4+ objectives and integer variables, e.g. AUGMECON 2 and AUGMECON-R

Mavrotas, *Effective implementation of the epsilon-constraint method in Multi-Objective Mathematical Programming problems*, Applied Mathematics and Computation 2009.
Mavrotas and Florios, *An improved version of the augmented e-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems*, Applied Mathematics and Computation 2013.
Niklas et al., *A robust augmented ε-constraint method (AUGMECON-R) for finding exact solutions of multi-objective linear programming problems*, Operational Research 2020.

Implementation

General Remarks

- Implementing AUGMECON with Backbone for the two objectives cost and CO2 emission
- Two parts: new features in Backbone and “external” python code with 4 steps to run different versions of Backbone
- Illustrative purpose, method **adaptable** to more and other objectives
- Method is easily parallelisable, therefore **scalable**
  - Large and complex systems
  - Many objectives



Step 1 – Determine Pareto front boundaries

- "External": Lexicographic optimisation

$$\min_{x\in V} \text{cost}(x) \text{ s.t. } \text{emission}(x) = \min_{x\in V} \text{emission}(x)$$

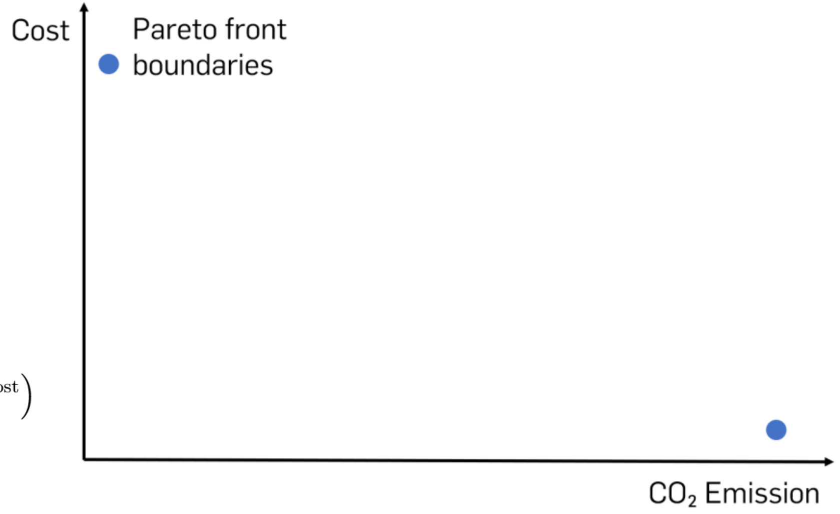
$$\min_{x\in V} \text{emission}(x) \text{ s.t. } \text{cost}(x) = \min_{x\in V} \text{cost}(x)$$

- New feature in Backbone
  - Emission minimisation…

$$v^{\text{obj}}_{\text{CO}_2} = \sum_{f,t} p^{\text{probability}}_{f,t} \cdot \left(v^{\text{generationEmission}}_{f,t,\text{CO}_2} + v^{\text{startupEmission}}_{f,t,\text{CO}_2} + v^{\text{penalties}}_{f,t} \right)$$

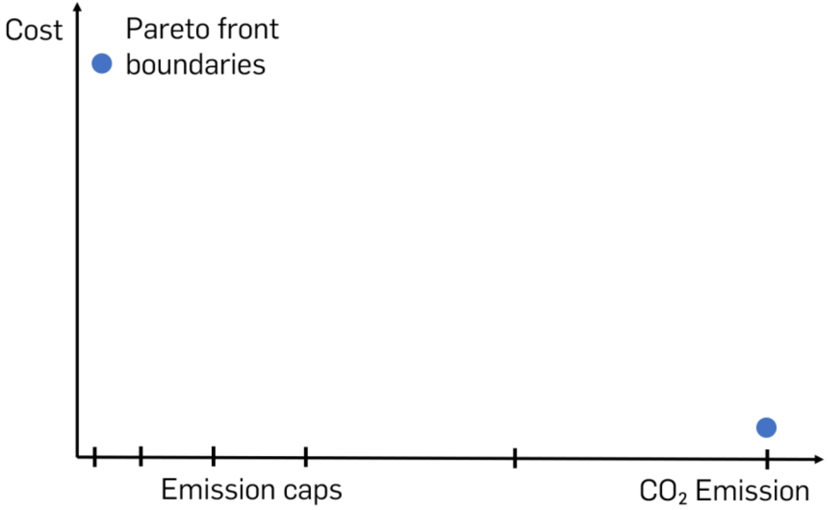
  - …with constrained cost

$$\sum_{f,t} p^{\text{probability}}_{f,t} \cdot \left(v^{\text{vomCost}}_{f,t} + v^{\text{fuelCost}}_{f,t} + v^{\text{startupCost}}_{f,t} + v^{\text{shutdownCost}}_{f,t} + v^{\text{rampCost}}_{f,t} + v^{\text{stateCost}}_{f,t} \right)$$
$$+ v^{\text{fomCost}} + v^{\text{unitInvestCost}} + v^{\text{lineInvestCost}} \leq p^{\text{costLimit}}$$



