





NIELS LINDNER¹, KAROLINA BARTOSZUK,
SRINWANTI DEBGUPTA, MARIE-CLAIRE GERING²,
CHRISTOPH MUSCHNER³, JANINA ZITTEL⁴

Warm-starting modeling to generate alternatives for energy transition paths in the Berlin-Brandenburg area

¹  0000-0002-8337-4387

²  0009-0001-9355-8964

³  0000-0001-8144-5260

⁴  0000-0002-0731-0314

Zuse Institute Berlin
Takustr. 7
14195 Berlin
Germany

Telephone: +49 30 84185-0
Telefax: +49 30 84185-125

E-mail: bibliothek@zib.de
URL: <http://www.zib.de>

ZIB-Report (Print) ISSN 1438-0064
ZIB-Report (Internet) ISSN 2192-7782

Warm-starting modeling to generate alternatives for energy transition paths in the Berlin-Brandenburg area

Niels Lindner¹[0000-0002-8337-438], Karolina Bartoszuk¹, Srinwanti Debgupta¹,
Marie-Claire Gering²[0009-0001-9355-8964],
Christoph Muschner²[0000-0001-8144-5260], and
Janina Zittel¹[0000-0002-0731-0314]

¹ Zuse Institute Berlin, Takustr. 7, 14195 Berlin, Germany

² Reiner Lemoine Institut, Rudower Chaussee 12, 12489 Berlin, Germany
lindner@zib.de

Abstract. Energy system optimization models are key to investigate energy transition paths towards a decarbonized future. Since this approach comes with intrinsic uncertainties, it is insufficient to compute a single optimal solution assuming perfect foresight to provide a profound basis for decision makers. The paradigm of modeling to generate alternatives enables to explore the near-optimal solution space to a certain extent. However, large-scale energy models require a non-negligible computation time to be solved. We propose to use warm start methods to accelerate the process of finding close-to-optimal alternatives. In an extensive case study for the energy transition of the Berlin-Brandenburg area, we make use of the sector-coupled linear programming oemof-B3 model to analyze a scenario for the year 2050 with a resolution of one hour and 100% reduction of greenhouse gas emissions. We demonstrate that we can actually achieve a significant computational speedup.

Keywords: Energy System Optimization · Energy Transition · Modeling to Generate Alternatives

1 Introduction

The transition towards a decarbonized energy future is a critical challenge for achieving sustainability goals and mitigating climate change. Energy system optimization models (ESOM) are essential tools in this endeavor. However, neither these models nor their input data are perfect, but come with inherent uncertainties. Instead of computing a single optimal solution assuming perfect foresight, decision makers need a broader perspective on potential energy transition pathways given by solutions of close-to-optimal quality demonstrating different trade-offs or benefits. Since a complete description or an enumeration of the near-optimal solution space is typically intractable, several methods have been developed to cope with uncertainties in optimization models, and have been applied for energy systems specifically as well [14].

In this paper, we focus on the paradigm of *modeling to generate alternatives* (MGA). The basic principle behind MGA is to first compute a solution to the optimization model, and then to repeatedly solve the same model again, but with modified objective functions and a constraint that limits the deviation from the original optimal objective value. MGA has been considered for ESOMs in various forms. The aim of the *hop-skip-jump method* [1] is to iteratively minimize the chosen decision variables. This technique has been successfully applied to energy problems [2,3,12], also with different choices of objective coefficients [4,10,13].

Still, several significant computational challenges exist, especially when applied to large-scale ESOMs. We therefore propose using *warm start* methods. These leverage information from previously solved optimization problems to solve subsequent problems more efficiently, and are particularly useful when the problems are similar, as is the case for MGA: Two iterations differ only by their objective function, while model variables and constraints do not change at all.

In this study, we apply warm start methods within oemof [6], a sector-coupled linear programming framework designed to analyze energy systems with high temporal resolution. Although large-scale linear programs are often solved with interior point or barrier algorithms, we propose to explicitly use simplex techniques, as simplex bases allow for efficient warm starts and are less sensitive to numerical issues [7]. We conduct a case study focusing on the energy transition of the Berlin-Brandenburg area [8], examining a scenario for the year 2050 with an hourly resolution and 100% greenhouse gas emission reduction [9].

We recall the MGA technique in Section 2 and present the evaluation of our case study in Section 3 before concluding the paper in Section 4.

