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Perspective

Near-optimal energy planning strategies with modeling to generate alternatives to flexibly explore practically desirable options

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CONTEXT & SCALE Energy planning models majorly influence energy transition decisions. Model-based analyses by international organizations shape global discussions, while energy system operators and governments use models to plan investments. Because most models hinge solely on minimizing costs to devise planning strategies, they overlook strategies with comparable costs that may have other desirable features. Some of these preferable strategies, such as those ensuring increased resilience, can be efficiently found with established decision support methods, like robust optimization. Still, alternatives that avoid harder-to-model but practically critical barriers, such as socially unacceptable or underutilized infrastructure, are less straightforward to discover.

Recent developments in "modeling to generate alternatives" (MGA) enable mapping out many viable strategies and their trade-offs, overcoming the above limitations while facilitating combined use with other decision support methods. Accordingly, we illustrate how to integrate MGA in energy planning in five levels of increasing potential. The entry levels ensure higher-quality insights than pure cost minimization for limited computational effort. At the highest level, MGA enables interactive co-design of energy plans with policymakers and other stakeholders. Thus, MGA is accessible and versatile enough to become a standard in improving the reliability and usefulness of the analyses shaping urgent energy transition decisions globally.

SUMMARY

Cost-optimizing energy planning models are widespread in supporting energy transition planning decisions. Nonetheless, finding a "cost-optimal" planning strategy provides only a false sense of certainty. Stakeholders may prefer other economically comparable alternatives due to unaccounted-for features. Multi-objective or robust optimization, among others, can efficiently explore alternatives whose desired secondary features are well defined. "Modeling to generate alternatives" (MGA) explores alternatives systematically, including alternatives whose features, such as social viability, are hard to model, albeit key to practical implementation. Computational and interpretation barriers hindered past MGA usage and integration with other methods, but recent developments enable going beyond such barriers. We synthesize such developments and provide practical recommendations for applying MGA in five levels of increasing benefit. Even the simplest levels, requiring little computational effort, can substantially improve the quality of energy planning analyses. At the highest level of integration, MGA can facilitate identifying consensus strategies, accelerating the energy transition.

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INTRODUCTION

The urgency of the energy transition calls for complex energy system planning decisions between equally viable technologies, energy carriers, and system configurations.[1] To unravel such complexity and support decisions, legislators, system operators, international organizations, and other stakeholders increasingly look at energy system optimization and integrated assessment models.[2–4] Energy system optimization models focus on the energy system exclusively—either limited to the power sector or including heat, mobility, and industry sectors—while integrated assessment models look at a broader picture that includes economic and environmental dynamics at the global scale, at the expense of a lower detail in representing the energy system.[5] Either of these broad model categories typically hinges on the idea of identifying, for a given set of assumptions, or "scenario," a deterministic "optimal" energy planning strategy or system design that minimizes the total cost for society to achieve the transition.[6,7]

And yet, striving to identify a single, "cost-optimal" solution for one or a handful of narrative scenarios can be short-sighted, particularly in the context of a complex issue involving multiple actors with conflicting interests and deeply uncertain information, such as the energy transition.[2,7] For instance, in regard to system resilience to uncertain shocks, such as fuel price spikes or energy droughts, recent work showed how planning strategies grounded in a large capacity of a few types of generators—a typical outcome of cost-optimization under static fuel price and weather assumptions[8]—may be less resilient compared with marginally more costly strategies based on a more diverse portfolio of generators.[9] Moreover, investing early in diverse generation portfolios can reduce the risk of tardive investments in overcapacity that often occur after similar shocks materialize.[9] Beyond a lack of resilience, reality checks applied to cost-optimal energy system designs have shown that these designs tend to entail features, say the over-concentration of wind farms in a few most-windy sites or investments in heavily under-utilized transmission capacity, that are likely undesirable from the perspective of different real-world stakeholders.[10–12] More generally, attempts at modeling the historical evolution of the British energy system with hindsight have shown that real-world energy planning decisions deviate substantially from those suggested by cost-optimal scenarios for several reasons, most notably because real-world decisions value the inclusion of system features prized by a given stakeholder more than the associated higher-than-optimal costs.[6] In all such cases, equally feasible but radically different carbon-neutral system designs—more resilient to uncertain parameters or more aligned to the multi-faceted nature of real-world decision factors—have been shown to exist for a marginally higher system cost. Except, they are hidden from view by the insistence on "cost optimality."[6,10,13] Many more recent studies, which we further discuss in "The implications of not looking beyond the optimum," have substantiated the same finding and shown how extensive the range of economically comparable design possibilities precluded by the common practice of looking only at a single cost-optimal solution can be.

