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Robust pathway analysis of electricity investments under net-zero uncertainties

Erin Baker [a,*], John Bistline [b], Nexus Attiogbe [b,c]

[a] Department of Mechanical and Industrial Engineering, University of Massachusetts, Amherst, MA 01003, United States
[b] Electric Power Research Institute, 3420 Hillview Avenue, Palo Alto, CA 94304, United States
[c] Department of Chemical Engineering, University of Massachusetts, Amherst, MA 01003, United States

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ABSTRACT

Policy-makers and planners are looking to make robust power system investments under deep uncertainty and conflicting objectives. This paper presents a robust pathway approach to address a range of uncertainties and multiple objectives and provides a proof-of-concept applied to U.S. electric sector decisions under deep decarbonization. Results show the importance of considering a range of criteria: considering cost alone or CO_2 alone resulted in just two non-dominated pathways in each case; adding in the consideration of co-pollutants increased the number of non-dominated pathways to six of the nine considered. This analysis highlights the importance of considering fuel price uncertainty and, in particular, the possibility of high natural gas prices, which can lead to high co-pollution in otherwise low-polluting pathways. Results illustrate trade-offs between emissions and costs; as well as between CO_2 and co-pollutants, which is largely due to carbon removal use. The robust pathway framework is illustrative; we discuss how future work with harmonized multi-model outputs and spatially explicit pollutant metrics can provide additional insights.

1. Introduction

As the energy transition proceeds and electric companies target net-zero carbon emissions, they face complex decisions. Emerging studies suggest that there are many pathways to net-zero emissions in the power sector and across the economy, which can be achieved by a range of resource portfolios [1–4]. Utilities and other decision-makers are looking for guidance into medium- and long-term planning, which is particularly challenging due to deep uncertainty (e.g., about future technologies and policies) and conflicting objectives (e.g., sustainability, affordability, reliability, equity).

These two layers of uncertainty and disagreement have been addressed in different ways in the literature. One way to address disagreement over objectives is to apply multi-criteria methods. For example papers in the literature compare power-sector pathways on two or more criteria (e.g., cost versus CO_2) using multi-objective optimization [5], post processing to narrow down to a single alternative [6], or post-processing evaluation of a range of alternatives [7]. These and other similar studies, however, rarely address uncertainty, and even more rarely address deep uncertainty over the science, i.e. what has been described as “futures, models and outcomes” [8]. We will use the word “beliefs,” adopted from the Bayesian literature, to represent predictions about parameters, futures, models, and outcomes.

When it comes to disagreement over beliefs, the literature often distinguishes between parametric and structural uncertainties [9]. Parametric uncertainties arise from unknowns about future values in the decision-making environment such as the cost of solar power, natural gas prices, or stringency of climate policy. In contrast, structural uncertainty refers to unknowns about how closely model formulations approximate the underlying dynamics of the system. Both sources of uncertainty are present in energy-economic models [10,11]. The literature has proposed a range of methods to address parametric uncertainty through sensitivity and scenario analysis [12], uncertainty propagation approaches such as Monte Carlo analysis [13], or sequential decision-making frameworks such as stochastic programming and robust optimization [14–16]. These approaches explicitly address uncertainty, and robust optimization addresses deep uncertainty; but rarely include multiple objectives. A small number of papers use a multi-objective robust optimization framework [17,18], but focus only on dispatch, not planning, and only account for cost and co_2, rather than a wide range of metrics.

Structural uncertainty is commonly addressed through model

* Corresponding author.
E-mail address: edbaker@umass.edu (E. Baker).

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Table 1
Overview of EMF 37 models used in this analysis.

Analysis abbreviation	Model(s)	Analysis institution	Equilibrium approach; Foresight	Geographic coverage	Link
AnyMOD	AnyMOD	TU Berlin	Partial; perfect	North America	Link
EP-RIO	Energy PATHWAYS and RIO	Evolved Energy Research	Partial; perfect	27 U.S. regions	Link
EPA-TIMES	The Integrated MARKAL-EFOM System	USEPA/ORD	Partial; perfect	9 U.S. regions	Link
EPS	Energy Policy Simulator (EPS)	Energy Innovation	Partial; myopic	Single region	Link
FECM-NEMS	Fossil Energy and Carbon Management National Energy Modeling System	OnLocation	Partial; varies by module	Aggregation varies by module	Link
GCAM	Global Change Analysis Model	PNNL	Partial; myopic	Single region entire U.S.	Link
GCAM-USA	Global Change Analysis Model for USA	UMD-CGS	Partial; myopic	50 U.S. states and D.C.	Link
MARKAL-NETL	MARKet ALlocation	NETL	Partial; perfect	9 U.S. regions	Link
US-REGEN	Regional Economy, Greenhouse Gas, and Energy	EPRI	Energy end use: Lagged logit choice; Power: Least-cost LP	16 U.S. regions	Link