2 Modeling to Generate Alternatives

We begin with a general optimization problem

$$\text{Minimize } f(x) \text{ subject to } x \in X, \quad (1)$$

where $X \subseteq \mathbb{R}^n$ is the space of decision variables $x = (x_1, \dots, x_n)$, and f is an objective function. Given an optimal solution x^* , the process of *modeling to generate alternatives* (MGA) considers the optimization problem

$$\text{Minimize } \sum_{i \in I} w_i x_i \text{ subject to } f(x) \leq (1 + \varepsilon)f(x^*) \text{ and } x \in X. \quad (2)$$

for a given $\varepsilon \geq 0$, a subset $I \subseteq \{1, \dots, n\}$, and weights $w_1, \dots, w_n \in \mathbb{R}$. In words, we reoptimize (1) with a different objective function focusing on a subset of variables, but over the same space X , with the additional constraint that the objective value may only increase by a factor of $1 + \varepsilon$. Any scheme to update the weights w_i for $i \in I$ depending on the outcome of (2), e.g., the *hop-skip-jump method* [1,2], turns MGA into an iterative process that explores the space of those feasible solutions to (1) that are close-to-optimal in terms of f and ε .

An optimal solution to (1) is always a feasible solution to (2). Moreover, any feasible solution to (2) trivially remains feasible, when only the objective

Input: LP (1), parameter $\varepsilon > 0$, iteration limit $k \in \mathbb{N}$
Output: optimal solution $x^{(0)}$ to (1), optimal solutions $x^{(1)}, \dots, x^{(k)}$ to (2)
 $(x^{(0)}, b^{(0)}) \leftarrow$ solve (1) with simplex, or interior point + crossover
for $j \leftarrow 1$ **to** k **do**
 $w \leftarrow$ `update_weights`($x^{(0)}, \dots, x^{(j-1)}$)
 $(x^{(j)}, b^{(j)}) \leftarrow$ solve (2) w.r.t. ε and w with primal simplex and initial basis
 $b^{(j-1)}$
 if `termination_condition`($x^{(0)}, \dots, x^{(j)}$) **then**
 | break
end
return $x^*, x^{(1)}, \dots, x^{(k)}$

Algorithm 1: Basic warm start outline for MGA when (1) is a linear program. Solving a linear program always returns a pair (x, b) consisting of an optimal solution x and a simplex basis b .

function is altered, but not the set of constraints. Combining these two key observations suggests *warm start* methods: Solutions to (2) need not be computed from scratch by a black-box optimization algorithm, but rather by initializing such an algorithm with an already known and qualitatively good solution.

However, not all optimization techniques effectively exploit warm start information. We turn now explicitly to the *linear programming (LP)* case, i.e., the space X is described by a finite set of linear inequalities and equations, and the objective function f is linear. There are mainly two algorithmic paradigms in state-of-the-art LP software: *Simplex* methods and *interior-point (barrier)* methods. Although interior-point methods outperform simplex on large-scale instances, efficient warm start techniques are yet an open research topic. On the other hand, any simplex basis is sufficient to warm start a simplex algorithm: If (1) is an LP, then solving it with a simplex algorithm, or alternatively, an interior-point method with subsequent crossover, will output a primal and dual feasible simplex basis. This basis can be taken as an input for a primal simplex algorithm that solves (2). Note that the dual simplex, typically faster, is inadequate here, as the objective function has been modified. We summarize this basic procedure in Algorithm 1.

3 Berlin-Brandenburg Case Study

Our case study builds upon the oemof framework [6] applied to the Berlin-Brandenburg region in Germany [8,9]. The oemof-B3 model covers both the profile of a metropolitan region and its rural surroundings. E.g., the maximum capacity of wind farms that can be installed until 2045 in Berlin is rather limited, at 12 MW, while this is much less restrictive for Brandenburg with 34 GW.

The model uses a linear programming formulation to minimize the total energy system costs. Our base scenario is a greenfield approach for the full year 2050, working in time steps of one hour, assuming 100% reduction in green-

house gas emissions. As decision variables for the MGA procedure, we will consider the maximum installed capacity in MW for 17 technologies in each of the two regions. These include renewable energy sources and various energy conversion, storage, and transmission technologies. A cost sensitivity analysis with respect to the same set of variables has already been conducted in [11].