Some of these alternative design possibilities, namely those that allow stakeholders to hedge against uncertain future conditions such as weather and demand patterns or technology cost developments, can be identified with established methods specifically conceived to deal with this kind of uncertainty, also known as *parametric* uncertainty.[2,7] Such methods include, among others, global sensitivity analysis,[8] stochastic programming, and robust optimization.[9,14] However, these methods are often not suited to discover those planning options that may be preferred by stakeholders for some of the other reasons discussed above, such as social acceptability, individual asset value, or more nuanced factors arising as a compromise between many diverse stakeholder goals.[10] Such reasons are hard, when not entirely impossible, to parametrize in a model and are thus often referred to as *structural* uncertainties.[7] Notably, parametric and structural uncertainty tend to co-exist.[7] Recent work underscores that, even when resilience against given uncertain conditions is a clear goal, it is often valuable to have various options for a system to achieve the desired degree of resilience, so that stakeholders' preferences and knowledge of the problem can still shape the final decision and ensure its practical viability.[15–17]

This growing evidence suggests that, when using models to support complex energy planning decisions, it would be sensible to explicitly look for these technically feasible and economically comparable alternatives to the sought optimum, also known as "near-(cost)-optimal" solutions. Methods to do so are well established in the field of operations research and systems engineering under the name "modeling to generate alternatives," or MGA.[18,19] They were successfully applied to energy system models for the first time more than a decade ago[20] and to integrated assessment models a few years later.[21] However, identifying a single, cost-optimal solution for just a handful of narrative scenarios remains a standard practice in energy transition studies, including those that provide unequivocal planning or system design recommendations.[22] Among the reasons for such persistence are: a lack of awareness about the potentially misleading nature of cost-optimization[6]; the limitations and computational barriers of conventional MGA methods, especially when applied to state-of-the-art large-scale energy planning models[23–25]; and the trade-offs between expanding the decision space and meeting stakeholder calls for simplicity in the communication of results.[26] We acknowledge and further explore such barriers in "From conventional to next-generation MGA." The last few years, though, have been marked by an unprecedented rise in MGA applications to energy system models, including many original and innovative developments that go beyond the capabilities of conventional MGA and facilitate its integration with equally important methods to handle parametric uncertainty. Such developments, and the insights they have produced, call for a further rethinking of how energy planning results are generated and interpreted.

With this article, we set out to bring together and synthesize the latest MGA developments with application to energy planning models. And, based on this synthesis, to provide practical guidance on how to either apply next-generation MGA—whenever computational capabilities allow—or make a study's claims consistent with the lack thereof.

The remainder of the article is organized as follows. In "The implications of not looking beyond the optimum," we expand our

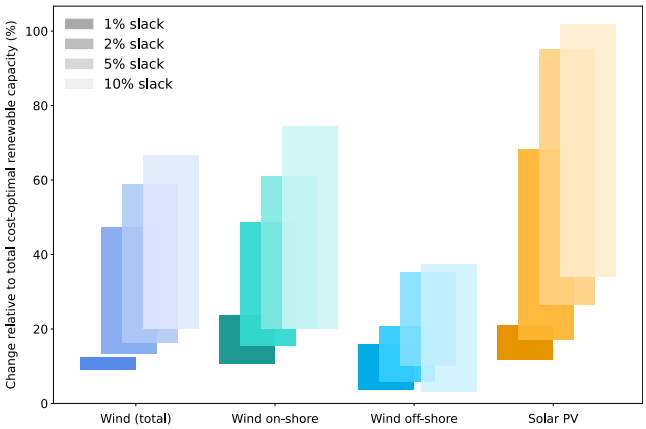

Figure 1. Percentage change in the deployed capacity of selected renewable generation technologies in near-(cost)-optimal solutions compared with the total renewable generation capacity in the associated cost-optimal solution

The bars represent the range between the minimum and maximum values that such a capacity change can experience according to a selection of six diverse recent studies, which encompass individual European countries,[10] the West of the United States,[13] and the entire European power[32,33] or sector-coupled energy[12,34] system. The data underlying the figure are available in our supplemental methods (Table S1) alongside additional details on the criteria we use for selecting the above studies. Results are shown for increasing cost relaxations (or slack values). We calculate the percentage change as the absolute difference between the capacity deployment of a given renewable generation technology in the cost-optimal and near-optimal solutions of a study, divided by the total cost-optimal renewable generation capacity. The division by the total cost-optimal renewable generation capacity allows us to normalize the change relative to a proxy of the total system size (as all the considered studies feature large shares of renewables) and thereby compute the change also when the cost-optimal deployment of a technology is zero.

discussion of the shortcomings of cost-optimal energy planning and the consequent need to move beyond that. In "From conventional to next-generation MGA," we outline the motivations that have so far prevented more widespread adoption of MGA in response to the above shortcomings. Hence, we discuss the latest developments brought about by next-generation MGA and how these contribute to overcoming past barriers, while also highlighting the most interesting open questions for future research. Finally, in "Practical solutions to advance energy planning beyond cost-optimization," we provide suggestions for advancing energy system and integrated assessment modeling analyses in light of these most recent scientific developments. We conclude with a discussion of the broader policy implications of our analysis.

THE IMPLICATIONS OF NOT LOOKING BEYOND THE OPTIMUM

We concede that, for an analysis whose scope is truly limited to assessing the theoretical order of magnitude of economic investments and operation costs required to achieve a set goal, without much emphasis on what the underlying planning decisions or system design look like, a single cost-optimization solution may suffice. However, energy system and integrated assessment models are more often used to influence decisions that go beyond ballpark economic estimates, discussing explicitly the concrete design and planning elements that come with the cost-optimal solution.[3,4,6] We focus here on this most frequent use. We can generalize two shortcomings of cost-optimization when applied to supporting energy planning strategies or system design decisions.

