

# A multi-perspective approach for exploring the scenario space of future power systems

Ulrich Frey<sup>1</sup>, Karl-Ki n Cao<sup>1</sup>, Thomas Breuer<sup>2</sup>, Manuel Wetzel<sup>1</sup>, Shima Sasaniour<sup>1</sup>,  
Jan Buschmann<sup>1</sup>, Kai von Krbek<sup>1</sup> and Aileen B hme<sup>3</sup>

<sup>1</sup> German Aerospace Center (DLR), Institute of Networked Energy Systems, Germany

<sup>2</sup> Forschungszentrum J lich (FZJ), J lich Supercomputing Centre, Germany

<sup>3</sup>GAMS Software GmbH, Germany

**Abstract.** There are many possible future energy systems – many of them unforeseen. We explore the range of parameter uncertainty and quantify parameter interrelations to generate multiple scenarios. Only sensible parameter combinations remain as inputs to an energy system optimization and coupled models. In the past, computational limitations have been a major obstacle to calculate such an enormous space of scenarios. Opposed to that, we use high-performance computing. To utilize the HPC-system efficiently the parallel solver for linear programs PIPS-IPM++ is applied. We integrate it into a tool chain of different components including scenario generation, energy system optimization and results evaluation and tackle the challenge of coupling a large diversity of software packages in a fully automated HPC workflow. This enables the calculation of all scenarios in a matter of days. Furthermore, we use a set of 37 indicators to provide a comprehensive assessment of the simulated energy systems. In this way, we cover multiple perspectives, such as system adequacy, security of supply or behavior of market actors. Whereas scenarios with low spatial resolution do not lead to clear results, higher resolutions do. Yet, we identified three clusters of scenarios, among which a group with high natural gas dependency is found. This allows to study disruptive events like price shocks in a vast parameter space and to identify countermeasures for the long-term.

**Keywords:** energy systems analysis, PIPS-IPM, high-performance computing

## 1 The 3 challenges of energy scenario analysis

Despite great progress in energy systems analysis in the last decades, three key challenges are still apparent when trying to answer questions on future energy systems. The first challenge is that computational limitations are a major obstacle. To analyze a multitude of scenarios, parallelization and thus, high-performance computers (HPC) are necessary. Many projects have, in contrast, gone the other way: shortcuts are used, like analyzing only typical days instead of complete timeseries [1]. The second challenge is that future pathways are highly contingent on assumptions. Different assumptions in different projects have led to very different scenarios [2]. As a consequence, compar-

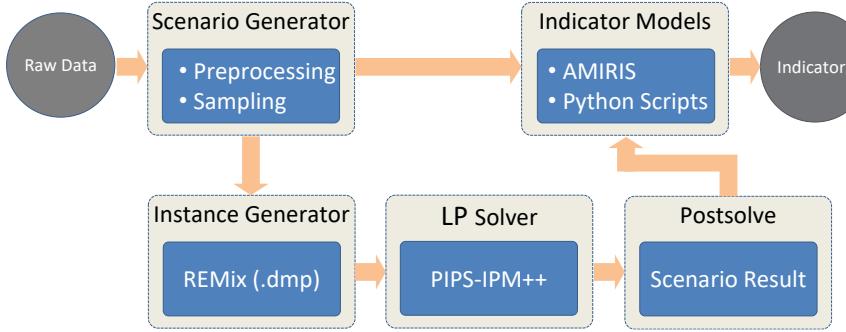
sions and evaluations are highly problematic. The traditional solution, while scientifically not satisfactory, has been to take a very selective set of assumptions. The last challenge is that, given a certain methodology, only certain aspects of future scenarios are typically analyzed. For example, optimization models tend to concentrate on system costs [3], whereas agent-based simulations focus on individual strategies of actors. Hence, there is a certain blindness to certain aspects just by the methodology the researcher has chosen.

Taken altogether, these problems substantially reduce the trust in energy systems modeling. Hence, this paper tries to address all three problems by answering: “If it would be possible to explore the full possibility space of future energy scenarios, could we select those that are near optimal from a multitude of perspectives?” This allows us to get nearer to our goal, a comprehensive assessment of future energy systems.