intercomparison exercises, where several different models run the same scenarios with similar harmonized assumptions (to the extent possible) to identify which insights are robust and which are more uncertain [19, 20]. However, these approaches can leave open the question for decision-makers about how to synthesize conflicting guidance across models, especially when multi-model studies cannot explain differences across models. These problems are even more complex when they involve multiple objectives.

Another approach, which we use in this paper, is to use dominance concepts to identify and evaluate pathways that are non-dominated across both a range of parameter values and a range of metrics. *Belief dominance*—known by several names in the literature (as in Savage [21] Etner et al. [22]; see Baker et al. [23] for a discussion)—identifies the set of pathways that are non-dominated over a set of beliefs, in this case about uncertain future costs. As described in Baker, Bosetti, and Salo [23], belief dominance is "employed to compare alternatives in the space of beliefs," whereas Pareto dominance "has traditionally referred to comparing alternatives in the space of objectives or criteria."[23] They show that belief dominance is compatible with most robustness and ambiguity-aversion methods in the literature, such as robust optimization [24–28], in the sense that the non-dominated set will include the set of optimal pathways that result from the robust optimization decision rules. The belief dominance concept does not require decision rules (such as min-max) to be agreed upon upfront, which provides flexibility to incorporate multiple objectives. Robust Portfolio Decision Analysis (RPDA) operationalizes belief dominance as a prescriptive decision rule [29]; applies this concept to portfolios of individual alternatives; and then identifies robust individual alternatives among the non-dominated set. While robust optimization has incorporated pareto dominance [30], existing papers all use a single, worst-case objective. RPDA has not yet been explicitly combined with *Pareto dominance* in any application, in the sense of identifying portfolios that are robust to multiple beliefs and multiple objectives. For a detailed discussion of these literatures, refer to Baker et al. [23].

A key contribution of this paper is to fill this gap, combining belief dominance and pareto dominance to identify robust electric sector investment decisions in the U.S. under economy-wide net-zero policies. Specifically, we apply both dominance concepts to evaluate and analyze a set of given alternatives; thus, extending RPDA to include both *belief dominance* and *Pareto dominance* [20,23,31]. We investigate robust net-zero pathways, which are made up of portfolios of individual technologies, and provide insights into investments into the individual technologies. These net-zero electric sector capacity pathways are based on the results of a structured multi-model analysis from the Energy Modeling Forum (EMF) 37 study and represent a range of models [2]. We reflect structural uncertainty by using the diverse pathways derived from the different models and by maintaining some of the key assumptions from the original models, including electricity demand and CO_2 prices that reflect decarbonization opportunities outside of the power sector. This multi-model process can be superior to generating pathways from a single model because of the diversity of underlying structural features of the models, including their spatiotemporal resolutions and decision-making approaches (Table 1), which has led earlier model intercomparisons to exhibit greater cross-model variability for the same scenario relative to intra-model variability across a range of scenarios [19]. RPDA is intended to synthesize conflicting models and beliefs, providing insight for utilities, policy-makers, and other decision-makers in this realm. Thus, this analysis is not intended to prescribe a single "optimal" pathway. Instead, we provide a proof-of-concept for how combining belief and Pareto dominance can screen pathways when models,parameters, and stakeholders disagree.

We can imagine an ideal study, in which all EMF models analyze all of the pathways under a full range of cost scenarios *and* calculate values for all criteria. This would provide an analysis that is more robust to structural uncertainty. At this time, however, this analysis is not available, as the models are computationally expensive and run by a diverse set of institutions. Thus, in this paper, we take a step in this direction, using a common value function to evaluate the pathways.