First, many other decision factors matter for real-world energy planning decisions beyond cost. Stakeholders are many and heterogeneous, from citizens to system operators, energy companies, and legislators at scales ranging from neighborhoods to entire continents. A solution that is cost-optimal from a system perspective does not guarantee alignment with the goals of most of these stakeholders. For instance, a cost-optimal solution may overlook public opposition to specific technologies because of landscape or land-use impact and NIMBY resistance,[10,13] the distribution of economic impacts,[11,27] or the practical viability of the rate of expansion of certain assets due to workforce or material limitations.[28] Granting that some of these aspects can be factored into the modeling, cost-optimization only allows treating them as strict constraints, while, in reality, they are typically blurry, and it is essential to understand the maneuvering space around them.[29] While multi-objective optimization does enable accounting for different objectives and looking at the trade-offs between them, it is not best suited to dealing with more than two or three objectives and is typically not used to explore relaxations of such objectives that may still be practically preferable.[18,30,31] As such, while an established and effective method to go beyond cost-optimization in cases when goals are limited in number and clearly defined, explicit multi-objective optimization is not best suited for dealing with many, often initially unclear goals, which are typical of large-scale planning problems.[24,31]

Second, even if we wanted to assume that all the above decision factors are secondary to minimizing the societal cost of energy planning decisions, cost-optimization alone would remain a poorly reliable approach. In an energy system or integrated assessment model, "cost" is merely an input parameter that is inherently uncertain, and the decision space around the minimum cost is often very "flat." This means that large deviations from the seemingly cost-optimal decision are possible for negligible cost variations.[21,32] Based on a selection of existing studies, Figure 1 showcases how large the deviations from the cost-optimal decision can be for selected system design variables and cost relaxations of 1%, 2%, 5%, and 10%. A relaxation of the total system cost as small as 2%, for instance, already entails deviations in the total deployed capacity of key assets, such as wind and solar renewable power capacity, as large as 47% and 68%, respectively. In other words, what a cost-optimal solution looks like is highly sensitive to even minimal changes in the assumed cost parameters. Considering the high uncertainty of cost assumptions for models that typically look at planning decisions over a time horizon of several years in the future, not looking at the radically different options available near this flat optimum easily leads to a false sense of certainty. For instance, a cost-optimal solution may prioritize investments in a given type of renewable energy generator, such as wind power, and not invest much or at all in another, such as solar power.[34] However, the situation may be entirely reversed for marginally different and

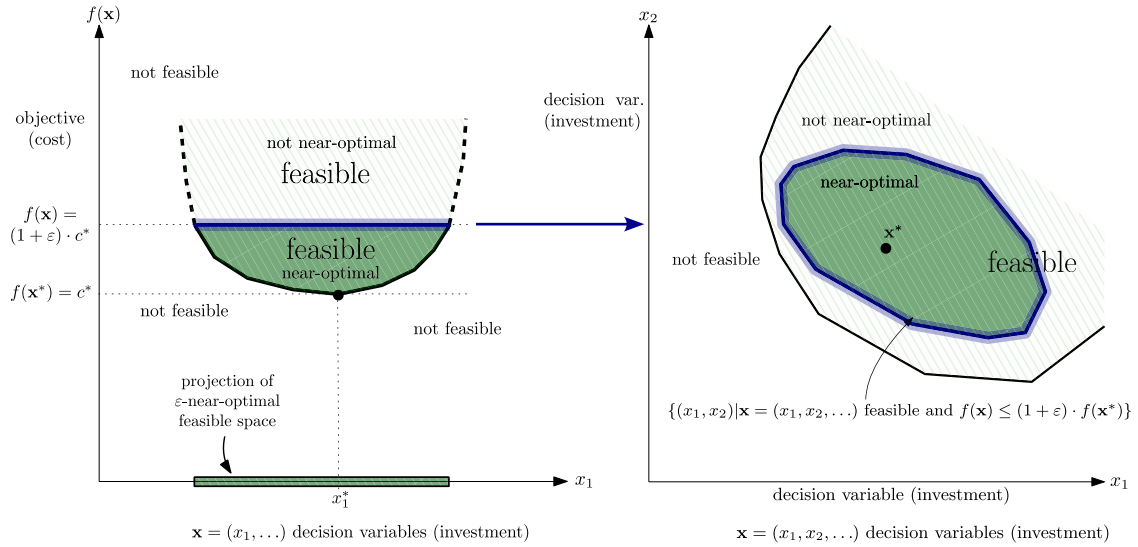

Figure 2. Illustration of near-(cost)-optimal feasible spaces (typically n-dimensional) projected onto 1- and 2-dimensional spaces, respectively