Our contribution to addressing the first challenge is the further application of the parallel solver – PIPS-IPM++ [4]. It allows us to solve Energy System Optimization Models (ESOMs) on HPCs by exploiting the block-structure of the corresponding linear programs (LPs). Our solution to the second problem is to sample from a huge parameter space, whereas the third problem is addressed by coupling different tools, e.g., the ESOM, REMix [5] and the agent-based simulation, AMIRIS [6]. The resulting indicators provide a comprehensive assessment of energy scenarios including security of supply and market impact. Only this makes a full analysis of points of interests (POIs) possible. We define POIs as a special space where many indicators across all scenarios evaluated are above average.

## 2 Methods

Our modeling goals require the integration of various complex steps. Therefore, we developed a pipeline of multiple software packages within a HPC workflow (see Fig. 1).



**Fig. 1.** Software components and data flow pipeline that is executed for each scenario on HPCs.

We start with a basic parameterization of REMix, which is already useable for energy scenario analysis without any uncertainty consideration. We automatically generate a large variety of scenarios with a newly developed parameter sampling tool (Scenario Generator) to describe the parametric uncertainty of various instances of the basic

REMix model. These model instances are LPs generated by GAMS, which are passed to the parallel solver PIPS-IPM++ for scenario solving. The optimal solution of each LP can be interpreted as one possible scenario in terms of power infrastructure required in the future. Each can be evaluated by calculating numerous indicators. The HPC workflow consists of executing this pipeline for each scenario, as well as providing the data structure to exchange data between individual components. Thus, we are able to evaluate all scenario indicators to observe the POI by statistical analyses.

## 2.1 Basic Energy System Optimization Model and Scenario Generation

The REMix parameterization represents a high-resolution network of the German power system on transmission grid level. The 479 nodes represent unique locations of transformer substations. Additionally, nine neighboring countries are included with fixed imports and exports to Germany. The model focuses on the power sector with several power plant, storage and grid technologies included. Due to the goal to decarbonize the German energy system stepwise, only already available coal and lignite power plants are deployed. Gas-fired power plants can be expended as transition technologies. High CO<sub>2</sub> prices increase the attractiveness of investments into CO<sub>2</sub>-poor technologies.

The input parameters include historical weather profiles for the dispatch of the renewable energies for the years 1995-2018. Additionally, techno-economic parameters such as investment cost, fuel cost, CO<sub>2</sub> allowance cost, efficiencies, fixed and variable operations and maintenance costs are included, which have been subject to our parameter sampling approach. Drivers are varied randomly to create different instances of the model. For consistency reasons (e.g., coupled oil and gas prices), we need i) a collection of possible parameter values, ii) information about the probability distributions of these values and iii) information about possible interrelations. For this, we define pseudo-correlations (strongly negative, negative, none, positive, strongly positive) of the drivers based on expert assessments.

Thus, a literature research with about 50 sources including energy scenario studies on both Europe, e.g., [7] and Germany, e.g., [8] derives statistical descriptors of the drivers' values. A statistical derivation of a probability distribution of parameter values from different studies is impossible. Instead, we use truncated normal distributions, which are defined by the collected statistical descriptors, which results in consistent REMix instances and thus, various scenarios to be passed to the solver.

## 2.2 Parallel computing of multiple optimization models using PIPS-IPM++

Each model instance to be solved by PIPS-IPM++ has to be annotated, which means that variables and constraints are assigned to independent blocks to be treated in parallel by the solver. Despite a large variety of conceivable criteria to define these blocks, we annotate each model instance into time blocks, which represent predefined time slices in the modeled operation horizon. We need to stress that the available computing hardware determines how model instances are annotated. In our case, the corresponding limitations are a maximal total wall-clock time of 24h and a maximum of 192 GB RAM

per compute node. We annotate the problem instances into 730 blocks to be solved in 216 MPI tasks distributed across 18 compute nodes with 4 cores per task. PIPS-IPM++ is executed using the hierarchical approach, which is for our application the best setup to avoid memory issues. As a result, we are able to solve model instances with about 94.6M variables (including 3713 linking variables and thereof 3356 globally) and 91.2M constraints (ca. 367k locally and 693 linking globally) in about 14 hours. After a successful solve, a post-solving process creates a solution as GDX file to be used by subsequent workflow steps (indicator models).

