Evaluation of uncertainties in linear energy system optimization models using HPC and neural networks

Thomas Breuer[1], Karl-Kiên Cao[2], Fred Fiand[3], Benjamin Fuchs[2], Thorsten Koch[4], Charlie Vanaret[5], Manuel Wetzel[2]

1. Background: The status quo of scenario analyses

Forecasting the future is fraught with large uncertainties. The state of the art in energy-system analysis is to tackle these uncertainties with ensemble modeling of a small subset of all possible scenarios. This has proved to be inadequate. Additionally, the widely-used commercial solvers show poor scalability and are limited to single shared-memory compute nodes.

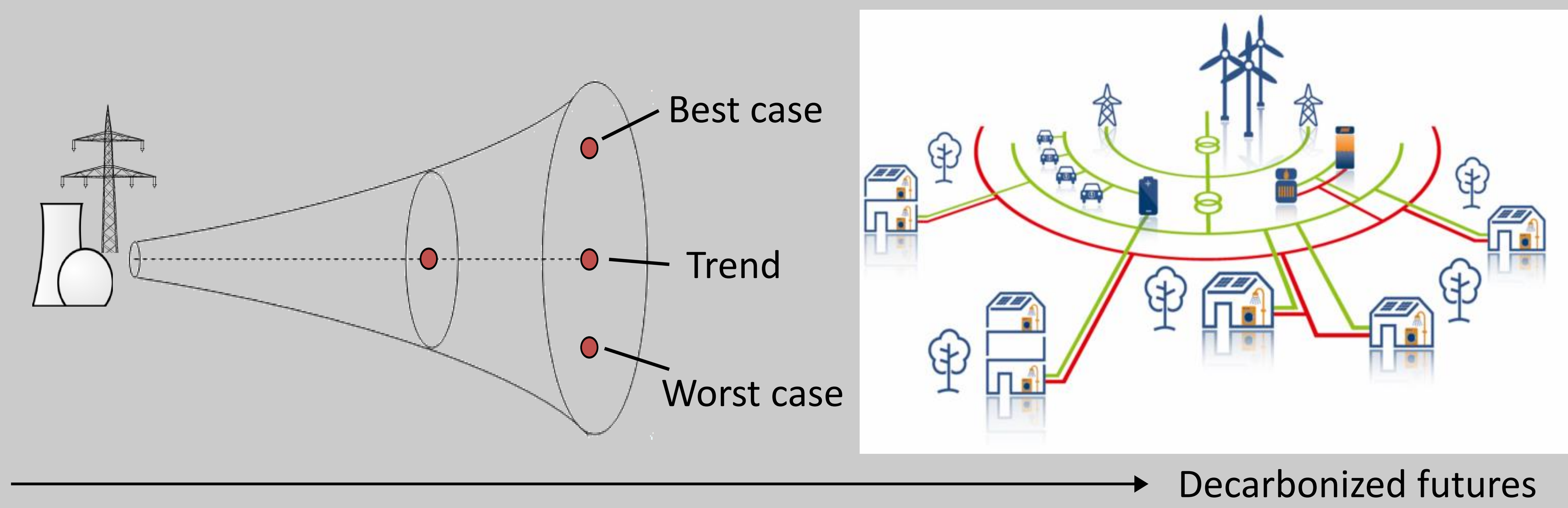

Fig. 1: The established scenario funnel for decarbonization pathways of energy systems

2. Objective: Implementing the theoretical best practice

We have instead opted to fully inspect the conceivable parameter space for the first time by using a hitherto unattained number of model-based energy scenarios. Efficiently leveraging the capabilities of HPC could be a game changer for the energy-system analysis community.