Although applicable to more general convex problems, the formalism in the figure refers to the most common type of energy planning models, which are formulated as linear problems. The linear program aims to minimize a cost function ($f(x)$) whose variables (x) are investment decisions for different types of energy technologies, including generators, transmission, conversion, and storage technologies. The constraints are typically summarized as per the linear-programming standard from: $Ax = b$, where A,b, are a matrix and a vector of coefficients that define the constraints that the decision variables must respect. On the left, the green shaded region corresponds to feasible combinations of decision variables (only shown in the variable x_1) and their objective value $f(x_1,\ldots)$. For a given $\epsilon > 0$, the near-optimal feasible combinations are filled in green; the isolines (lines of constant objective value) for the minimal objective as well as the near-optimal constraint are marked. On the right, we project the (typically high-dimensional) ϵ-near-optimal feasible space onto the (x_1, x_2) plane (filled in green, defined as in the equation) with the level set of the ϵ slack still highlighted in blue. The feasible region is shaded in green. Such a two-dimensional representation of the near-optimal space can facilitate quantifying trade-offs and interchangeability between pairs of critical decision variables in the planning process).[15,29,33] For a more thorough definition of near-optimal spaces and MGA methods to map them out, see Lau et al.[25]

equally plausible assumptions about the cost projections of the two technologies.[10] Relying overly on cost-optimal insights when making system design decisions may thus lead to unjustified technology lock-in, making it difficult to adapt to alternative emerging technologies and reducing the system's adaptability to off-design conditions due to the lack of technological diversity.

Generating alternative, near-(cost)-optimal decision options via MGA can reveal energy planning strategies that may cover unmodeled objectives, such as social viability,[27] resilience to different operating conditions, and sudden supply disruptions,[10] or better hedging against policy or market shifts.[33] While we acknowledge that some of these objectives, particularly those related to resilience, can be explicitly accommodated with global sensitivity analysis, stochastic programming, or robust optimization, combining such methods with the generation of near-optimal alternatives may be still valuable to expand the range of options that ensure a given degree of resilience, as illustrated by recent work.[15–17] Stakeholders can then appraise trade-offs between the many near-optimal options based on their preferences and knowledge of the problem and find practically viable consensus solutions.[24,25] The logic by which MGA makes this possible is also very simple. All it takes is defining a relaxation—or "slack"—of the optimal cost that is considered acceptable. This relaxation becomes a new problem constraint that delineates a region of feasible, near-optimal problem solutions—all different in terms of their underlying investment decisions but still economically comparable to the cost-optimal one. We provide a stylized illustration of this concept in Figure 2. Once a near-optimal region is defined, one can tailor the problem objective to something that enables finding as many alternative near-optimal solutions as desired. In the simplest, conventional version of MGA, also called "hop, skip, and jump" (HSJ), the objective consists of iteratively finding energy planning or design options that minimize the reliance on system features already explored in previous iterations based on mathematical weights, or penalties, that are incrementally assigned to such features. However, HSJ is only one option, which is not particularly efficient—due to its fully iterative nature—nor is it the most suited for application to state-of-the-art energy planning models. Detailed definitions of MGA, near-optimal spaces, and approaches to exploring such spaces are available from prior work from our author team.[25] In the next section, we elaborate further on how much more is now possible in terms of efficiency and scope of application, thanks to the next-generation MGA approaches developed in the last few years.

FROM CONVENTIONAL TO NEXT-GENERATION MGA

Despite the risks of relying overly on cost-optimization outcomes we outlined above, MGA has seen limited adoption until recently—less than methods to handle parametric uncertainty[7]—for a few distinct reasons.

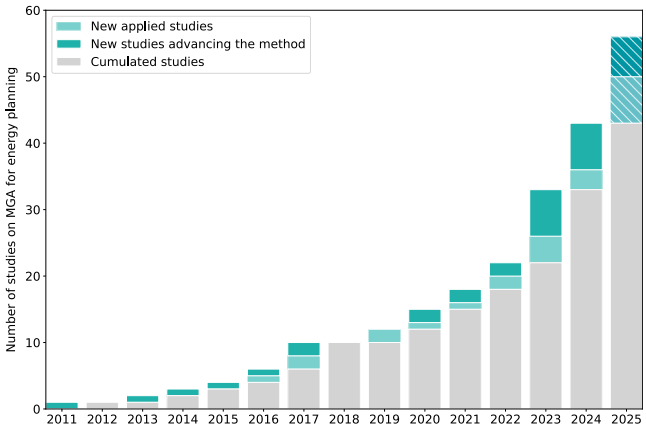

Figure 3. Growth over time of scientific studies whose focus is the use of MGA for energy system planning problems

We use different colors to highlight what is the share, among the new publications each year, of studies that include methodological advancements of MGA, going beyond applications of known methods. The years from 2023 onward also include pre-prints. This is inevitable to provide a complete picture of this rapidly expanding field of research. The area in the bar chart representing new publications in 2025 is patterned to highlight that the year is still ongoing at the time of performing the analysis. The data underlying the figure are available in our supplemental methods (Table S2) alongside additional details on the approach used to gather them.