Step 2 – Decide on emission caps

- Decide on emission caps within boundaries from Step 1, then all are feasible
- Number and distribution of solutions can well be controlled for sufficiently regular models, as desired by the modeller



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Step 3 – Caluclate Pareto-optimal Solutions

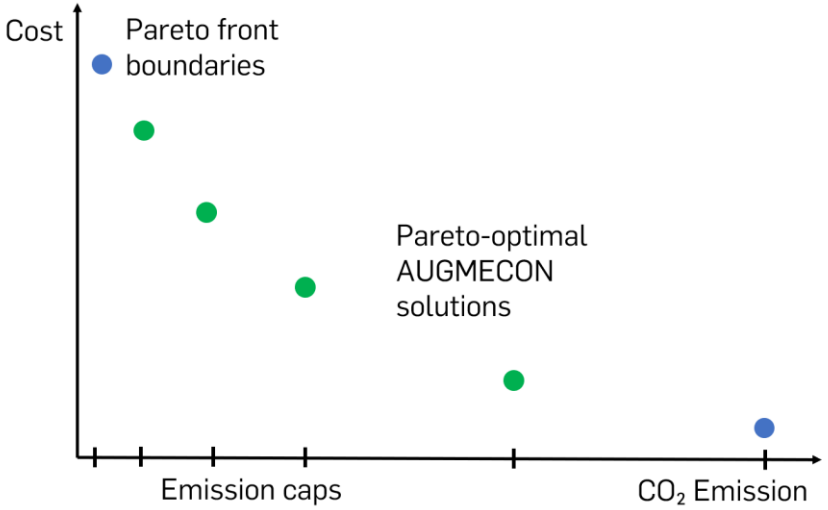
- “External”: Run AUGMECON implementation once for each emission cap from Step 2

- New feature in Backbone
  - Add slack variable to cost objective…

$$v^{\text{obj}}_{\text{AUGMECON}} = v^{\text{obj}}_{\text{BB}} + c \cdot s$$

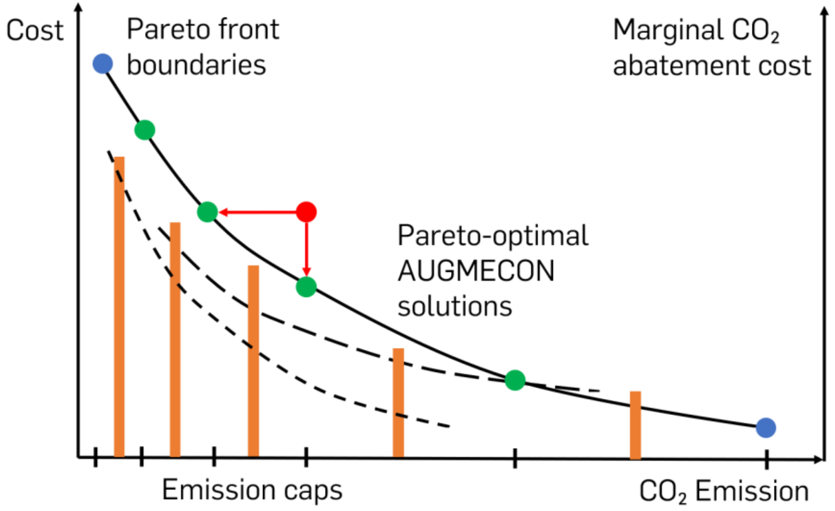
  - … and reformulate emission constraint

$$\sum_{f,t} p^{\text{probability}}_{f,t} \cdot \left(v^{\text{generationEmission}}_{f,t,\text{CO}_2} + v^{\text{startupEmission}}_{f,t,\text{CO}_2} \right) = p^{\text{emissionCap}}_{\text{CO}_2} + s$$



Step 4 – Conduct Further Analyses

- Analyse emission reduction scenarios “as usual”
- Approximate Pareto front from discrete solutions (solid black line)
- Vary assumptions to get different Pareto fronts (dashed black lines)
- Quantify trade-off between objectives, e.g. marginal CO_2 abatement costs (orange bars)
- Compare exogenous scenario to Pareto front and analyse potential improvements (red dot and arrows)