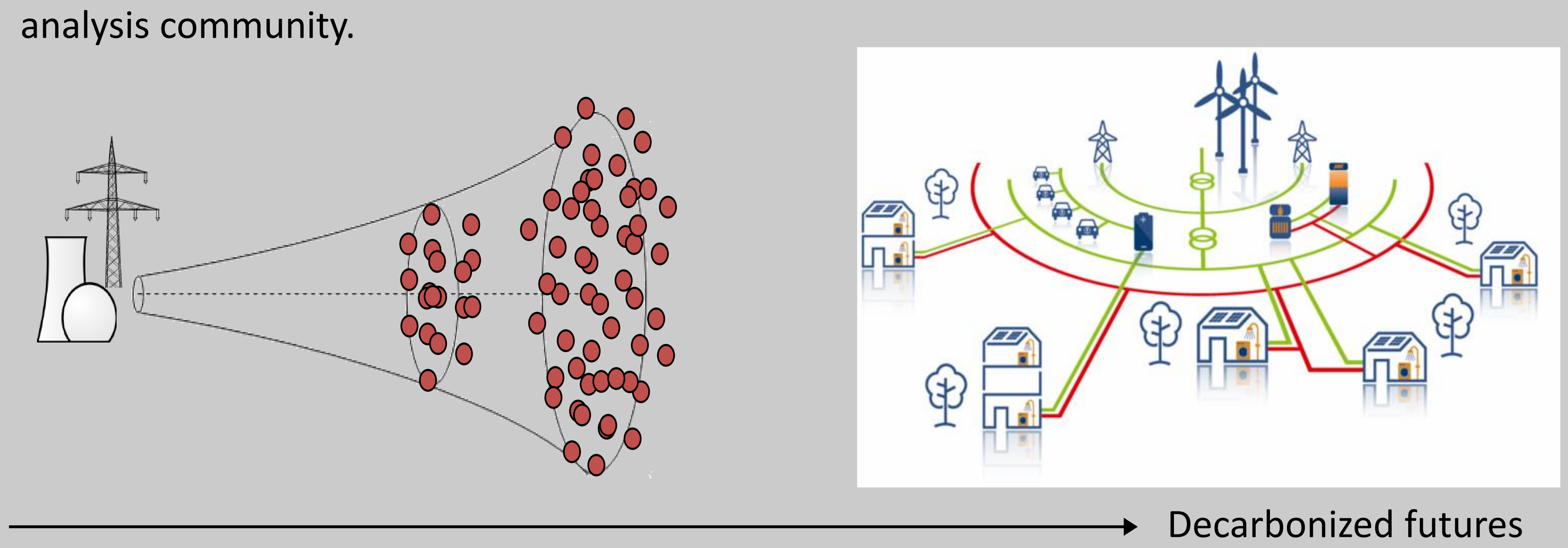

Fig. 2: The scenario funnel for decarbonization pathways of energy systems in UNSEEN

3. Approach and Methodology

We need to deal with an unprecedented number of large-scale scenarios:

- To ensure applicability for real policy support we aim to use both generic and applied models (i.e. **REMix**[6] on transmission grid level resolution) which are formulated as **Mixed Integer Programs** (MIPs).
- To keep computing times manageable we exploit the capabilities of customized algorithms designed for **High Performance Computing** (e.g. PIPS-IPM++[7]) and **Machine Learning** (GCNN).
- To obtain a comprehensive outcome from a multitude of model runs we aggregate to different domain-specific indicators using indicator models (e.g. **AMIRIS**[8]) and post-processing routines.

Outlook on Reinforcement Learning and the HPC workflow

Idea: Provide integer feasible points by learning the MIP optimization process from thousands of examples. Applied to large-scale instances, this provides an efficient upper-bound heuristic without the use of costly traditional techniques.