First, there is a lack of awareness about the pitfalls of cost-optimization. Previous work highlighted that decision-makers rely heavily on cost-optimization as they do not realize how high the risk of producing untenable and circumstantial findings is[22] and driven by the misleading sense of "exactness" that finding a single optimal solution conveys.[35] Second, MGA entails additional computational effort, which may become a barrier when applied to large-scale integrated assessment models[21] or energy system optimization models with high spatial and temporal resolution,[24,29] or when additional computational effort is already allocated to handling parametric uncertainty.[15,17] Third, the large number of energy planning options commonly produced by MGA may counterpoise the requests for simplicity and understandability in the communication of results that come from stakeholders.[26] Fourth, also due to these challenges in computation and data presentation, conventional MGA has focused rather narrowly on "macroscopic" aspects of system design, such as total solar or wind capacity, while insufficiently addressing spatial and distributional planning trade-offs, which are most critical for real-world discussions.[10,11,27]

However, the rate of publication on MGA has accelerated in the last few years. On the one hand, this has provided greater evidence of the shortcomings of cost-optimization, which our study synthesizes and further elucidates. On the other hand, an increasingly large share of studies—starting from 2020—proposed original advancements that enable addressing the remaining above barriers (Figure 3) by leveraging one or more of the following features: smart, tailored parallelization; accelerated computation of individual iterations; mapping of the entire space's geometry; capacity to focus on spatial aspects; integration of parametric uncertainty analyses; and, user-tailored post-processing methods. We call these advancements next-generation MGA, and we illustrate them below per macro-categories that mirror the barriers they address. A compact summary of the discussion below is also available in Table S3 to facilitate further reading for those who may be interested in the full underlying mathematical formulations, which lie outside the scope of this perspective.

More efficient and robust computation

In terms of lightening the computational burden of MGA, next-generation advancements can be grouped into two further sub-categories.

First, there are methods to more efficiently set up the "search strategy" by which MGA explores the near-optimal energy planning option space to generate a representative sample of options. Instead of relying exclusively on iterative solving to find more solutions, several approaches propose intuitive methods to split the search into many parallel runs that explicitly focus on different areas of the option space. For instance, areas where given technology groups are pushed to their limits[24,33] or where specific features of stakeholder interest are intensified or diversified.[28] Notably, the well-established "random vector" approach to MGA[11,25] could also be parallelized without predetermining any distinctive aim for each parallel run. The targeting of specific variables typical of next-generation MGA, instead, enables leveraging the parallelization potential in modern high-performance computing infrastructure more efficiently, ensuring that the generated sample of options is tailored to the analysis's needs. In fact, sample adequacy is goal-dependent.[24] Conveniently, recent studies offer an overview of the trade-offs of many different MGA search strategies, providing guidance on what is most effective to use depending on the goal of the analysis.[24,25] For some exploration goals, such as perfectly homogeneous exploration of the space or generation of a limited set of options, we note that traditional MGA methods may be a perfectly valid option.[24,25]

Second, there are methods that improve on the runtime of individual MGA iterations, for instance, leveraging surrogate modeling,[33] Benders' decomposition,[36] or MGA-tailored reformulations of the most common algorithms used to solve optimization problems, such as simplex.[37]

Several methods from both categories capitalize on the increasing focus on near-optimal feasible spaces as geometric objects, which enables leveraging geometric properties to make the exploration of alternatives more efficient. For instance, if focusing on a few planning decisions of higher interest—such as the deployment of power generation capacity—the boundaries of near-optimal spaces can be accurately captured via geometric approximations,[15,25] ensuring that the extreme planning options are known. The geometric perspective also enables quickly finding middle-ground options between the extremes via interpolation.[38,39] Some of the methods that leverage geometric properties face computational barriers when looking at more than 10 planning variables of interest.[25,29] However, recent work has shown that the same geometric properties can be efficiently approximated by explicitly exploring extreme options via established MGA methods, and then leveraging the properties of convexity to quantify the geometry around them without significant computational barriers.[38]