We evaluate the candidate pathways using the common value function model under a range of beliefs about capital and fuel costs and against multiple criteria, including costs, cumulative power-sector CO_2, and co-pollutants, specifically SO_2 and NO_x, which provides a consistent framework for comparing costs and emissions outcomes. In subjecting the EMF pathways to our common value function model, we are losing some of the important structural variation among the models. In particular, we note that each pathway represents a least-cost solution within its model and native input assumptions given economy-wide constraints on CO_2. In our value function model, by contrast, some pathways are never the least-cost among all other the pathways in any of the input assumption scenarios we consider.

However, by adding new criteria—cumulative power sector CO_2 and co-pollutants—we account for a wider range of relevant criteria. While other GHGs and aerosols are included in a range of models, local co-pollutants such as such as SO_2 and NO_x, are not reported in a number of the EMF 37 models, and are not used as a decision criterion in any of the models [32]. Adding this criterion is important because co-pollutants can harm the health of those who are exposed. It has been shown that in the US, marginalized populations live closer to large polluters, including power plants [33–35]. While decarbonization is likely to reduce co-pollution, there is evidence that some policies may lead to increased exposure in certain localities, increasing environmental injustice [36]. In addition, we go beyond a constraint for net-zero CO_2 in 2050 and consider cumulative CO_2 emissions, which is the relevant metric for climate change. We focus on power sector only because electricity is expected to play a central role in economy-wide decarbonization, through direct mitigation, end-use electrification, and electricity-derived fuels (e.g., electrolytic hydrogen) for sectors and applications that are costly to electrify [3].

We take the candidate pathways from EMF 37 models as given and do not model adaptive investment responses to cost realizations for

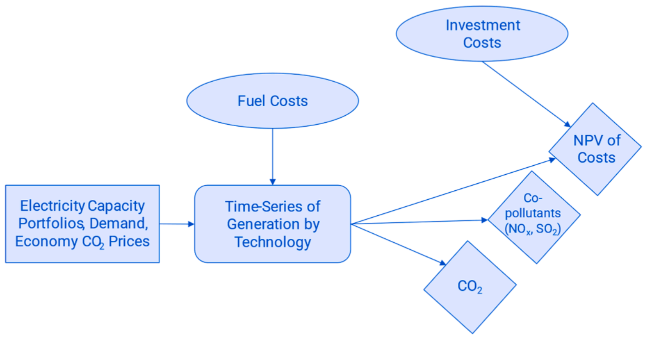

Fig. 1. Influence diagram for the decision problem of electric sector investments under uncertainty. The rectangle represents the decision, ovals represent uncertainties, the rounded rectangle represents calculations, and diamonds represent criteria.

several reasons, though we note that a study that creates additional hedging strategies would make a useful complement in future work. First, realizations of capital cost uncertainties are likely to occur after initial capacity deployment. The timing of investments for net-zero pathways in the EMF 37 study suggests that capacity additions are concentrated in the post-2035 period (see Fig. 10 in Additional Analyses), which means that recourse before 2050 is limited. For six of nine models, over 50 % of cumulative capacity additions occur between 2035 and 2050, which may not leave time for recourse. Thus, we focus on plans that are robust rather than adaptable in this analysis. Second, 29 US states include renewable pathway standards with technology-specific carveouts and mandates for technologies such as offshore wind, energy storage, and solar [37]. These standards reduce the flexibility of companies to adapt investments if costs are revealed to be higher than predicted, which constrains recourse even for technologies that have shorter lead times. More generally, a range of path-dependencies may make it challenging to adapt mid-course, including policy, siting, and supporting infrastructure for transmission, pipelines, and CO_2 storage.

Our methodology combines belief dominance with Pareto dominance, and thus can uncover interactions between specific scenarios and criteria that may otherwise be masked. It allows us to make sense of the conflicting outputs from complex models to derive insights, thus is a nod toward structural uncertainty. This study allows us to potentially narrow the set of candidate pathways, while uncovering compromise pathways that may be overlooked under a narrow focus on cost.

2. Methods and experimental procedures

2.1. Overview

This study evaluates electric sector generation capacity pathways from nine detailed energy-economic models (Table 1). These models span a range of structural assumptions (e.g., spatiotemporal resolution) and applications. These pathways come from the EMF 37 study that investigates deep decarbonization in North America, and we focus on pathways that reach economy-wide net-zero CO_2 emissions by 2050 [2]. These pathways are assessed across a set of technology cost scenarios and three evaluation criteria (Fig. 1).