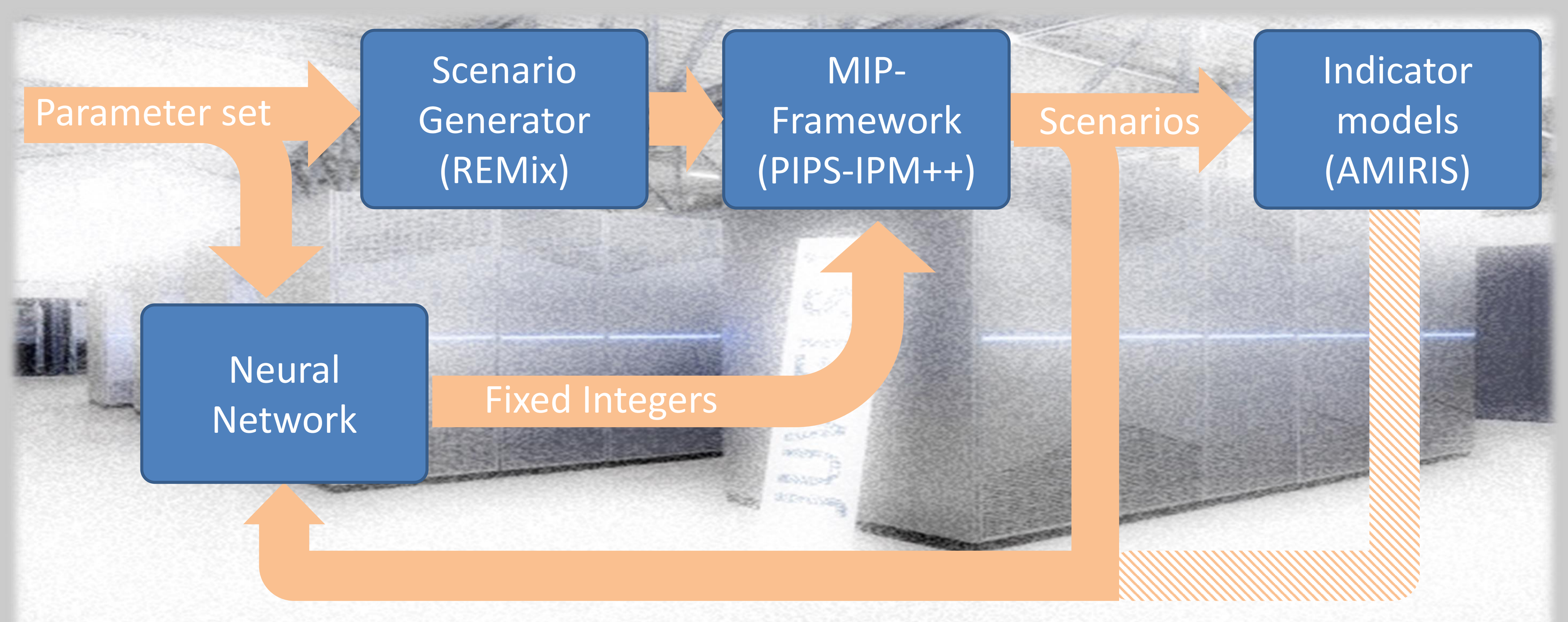

Fig. 3: Reinforcement learning in the HPC workflow. Each individual workflow block contains multiple codes, with the ones mentioned in parentheses among them.

4. Current status of the project

- Completed tool development for automatic parameter sampling
- Widely scalable model of the German power system available, with options to perform:
  - Optimal power flow on the transmission grid level
  - Discrete expansion planning for power plants, storage and transmission lines
  - Unit Commitment for thermal power plants
- Create a scenario-evaluation framework that assesses more than 20 indicators describing affordability, sustainability and security of the optimized energy scenarios
- Evaluated the structure of more than 1000 MIPs
- The development of a generic MIP solver framework is close to completion
- Initial concepts for the architecture of our neural network (NN)
- Workflow & benchmarking environment JUBE[9] successfully parallelized and tested within our HPC-workflow approach
- Our open-source solver PIPS-IPM++[7] can solve large-scale structured Linear Programs (LPs) and outperforms commercial solvers on massively parallel architectures

5. Intermediate/Preliminary Results

1. Comparison of PIPS-IPM++[7] against state-of-the-art commercial solvers on JUWELS[10]:

Benchmark instance:

- 5.1 Mio. rows; 5.6 Mio. columns
- Up to 32 nodes; 2 threads per MPI process

REMix model based on PyPSA-Eur dataset

- 234 Mio. rows; 213 Mio. columns
- 16 nodes; 96 MPI tasks; 8 threads per task

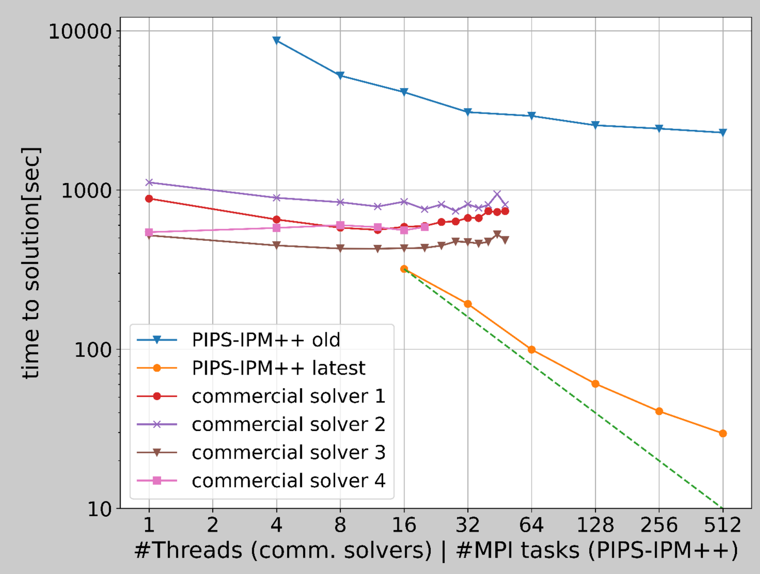

Fig. 4: Benchmark instance of the SIMPLE model

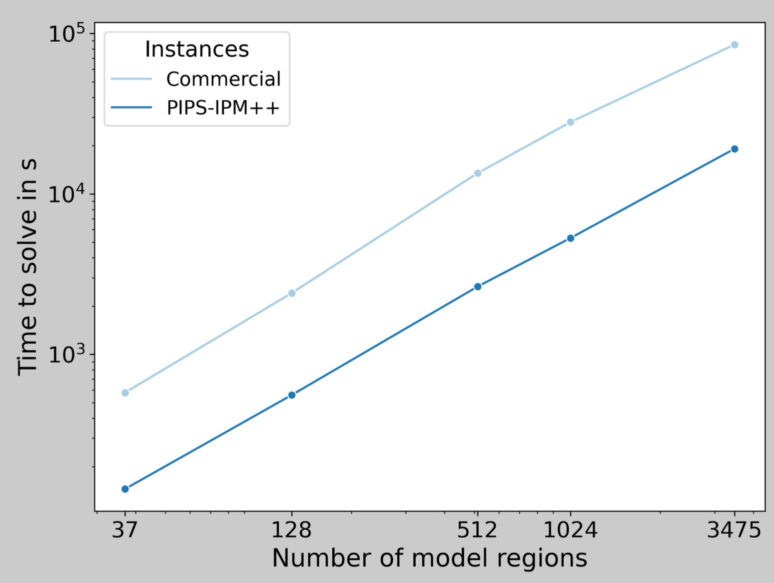

Fig. 5: REMix model based on PyPSA-Eur dataset

2. A first analysis of 1000 instances confirmed our approach for the solver framework. Without our newly developed software infrastructure for HPC, it would have been infeasible to solve such a large amount of instances with the envisaged size.

6. Roadmap

- Q1/2022: Improve robustness of HPC workflow and NN training on small instances
- Q2/2022: Adaptation of HPC workflow to solve energy scenarios based on MIPs
- Q2/2022-Q4/2022: Performance tuning and up-scaling of model size for MIP based energy scenarios; NN experimentations with large-scale instances
- Q3/2022-Q4/2022: Analysis of indicator space and finalisation of development of new energy system modeling concept

7. Project Partners and Funding

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1 JÜLICH Forschungszentrum
2 DLR Deutsches Zentrum für Luft- und Raumfahrt German Aerospace Center
3 GAMS
4 ZIB
5 TU berlin

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Contact: Thomas Breuer (t.breuer@fz-juelich.de)
Jülich Supercomputing Centre (JSC)

[6] https://www.dlr.de/ve/remix
[7] https://github.com/NCKempke/PIPS-IPMpp
[8] https://www.dlr.de/ve/amiris
[9] https://www.fz-juelich.de/ias/jsc/jube
[10] https://www.fz-juelich.de/ias/jsc/juwels
[11] https://unseen-project.gitlab.io/home