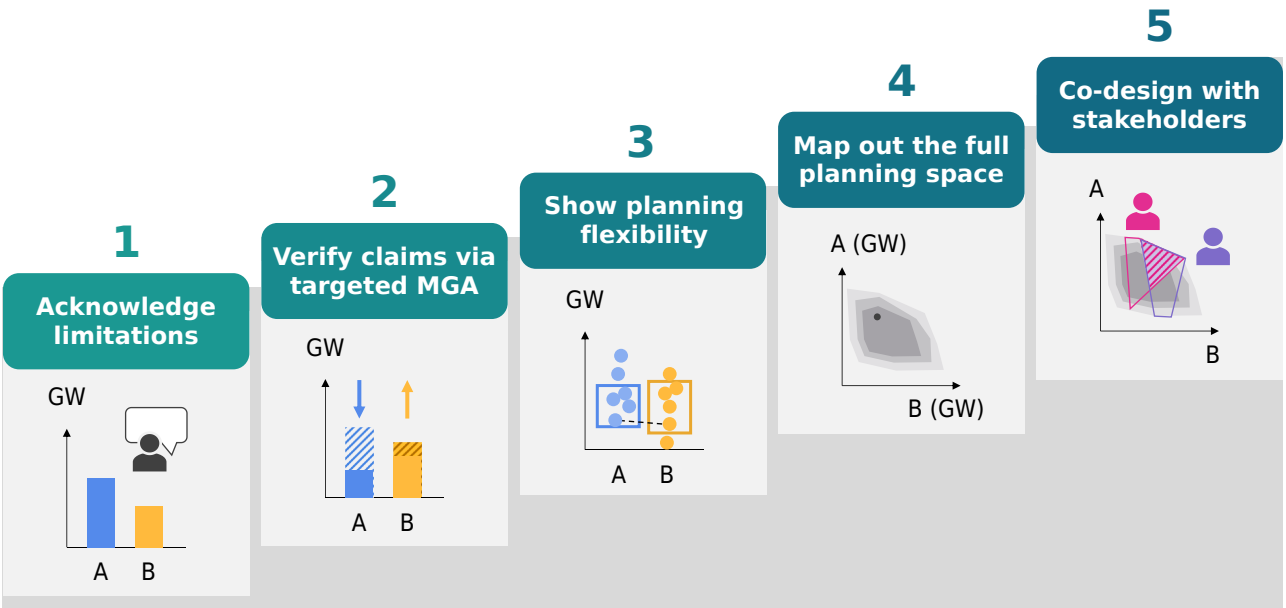

Figure 4. Concise representation of the five-level "MGA integration ladder" that we propose in this article to foster MGA adoption in energy planning analyses

The five levels are in ascending order of potential to enhance the analysis and corresponding implementation effort. While the highest levels of integration provide the highest benefits, even the simplest and most readily implementable ones can ensure a substantial improvement in the quality of an energy planning analysis compared with standard cost-optimization.

Tailored search for spatial aspects

Recent work has also demonstrated the utility of exploring spatially diverse alternatives and how to do so efficiently.[10–12,34,40] For instance, spatially explicit variables can be targeted with penalties in the MGA objective formulation, disincentivizing new solutions from featuring not only technologies but also deployment locations already featured in prior iterations.[10] Moreover, mapping spatially diverse alternatives is most effectively achieved via mathematical formulations of the penalties that differ from those used to map out trade-offs between aggregated dimensions due to increased dimensionality.[24] Once spatially diverse alternatives are generated via appropriate methods, the above-mentioned advances in geometric approximation can build on those and allow these alternatives to be interpolated and intersected in a computationally inexpensive way in spite of their higher dimensionality.[38] This, too, contributes to making the tailored search for spatial aspects a more accessible option.

Integration with parametric uncertainty methods

As highlighted earlier, resilience to parametric uncertainty is often a critical factor for energy planning decisions.[14] When generating alternatives with MGA, it can thus be important to communicate the degree of resilience associated with each option,[10] which can be achieved by combining MGA with methods designed to handle parametric uncertainty.

Insofar as both methods for parametric uncertainty and MGA require additional computational effort, their combination has been enabled only recently by the computational advancements of next-generation MGA. For instance, the geometric perspective of MGA option spaces discussed above also enables looking at the intersections of several near-optimal spaces generated under different parametric assumptions to identify subsets of robust options, which perform well regardless of the assumed operating conditions or cost projections.[12,15,16] More generally, recent work showed how surrogate modeling techniques enable combining any MGA method with large sweeps of uncertain parameters, similarly to global sensitivity analysis, leading to more than 50,000 results to choose from, with different degrees of resilience to uncertainty.[33] Alternatively, a subset of "most-promising" MGA solutions, selected either based on stakeholder inputs[28,39] or data analysis methods such as clustering,[30] can be further analyzed for resilience based on out-of-sample testing of their operation.[17]

Intuitive and practically applicable outputs

While methodological work has shown how to chart near-optimal alternatives effectively and efficiently, useful applications of MGA inevitably involve the communication of results to stakeholders to support deliberation and the identification of actionable consensus solutions.[28,39]

MGA can easily lead to large volumes of data, but recent work showcased how this barrier can be effectively and substantially lowered by means of interactive interfaces to explore the generated near-optimal solutions in a frictionless, user-friendly manner. For instance, simple filtering mechanisms, such as sliders[34,39] or decision trees,[41] can be used to narrow down the options to those that match the desired preferences. In addition, the on-the-fly interpolation methods mentioned earlier[38] empower users to explore a wider variety of options around

those generated initially, increasing the likelihood that a consensus solution may emerge.[39] Recent work also showed that human-in-the-loop approaches can be used to let stakeholder preferences—including those emerging only after a first exploration of the possibilities—automatically guide MGA algorithms toward options of particular interest, further facilitating consensus formation.[28]

Potential for further development

Next-generation MGA methods thus enable the fast and computationally affordable exploration of many energy system planning options, including spatially explicit ones, while simultaneously offering stakeholders tools to smoothly navigate, interact with, and even expand or refine the vast option spaces generated. Overall, these advancements enable overcoming the key barriers to the establishment of MGA as a standard best practice. Still, there is further potential to solidify and deepen our understanding of the possibilities enabled by MGA and its synergy with methods to deal with uncertainty.