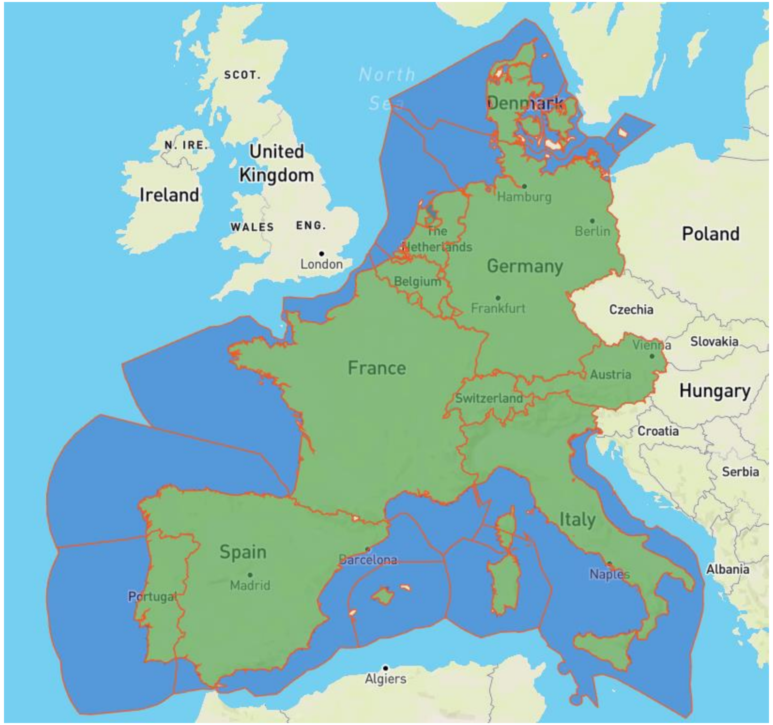
Case Study

Western & Southern European Power System Model

- Power network model based on PyPSA-Eur
- Including 11 countries
- Modelling one year at hourly resolution

- Investment planning for
  - Generation: solar PV, onshore & offshore wind, gas
  - Storage: battery, hydrogen
- Cost and demand assumptions for 2050[1]

- Main limitations
  - Electricity sector only
  - Geographical boundaries

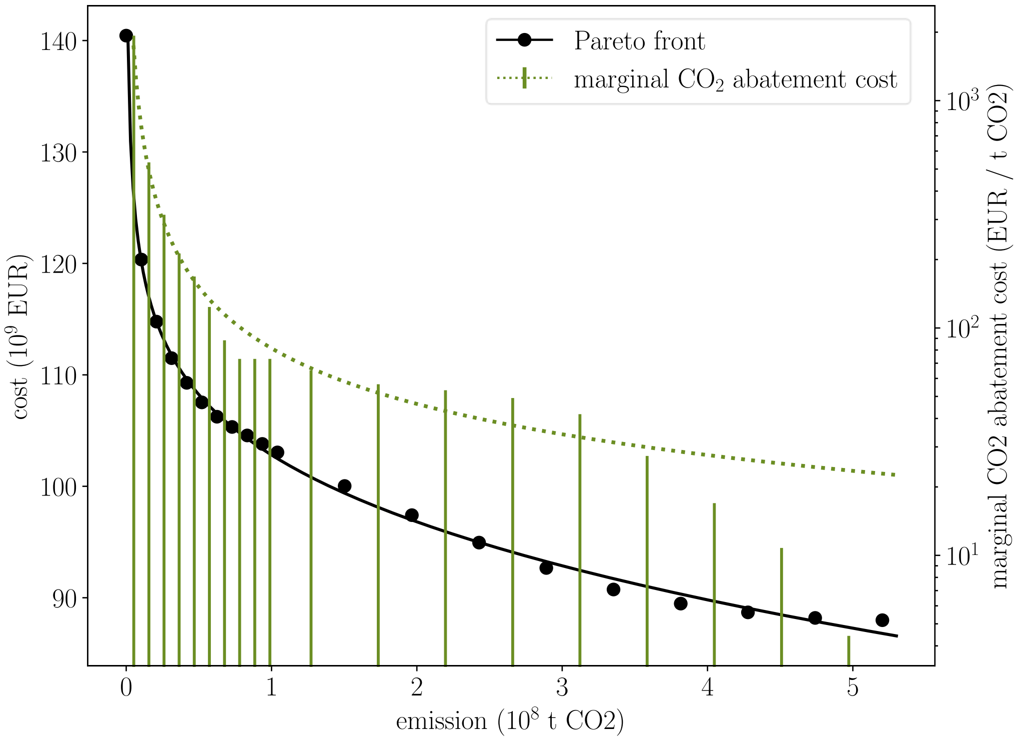


Hörsch et al., *PyPSA-Eur: An Open Optimisation Model of the European Transmission System*, Energy Strategy Reviews 2018. (See also https://github.com/PyPSA/pypsa-eur)

[1] Largely based on Pietzcker et al., *Tightening EU ETS targets in line with the European Green Deal: Impacts on the decarbonisation of the EU power sector*, Applied Energy 2021.