### 2.3 Indicator Assessment

To assess the various aspects of future energy system scenarios, we coupled several models (see section 2.5) for a more comprehensive analysis of the solved ESOM instances. For that, 37 indicators [9] are defined, which are computed by indicator models (e.g., an agent-based model that simulates the behavior of stakeholders at the electricity market for each scenario). For some indicators, the interpretation is clear, e.g. system costs or CO<sub>2</sub> emissions – lower is better. However, for some indicators this is less clear. Therefore, indicators are scored in respect to the overall mean of all scenarios. If it is above or below one standard deviation in the desired direction (if possible), it is considered for further investigation. Scenarios that have a lot of these indicators, are selected and dubbed points of interest.

### 2.4 Workflow automatization

The overarching goal of our workflow automatization is to provide a basis for analyzing a large number of scenarios, but also to allow massively parallel implementation on HPC with automatic data exchange. The challenge is to maintain a bug-free workflow consisting of dozens of scripts or program calls, which are linked in a serial manner and are subject to continuous development. Hence, any change in just one component might break the whole workflow. I, whereas bugs are detected at the end of the workflow by persons who are not in charge of the component that causes the unexpected behavior at the start. In addition to the already existing HPC software stack, we had to install about 28 software packages, each with its own dependencies. Parser scripts used for data transformation require exception handling, which were usually not implemented initially. Nevertheless, replacing broken workflow components is not always possible, e.g., replacing PIPS-IPM++ by a commercial solver.

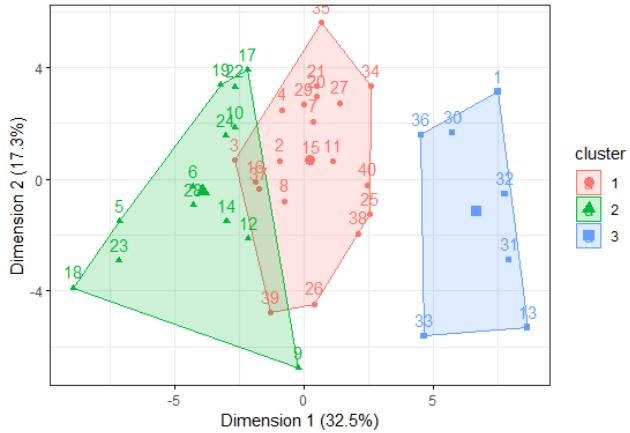
To keep an overview of this complex workflow we extended the software JUBE [10], which manages the tailor-made naming scheme and hierarchical data structure consisting of ~ 1.000 directories and ~ 42.000 files and almost 1 TB of data in total.

The JUBE extension introduces another layer of parallelism to the workflow besides the solver resulting in a reduction of the total workflow runtime. Implementing this exchange of independent and highly specialized software in a stable manner took a team of 10 about 1.5 years, calculations took about 550.000 core hours.

The next section presents these results in condensed form.

### 3 Results

First, we cluster indicators and inputs. For robustness reasons, both k-means and k-medoids are employed, using both the BIC and GAP method to determine the optimal number of clusters. For 1000 scenarios with a low spatial resolution leads not to discernible clusters. Hence, we evaluate a lower number of highly resolved ESOMs. As shown in Fig. 2 (indicators are collapsed into two dimensions), we observe three clearly delineated clusters. The first cluster (green) is in-between extremes for most indicators. The second one (red) is opposite to the first one with the highest dependencies on natural gas, more CO<sub>2</sub>-emissions, but high technological flexibility to adjust to fluctuations in demand and supply. The third cluster (blue) subsumes power systems with high shares of renewables (RE-share), low CO<sub>2</sub>-emissions, high demand and somewhat higher system costs, but less capability for flexible load-balancing.