The rectangular node represents the key decision that is the focus of this paper—the time path of investments in electricity generation capacity. We also take electricity demand levels and economy-wide CO_2 prices from the individual models. In our analysis, the alternatives we considered are derived from the EMF 37 study. The rounded rectangle represents the value function model, described in Section 2.5, which calculates the resulting cost, cumulative CO_2, and co-pollutants from each of the generation capacity pathways conditional on uncertainties in fuel costs and capital costs. The CO_2 and co-pollutants depend entirely on the generation, while the net present value (NPV) of costs also depends on capital cost assumptions.

We apply RPDA to identify which pathways are non-dominated and to analyze the implications about individual generation technologies. Fig. 2 provides an illustration of the method. Similar to Fernandez et al. [38], we evaluate multiple generation capacity pathways using a single model. We then apply the RPDA framework to these results, expanding upon previous work by considering multiple criteria along with multiple beliefs. (See Baker et al. [23] for a detailed review discussion of RPDA and how it relates to robust optimization).

The rest of this section is organized as follows. We describe the method for identifying non-dominated electric generation capacity pathways in 2.2. We define the evaluation criteria in Section 2.3 and the alternative pathways in Section 2.4. In Section 2.5, we describe the value function model used to estimate the values of the criteria for each pathway. Finally, Section 2.6 describes the cost scenarios.

2.2. Dominance analysis

We consider a set of 24 cost scenarios (Ω), which include different assumptions about the capital costs and operating costs of the technologies. We also consider a set of three criteria. We look for non-dominance across the cost scenarios and the criteria among the pathways derived from nine energy systems models. By pathways, we mean the time paths of investments in electricity generation capacity. In words, a pathway *p* (from one model) dominates pathway *p'* (from

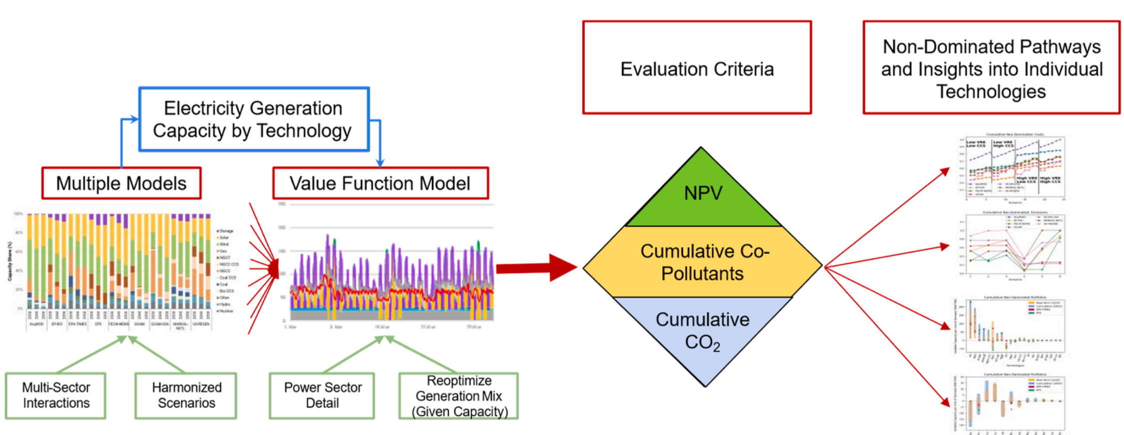

Fig. 2. Overview of the framework for this analysis.

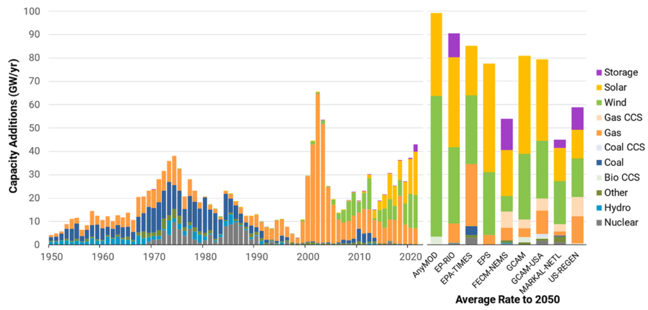

Fig. 3. Historical and projected capacity additions by technology and model. The right panel shows the average annual additions through 2050 in pathways that reach economy-wide net-zero CO_2 in 2050.

another model) if it is better on all 3 criteria in each of the 24 cost scenarios.