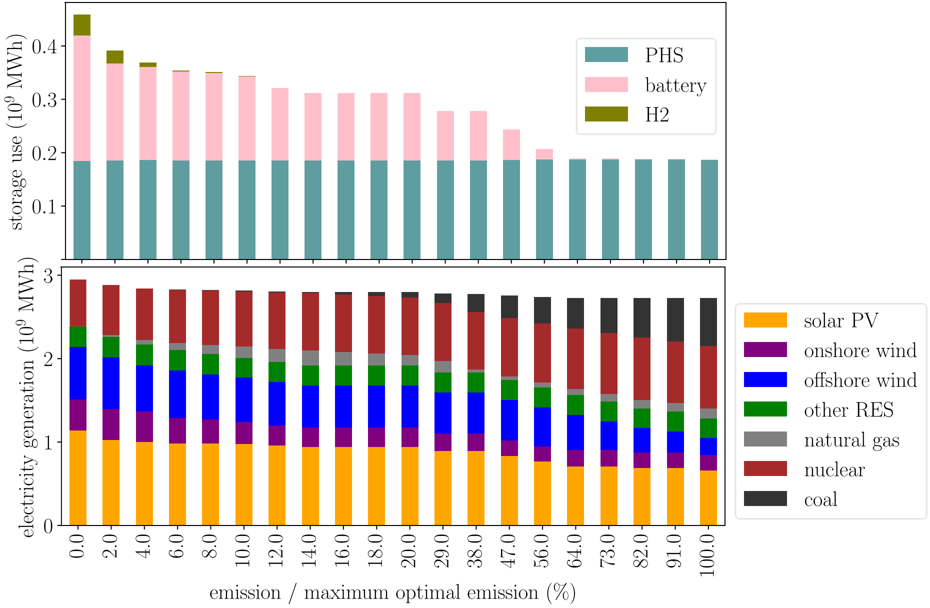
Results – Pareto Front and Trade-Offs

- Objectives' ranges
  - 90…140 x10^9 €
  - 0…5.2 x10^8 t CO_2
- Marginal CO_2 abatement cost
  - 5…2000 € / t CO_2
- CO_2 reductions of up to 90% at marginal abatement costs below 100 € / t CO_2

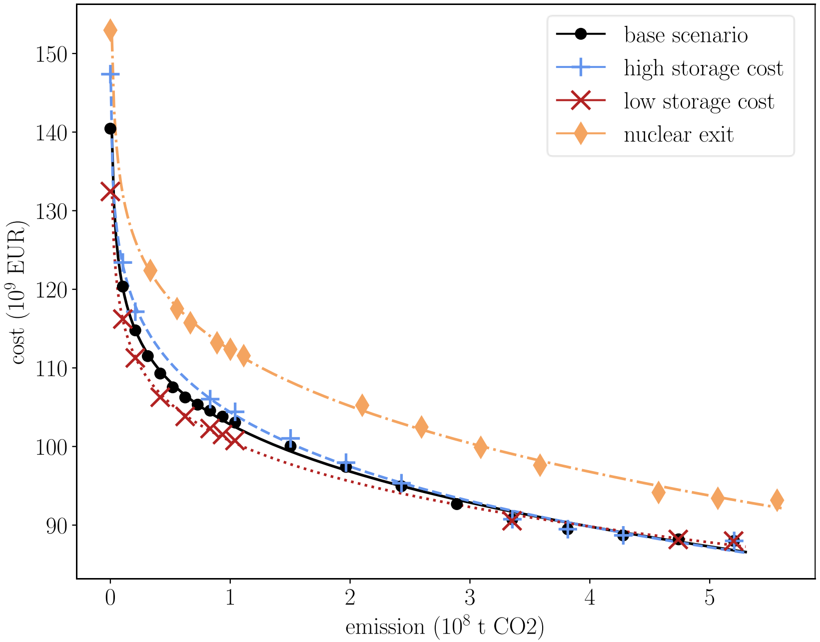


Results – Further Analyses

- Generation and storage mix across different CO_2 reduction scenarios



- Nuclear exit (BE, DE, ES) and sensitivity of storage cost (battery ± 25%, H_2 ± 15%)



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Conclusion & Outlook

Conclusion & Outlook

- The implementation enables for energy systems to
  - determine **cost-emission-optimal solutions** and their **objective range** and
  - further analyse and compare scenarios, e.g. regarding **trade-offs** or **assumptions**.

- The implementation is **adaptable** and **scalable** to various energy systems and objectives.

Future work

- Combine life cycle assessment and energy system modelling – see Sophie Pathe´s work[1]
- Include more objectives and improve algorithm for that
- Ease exploration of 4+D Pareto front to support decision making

[1] Pathe, S. & Bertsch, V. (2021) Electricity system expansion planning of the Rheinish mining area considering environmental impacts by using multi-criteria-optimization. Work in progress.

Thank you for your attention!