For one, the relaxation of the total system cost deemed acceptable often defaults to values between 2% and 20%. This is narrowly supported by historical evidence from the UK[6] and corroborated by recent insights from pilot studies with real-world stakeholders.[39] Nonetheless, additional research in this area would be beneficial to further validate the ranges of willingness to pay in a variety of contexts.

A second topic of interest is MGA in the context of multi-horizon optimization. In other words, planning pathways for infrastructure capacity expansion from today into the future. The vast majority of MGA studies operate under a single-horizon planning regime for a future year, neglecting the transition path toward it. Only few studies apply MGA to multi-horizon optimization with either myopic[16] or perfect foresight[21,42] over the planning horizons. Further research, however, could shed light on the efficiency and effectiveness trade-offs of different ways of applying MGA over multiple successive planning horizons—the definition of a near-optimal space and its exploration are less straightforward in this context. Moreover, the generation of diverse planning options over multiple investment periods lends itself to integration with result analysis methods developed in systems engineering, such as dynamic adaptive policy pathways,[43] that may maximize the interpretability and practical usefulness of the results.

Third, while already demonstrated in a few forms, the integration with methods conceived to handle parametric uncertainty has a large untapped potential.[10,17] Going beyond parameter sweeps typical of sensitivity or out-of-sample robustness analyses, methods such as stochastic programming and robust optimization are at the forefront of handling parametric uncertainty and are best suited to offer insights on how to hedge against it.[7,14] Their combination with MGA should be explicitly explored, as both fields could benefit from it: from an MGA perspective, the combination would enable generating systematically "resilient" alternatives, while, from a parametric uncertainty analysis perspective, MGA would enable exploring several instead of a single hedging strategy for a desired degree of resilience.

In addition, while many of the discussed recent advancements are broadly applicable from linear to mixed-integer linear and more complex optimization problem formulations, a few of them are not. In particular, methods leveraging the geometric properties of convexity to map out the volume of the near-optimal space[15,29] or to enable fast interpolation of previously-generated solutions[38] are currently only applicable to convex problems. It is thus important to research alternative methods to achieve similar goals that may be more broadly applicable. For instance, recent work advocated for more research in artificial intelligence methods such as meta-heuristics,[24,28] building on pilot experiments from the early years of MGA,[44] and on the proven applicability of meta-heuristics to energy planning problems for the mathematically affine field of multi-objective optimization.[30]

Finally, there is also high potential for more research on applying MGA together with stakeholders in the field. There are clear methods for interactive iteration of MGA spaces with stakeholders[28,38] and recent empirical insights, which corroborate and expand those from the earliest MGA experiments for simple problems,[45] on typical stakeholder preferences regarding how to explore such spaces smoothly and effectively.[39] Now, it is important to systematically evaluate these developments in a larger and more diverse number of field trials.

PRACTICAL SOLUTIONS TO ADVANCE ENERGY PLANNING BEYOND COST-OPTIMIZATION

We have illustrated the shortcomings of simple cost-optimization in energy planning analyses and the potential for next-generation MGA to go beyond such shortcomings. Here, we provide a practical guideline for the use of MGA that may facilitate and foster its establishment as a standard in this field. Our compilation of actionable recommendations is inspired by Arnstein's ladder of citizen participation[46] and the study by Wilson et al.[47] outlining good (enough) practices in scientific computing. We classify the recommendations into five levels—from the simplest and most computationally inexpensive to the most powerful and sophisticated—of how deeply MGA can be integrated into energy planning studies. We summarize these five levels in Figure 4 and elucidate them below.

Level 1—Acknowledge limitations of cost optimality

If your study does not include any MGA, clearly state that there are potential near-optimal solutions that may be overlooked. Consider reflecting in the discussion on whether incorporating near-optimal alternatives could influence the results, conclusions, and recommendations.

Level 2—Verify key claims with targeted tests

Any claim that one technology is an indispensable (or, vice-versa, unnecessary) feature for a system, if only derived from a cost-optimal result, should be verified by MGA or an equivalent method. You can obtain a rebuttal or support for the claim with little computational effort by simply minimizing (or maximizing) the investment in the technology in question within a set budget. If there is no or little change in the technology, this boosts confidence in your results. If the outcome differs substantially, you can broaden the discussion to what alternative technologies—that were out-competed in the cost-optimum—could

also represent a real choice. This approach is similar to a one-at-a-time sensitivity analysis and computationally inexpensive, but it already substantially improves the quality of your analysis. Notably, one-at-a-time or global parametric sensitivity analyses can serve similar purposes; still, they are based on variations of inputs, for instance, technology cost reductions that may not be directly controllable in the real world. As such, they may not be as intuitive in verifying a specific claim as a targeted MGA test for fixed input parameters.[12]

Level 3—Showcase flexibility in energy planning choices

Rather than focusing on single solutions and testing for the validity of specific features of theirs under marginal cost relaxations, consider expanding the use of MGA to quantify the diversity of options to achieve set goals in your energy planning model. In analyzing this planning flexibility, you can, for instance, focus on finding minimal investment levels that occur in all cases,[33,34] technology interchangeability,[32,34] timing,[16] and spatial diversification[10] of technology deployment. Be aware of the impact of the assumed acceptable cost relaxation on the found trade-offs, communicate such a relaxation transparently, and, ideally, test the impact of both tighter and wider relaxations.