Mathematically, we define $V^{\omega}_{p,m}$ to be the value of criteria m under pathway p and cost scenario ω. We say that pathway p dominates pathway p' over the criteria set ϕ and the set of all cost scenarios Ω if:

$$V^{\omega}_{p,m} \geq \ V^{\omega}_{p',m} \ \forall m \in \phi \ \omega \in \Omega \tag{1}$$

with at least one inequality being strict. A pathway is non-dominated if there is no pathway that dominates it.

2.3. Evaluation criteria

There are three evaluation criteria used in this analysis, which are intended to illustrate the framework using available data from the EMF 37 study:

- **Costs:** Costs are the NPV of all electric sector costs over time for given pathways under different scenarios. Costs include all investments and operations costs (see Eq. (4) in Section 2.5), which vary based on the realizations of capital cost and fuel cost uncertainties. These are measured in units of 2020$ per MWh: they are normalized by electricity demand for comparability across models (since different models have varying levels of end-use electrification and use of electricity-derived fuels to meet economy-wide net-zero targets).
- **Cumulative electric sector CO_2 emissions (χ):** These are cumulative CO_2 emissions over time normalized by electricity demand. Electricity CO_2 is used because, while total economy-wide CO_2 is constrained to net-zero in 2050, interim electricity emissions drive both cumulative warming and the scale of negative emission deployment required in other sectors. In addition, states and regions may regulate power systems emissions, either explicitly (e.g., Colorado, Regional Greenhouse Gas Initiative in the Northeast) or implicitly through clean electricity standards. When combined with company targets for net-zero emissions reductions, utility planners may care explicitly about power system CO2. We acknowledge this metric privileges pathways with early power sector decarbonization and works against pathways with negative emissions outside the power sector. Unlike cost, CO_2 and co-pollutant emissions are undiscounted. Emissions vary by fuel cost, since different fuel costs lead to different operations, but not by capital cost, since the capital investment is fixed for each pathway. This criterion is calculated for pathway p with demand d over the timeframe from 2030 to year t using the formula below.

$$\chi^{\omega}_{p} = \frac{\sum_t \chi^{\omega}_{p,t}}{\sum_t d_{p,t}} \tag{2}$$

- **Co-pollutant emissions (π):** These are cumulative non-GHG co-pollutants normalized by electricity demand, where co-pollutants are the sum of NO_x and SO_2 (summed without weighting). With finer spatial-resolution data on population exposure and emissions concentrations, future work could apply marginal mortality damage weighting to NO_x and SO_2 emissions, thereby capturing the heterogeneous health impacts of co-pollutants across different regions (see [39] for an example of differential impacts on health based on location and type of pollutant). Like CO_2 emissions, co-pollutants vary under different fuel price scenarios but not by capital cost uncertainties. This criteria is calculated for pathway p with demand d over the timespan from 2030 to year t using the formula below.

$$\pi^{\omega}_{p} = \frac{\sum_t \pi^{\omega}_{p,t}}{\sum_t d_{p,t}} \tag{3}$$

2.4. The alternatives: EMF 37

The portfolios of generation capacity over time come from the EMF 37 study, which is the first multi-model comparison of net-zero emissions for the U.S [2]. The nine models in this study use different approaches (Table 1) to identify pathways that achieve economy-wide net-zero carbon dioxide (CO_2) emissions in the U.S. by 2050. Note that these pathways do not reflect Inflation Reduction Act (IRA) incentives, and although these tax credits are expected to alter near-term reference case trajectories [40], their impacts on longer-run outcomes in the presence of economy-wide net-zero policies is small relative to these net-zero policies [41]. The wider study explored the implications of technology evolution, policies, and behavioral assumptions affecting energy supply and demand. We focus on the models from the overview paper that report power sector capacity and reach net-zero emissions by 2050.

A summary of the capacity mixes by model is shown in Fig. 3. Compared with historical investments, additions of low-emitting resources are at levels many times their historical maximum rates. The composition of clean generation investments varies by model—including variable renewables, energy storage, carbon-capture-equipped capacity, and nuclear.