**Fig. 2.** Scenario clusters for the two main dimensions

Correlations between indicators are as expected, e.g., a high RE-share corresponds to low CO<sub>2</sub>-emissions, etc. This lends credibility to scenario generation and analysis.

Points of interest are all scenarios where a majority of indicators show values one standard deviation above (e.g. RE-share) or below (e.g., CO<sub>2</sub>-emissions) the mean of all scenarios. Overall, there are few points of interest, i.e. systems where many indicators would point to a system that is satisfactory concerning system adequacy, security of supply, and economic performance. Differences between scenarios are small, i.e. t-tests between potential “good” and “bad” systems are not significant.

### 4 Discussion and Conclusion

This paper addresses three problems of current energy systems analysis, i.e. computational limitations, model results that are highly dependent on varying assumptions

and the limited perspectives of single models on only some aspects<sup>1</sup>. By implementing a complex and scalable HPC work flow through coupling a number of specialized models, application of PIPS-IPM++, and a comprehensive set of indicators, this paper proposes a solution to these problems. However, some limitations remain. First, the initial high number of scenarios had a too low spatial resolution. Hence, relevant bottlenecks could not be identified. After switching to a much higher spatial resolution, not too many high-resolution scenarios could be calculated, yet. Second, POIs are defined statistically, not from a system perspective.

What is achieved? Our results pave the way to more robust energy system modeling, since they cover a large range of assumptions and future pathways. We found a few scenarios that seem to satisfy a number of desiderata for a near-optimal energy system. Our indicator set is easily reusable and allows a comprehensive assessment of energy systems, most notably system adequacy, security of supply, sustainability, and economic performance.

The established broad scale analysis can be reused for future analyses which also put emphasis on systems beyond the power sector and solving of mixed-integer linear programs. Due to the HPC capability and automation this workflow provides full scalability, which can be further improved by making the parallel solver PIPS-IPM++ more robust and computationally more performant.

## 5 References

1. Cao, K.-K., et al. Classification and evaluation of concepts for improving the performance of applied energy system optimization models. *Energies* 12.24 (2019)
2. Gils, H.C., et al. Model-related outcome differences in power system models with sector coupling—Quantification and drivers. *Renew. Sustain. Energy Rev.* 159 (2022)
3. Ringkjøb, H.-K. et al. A review of modelling tools for energy and electricity systems with large shares of variable renewables. *Renew. Sustain. Energy Rev.* 96 (2018)
4. Rehfeldt, D., et al. "A massively parallel interior-point solver for LPs with generalized arrowhead structure, and applications to energy system models. *Eur. J. Oper. Res.* 296.1 (2022)
5. Gils, H.C., et al. Integrated modelling of variable renewable energy-based power supply in Europe. *Energy* 123 (2017)
6. Deissenroth, M., et al. Assessing the plurality of actors and policy interactions: agent-based modelling of renewable energy market integration. *Complexity* 2017 (2017)
7. Ruiz, P., et al. ENSPRESO—an open, EU-28 wide, transparent and coherent database of wind, solar and biomass energy potentials. *Energy Strategy Rev.* 26 (2019)
8. Bernath, C., et al. Langfristszenarien für die Transformation des Energiesystems in Deutschland—Modul 3: Referenzszenario und Basisszenario. Karlsruhe, Germany (2017)
9. Energy System Indicators, doi: 10.23728/b2share.fe70b138419243c0817425a0d2d5ae32.
10. JUBE Benchmarking Environment 2008–2022, Available: <http://www.fz-juelich.de/jsc/jube>

---

<sup>1</sup> **Acknowledgement:** We thank our colleagues from UNSEEN, a project funded by the German Federal Ministry for Economic Affairs and Climate Action, grant number FKZ 03EI1004. We gratefully acknowledge the Gauss Centre for Supercomputing e.V. ([www.gauss-centre.eu](http://www.gauss-centre.eu)) for funding this project by providing computing time through the John von Neumann Institute for Computing on the GCS Supercomputer JUWELS at Jülich Supercomputing Centre (JSC).