3.1 Experiments

We conduct two experiments using Algorithm 1: The first one considers the hop-skip-jump weight update scheme

$$\text{update_weights}(x^{(0)}, \dots, x^{(j)}) := \left(\sum_{r=0}^{j-1} \frac{x_i^{(r)}}{\sum_{i \in I} x_i^{(r)}} \right)_{i \in I}, \quad (3)$$

that adds in each iteration the relative share of the objective value of the previous iteration to the weight of each variable. We stop when an iteration limit of $k = 50$ has been hit, or as soon as their Manhattan distance is less than 20 MW.

The second experiment minimizes and maximizes each single variable in I , always performing a single warm-started MGA iteration. This allows a parallel setup. In both experiments, we consider the objective parameters $\varepsilon = 0.01$ and $\varepsilon = 0.02$. We use Gurobi 11 [5] as linear programming solver on an Intel Xeon E5-2697 v3 CPU with up to 24 threads and 512 GB RAM. For all LPs, we set a time limit of 24 hours wall time.

3.2 Results

We first solve the base scenario with Gurobi’s concurrent solver, which runs the primal simplex, dual simplex, and interior point algorithms in parallel, until the first method has solved the problem. Unsurprisingly, an interior point method is the fastest, but requires a crossover process, as we require a simplex basis for MGA. In total, this takes 766 seconds.

In Table 1, we compare the running times with and without warm start for the first experiment. The warm start ties to primal simplex, while the concurrent solver is invoked for cold starts. However, it turns out that the additional constraint in the MGA iterations linking all time steps in the otherwise block-structured problem imposes numerical challenges that cannot be overcome by Gurobi’s interior point algorithms, even when setting the NumericFocus parameter. In effect, the cold start models are then solved mostly by the dual simplex method. While warm starts take minutes to seconds, cold starts take hours and for some instances hit the time limit of 24 hours. In particular, we can report speedups by several orders of magnitude and state that warm starts are indispensable to making the evaluation of MGA accessible at all.

To evaluate our second experiment, we depict in Figure 1 the solution of the MGA iterations of the first experiment, and the minimum and maximum capacities for each technology. It turns out that the hop-skip-jump method changes the base scenario only in few spots, as is also indicated by the Manhattan distances in Table 1, most notably in solar energy capacities.

Iteration	$\epsilon = 0.01$				$\epsilon = 0.02$			
	Difference [MW]	Warm time [s]	Cold time [s]	Speedup [\times]	Difference [MW]	Warm time [s]	Cold time [s]	Speedup [\times]
(base) 0	—	—	766	—	—	—	766	—
1	19170	1664	51878	31	30760	1739	54223	31
2	667	61	≥ 86400	≥ 1412	16189	429	68717	160
3	2771	95	76471	806	1130	65	66397	1017
4	1733	63	66982	1066	653	44	77862	1768
5	421	37	55015	1478	187	26	56892	2227
6	30	19	43722	2286	728	27	72108	2623
7	203	26	49942	1924	572	31	43571	1419
8	158	24	86361	3529	291	26	55081	2103
9	104	31	81696	2596	301	31	51261	1662
10	4	27	68123	2518	260	28	57379	2020
11	—	—	—	—	436	24	74540	3160
12	—	—	—	—	314	23	55141	2450
13	—	—	—	—	119	18	71040	4029
14	—	—	—	—	14	30	≥ 86400	≥ 2880

Table 1. Experiment 1: Comparison of solution differences, running times with and without warm start, and speedup factors. All numbers are rounded to integers.

4 Conclusion

We conclude that warm start methods cannot only achieve significant computational speedup, but are also essential to effectively explore near-optimal solution spaces in large-scale ESOMs within the scope of modeling to generate alternatives. This is true in terms of computation times and for computing solutions within a reasonable time limit. Since the hop-skip-jump method explores only a narrow subset of the near-optimal solution space, we suggest extending the warm start idea to other MGA update schemes, e.g., [4,13].

Acknowledgments. The work for this article has been conducted in the project “Stadt-Land-Energie - Robustheit und Übertragbarkeit von interkommunalen Energiewendeszenarien im Stadt-Land-Nexus” (Stadt-Land-Energie) funded by Forschungszentrum Jülich GmbH with funds of the Ministry for Economic Affairs and Climate Action (BMWK) (fund number 03EI1051A-B).