Level 4—Systematically map out the space of near-optimal planning alternatives

For convex problems, recent theoretical advances allow for describing the full geometry of near-optimal feasible spaces for key variables of interest, interpolating within them, and gauging their size. This development offers new opportunities for reliably investigating ex-post-secondary objectives beyond costs, such as land use,[13] justice,[27] system vulnerability,[39] or—when combined with an appropriate parametric uncertainty method—the degree of resilience to selected parametric assumptions.[12,15] The computational burden of determining the near-optimal space can be a limiting factor here, so you might need to select a reduced set of metrics and variables to investigate.[15,25,39] Furthermore, communicate insights with care: in visualizing broad ranges of near-optimal design choices, it can be easily overlooked that extremes in one technology are often conditional on fixed choices in other technologies. For instance, onshore and offshore wind might be able to substitute for each other, but this does not imply that the studied system is feasible and cost-effective without either technology. Nevertheless, a systematic delineation of near-optimal spaces and their dependencies[15,29,34,38] provides a more comprehensive view of long-term infrastructure planning flexibility.

Level 5—Co-design viable planning alternatives with stakeholders

This level extends beyond using MGA for exploring flexibility in cost-effective planning strategies or system designs and buttressing insights from cost-optimization. Involve policymakers, industry, civil society, and other stakeholders. Use their input to first expand the search along directions of particular interest, which may be more granular or specific than what originally mapped,[28,38] and then to consolidate diverse stakeholder visions into a consensus.[39] Here, multi-objective optimization or multi-criteria decision methods can be applied efficiently to the simpler problem of finding those options that best match a shared set of given preferences, complementing MGA with higher user friendliness with little to no additional computational cost.[28,38,48] Having research guided by actual stakeholder preferences increases the likelihood of real-world impact, and interactive elements that would enable such engagement have been the focus of recent developments.[28,38,39]

Conclusion

Interest in using MGA is growing fast as a promising solution to some of the critical pitfalls of conventional energy system and integrated assessment models in supporting planning decisions. However, for various reasons, it has not yet become a standard. Our contention is that recent literature has seen many advances that allow overcoming some of the prevailing barriers to the widespread adoption of MGA and facilitate its integration with equally important methods to handle parametric uncertainty. Moreover, there are also clear avenues for further methodological developments and improvement that the next generation of modelers could pursue. By systematically mapping and synthesizing them, we aim to contribute insights that may spur the further establishment of MGA as a best practice in energy planning analyses.

To lower entry barriers, we provide concrete suggestions for incorporating MGA into energy planning analyses. Even minimal MGA checks on the key claims of a study—which require little computational effort—would already be a huge step in making such claims more consistent. We categorize applications of MGA into multiple levels with increasing scope and complexity, encouraging researchers to find an approach that best balances added insights with computational expense. More ambitious levels of integration unlock further potential for understanding the broad range of planning or design choices and infrastructure trade-offs in future energy systems. At the highest level of integration, MGA becomes an enabler of participatory co-design of energy planning strategies with real-world stakeholders, with the potential to facilitate the identification of practically viable consensus solutions and thereby accelerate the urgently needed energy transition.

While proven for both energy system and integrated assessment models, the majority of the recent MGA advancements have occurred with application to energy system models. This occurred in spite of prior work explicitly advocating for a more systematic adoption of MGA in integrated assessment models.[49] We hypothesize that our concrete suggestions on the tailoring of the computational effort may also facilitate a higher adoption of the method in the field of large-scale, complex integrated assessment models, where the manageability of the computational effort is often a priority similarly to the high-resolution, sector-coupled energy system models at the core of recent developments.

For all applications, we acknowledge that MGA is not a panacea nor necessarily always the sole or best-suited solution to go beyond simple cost-optimization. As noted earlier, explicit multi-objective optimization may be more effective when stakeholders are less heterogeneous, or goals are more neatly defined. Recent work suggests combining multi-objective

optimization and MGA to efficiently map the trade-offs between selected goals, while simultaneously providing a diversity of options along the frontier between such goals.[31] Moreover, methods focused on handling parametric uncertainty may be preferable when the main goal is planning for resilience; still, such methods are highly complementary to MGA and are increasingly integrated with it to provide insights on resilience while still exploring different planning possibilities.[16,17] We encourage further development of this synergistic integration. Finally, MGA needs to be facilitated by complementary expertise in participatory research when applied interactively in real-world settings. The recent studies that our perspective synthesis have shown that this is possible and valuable to various interest groups. Regardless of the method used, clear communication of what claims can be supported by an analysis is essential.

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AUTHOR CONTRIBUTIONS

Conceptualization, data curation, methodology, formal analysis, and writing (original draft and review & editing), F.L., K.v.G., A.G., M.L., F.N., N.P., and O.V.; visualization, F.L. and A.G.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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