Disclosure of Interests. The authors have no competing interests to declare.

References

1. Brill, E.D., Chang, S.Y., Hopkins, L.D.: Modeling to Generate Alternatives: The HSJ Approach and an Illustration Using a Problem in Land Use Planning. *Management Science* **28**(3), 221–235 (1982). <https://doi.org/10.1287/mnsc.28.3.221>
2. DeCarolis, J.F., Babaei, S., Li, B., Kanungo, S.: Modelling to generate alternatives with an energy system optimization model. *Environmental Modelling & Software* **79**, 300–310 (2016). <https://doi.org/10.1016/j.envsoft.2015.11.019>

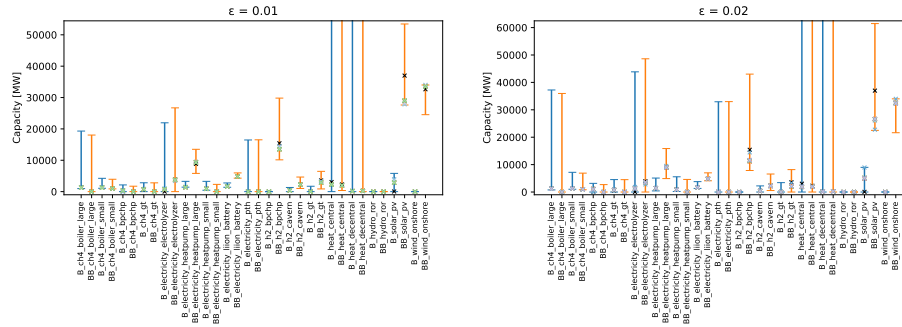


Fig. 1. Experiment 2: Min and max values for the 17 technologies, and the solutions of the base scenario (black) and the MGA iterations of Experiment 1. The (de)central heat storages have very small capacity costs, leading to large maximum capacities.

3. DeCarolis, J.F.: Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. *Energy Economics* **33**(2), 145–152 (2011). <https://doi.org/10.1016/j.eneco.2010.05.002>
4. Esser, K., Finke, J., Bertsch, V., Löschel, A.: Modelling to Generate Alternatives for Decarbonising the Energy Supply of University Campuses (2024). <https://doi.org/10.2139/ssrn.4766711>
5. Gurobi Optimization, LLC: Gurobi Optimizer Reference Manual (2024)
6. Hilpert, S., et al.: The Open Energy Modelling Framework (oemof) - A new approach to facilitate open science in energy system modelling. *Energy Strategy Reviews* **22**, 16–25 (2018). <https://doi.org/10.1016/j.esr.2018.07.001>
7. Klotz, E., Newman, A.M.: Practical guidelines for solving difficult linear programs. *Surveys in Operations Research and Management Science* **18**(1), 1–17 (2013). <https://doi.org/10.1016/j.sorms.2012.11.001>
8. Launer, J., et al.: oemof-B3 (2023), <https://github.com/rl-institut/oemof-B3>
9. Launer, J., Haas, S., Gering, M.C.: oemof-B3 Raw Data (2023). <https://doi.org/10.5281/zenodo.8364204>
10. Lombardi, F., Pickering, B., Pfenninger, S.: What is redundant and what is not? Computational trade-offs in modelling to generate alternatives for energy infrastructure deployment. *Applied Energy* **339**, 121002 (2023). <https://doi.org/10.1016/j.apenergy.2023.121002>
11. Muschner, C., et al.: Sensitivity analysis of the energy transition path in the berlin-brandenburg area to uncertainties in operational and investment costs of diverse energy production technologies. In: *Proceedings of ECOS 2024* (2024), accepted
12. Neumann, F., Brown, T.: The near-optimal feasible space of a renewable power system model. *Electric Power Systems Research* **190**, 106690 (2021). <https://doi.org/10.1016/j.epsr.2020.106690>
13. Price, J., Keppo, I.: Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models. *Applied Energy* **195**, 356–369 (2017). <https://doi.org/10.1016/j.apenergy.2017.03.065>
14. Yue, X., et al.: A review of approaches to uncertainty assessment in energy system optimization models. *Energy Strategy Reviews* **21**, 204–217 (2018). <https://doi.org/10.1016/j.esr.2018.06.003>