2.5. Value function model to evaluate criteria

In order to evaluate the cost, CO_2, and co-pollutants from each generation capacity pathway, we use a single model, which takes the capacity mix as given. We use a single model for three reasons. First, our aim is to assess system costs and emissions across pathways, and using a single value function model provides comparability in these criteria using a ceteris paribus framework. In addition to the comparability of outputs for the robustness analysis, it would be prohibitively challenging computationally and logistically to re-run each EMF 37 participating model for all 24 scenarios with fixed capacity. Second, the

EMF 37 study does not report data on co-pollutant emissions rates and other operational parameters, thus we needed to develop a model for this. Third, the EMF study results are based on unharmonized assumptions across models, including for capital costs and fuel prices, and do not consider a range of capital and fuel costs, as we do in this analysis.

In this study, each capacity investment pathway (i.e., the time series of installed wind, solar, nuclear, gas, energy storage, and other generation technologies) is taken directly from EMF 37 model outputs and treated as an exogenous input to our value function model. We evaluate system costs and dispatch under a fixed, pre-specified capacity trajectory. This approach simplifies computation and ensures direct comparability to the original EMF 37 results, but it also introduces biases. Because the value function model cannot shift capacity between technologies or adjust build timing, it may understate the cost of pathways that require intra-annual or inter-hourly flexibility, particularly those with high shares of variable renewables and energy storage. We revisit these limitations in Section 4.2 and discuss how they could skew comparisons.

Our results must be interpreted carefully. We acknowledge that each of the models internally minimized costs, thus all the paths could be considered non-dominated over costs in the sense that no other pathway had a lower cost if evaluated in that model. Moreover, it is plausible that a different value function model would result in a different set of non-dominated models. We argue that moving forward using a single model provides insights not otherwise attainable at this time. We leave it open to important future work to evaluate pathways under multiple structural assumptions, as highlighted in Section 4.2.

Given these capacity pathways and a set of cost assumptions (discussed below), the value function model minimizes the NPV of electric sector costs through 2050 subject to constraints for market clearing and upper bounds on generator availability:

$$\sum_t \delta_t \left(\sum_i c^{\omega}_{pit} x_{pit} + f^{\omega}_{pit} y^{\omega}_{pit} \right) \tag{4}$$

where y^{ω}_{pit} is dispatch of technology i in pathway p during period t for cost scenario ω. The model uses annual timesteps at a national level, given the temporal and spatial resolution of reported EMF 37 outputs. The model takes the pathway x_{pit} as given, which means that new capacity investments of generation, energy storage, and transmissions are exogenously specified and do not vary across scenarios, though the NPV of investments depends on the scenario-specific capital cost assumptions c^{ω}_{pit}. Annual dispatch costs f^{ω}_{pit} not only include fuel and variable maintenance costs but also include carbon prices, which are model outputs from EMF 37 and represent shadow prices on the economy-wide CO_2 constraint [2]. Like electricity demand trajectories, these carbon prices vary by pathway and reflect abatement opportunities and cost outside of the power sector. The discount factor δ_t assumes a 7 % cost of capital for all models.

The load balancing (market-clearing) constraint for each annual period t is:

$$\sum_i y^{\omega}_{pit} \geq d_{pt} \tag{5}$$

where output across all generators is greater than or equal to demand d_{pt}, which varies by model p based on electricity demand changes to reach economy-wide net-zero CO_2 levels. Production capacity bounds are:

$$y^{\omega}_{pit} \leq a_{pit} x^{\omega}_{pit} \tag{6}$$

where dispatch cannot exceed the product of installed capacity and availability factor a^{ω}_{pit}. This availability uses model-specific capacity factors for variable renewable resources and hydro, given how resource quality varies significantly regionally but EMF 37 pathways are only provided at the national level. Availability factors for dispatchable generation reflect annual outage rates and come from EPRI's U.S. Regional Economy, Greenhouse Gas, and Energy (REGEN) model.[1] Models do not provide more temporally granular outputs to simulate detailed system operations at a sub-annual level, so the analysis assumes that the model-specific pathway satisfies resource adequacy criteria in the native framework. Due to this limited sub-annual detail, we apply a constraint on dispatchable technologies j to ensure that the optimized annual dispatch in this analysis is greater than or equal to dispatchable generation from the native pathway run (Y_{pjt}) from EMF 37:

$$\sum_j y_{pjt} \geq \sum_j Y_{pjt} \tag{7}$$

Outputs include the NPV of system costs, annual generation by technology, as well as emissions of CO_2, NO_x, and SO_2.

The formulation is similar to power sector capacity expansion models used in EMF 37, including endogenous dispatch, but exogenous pathways for generation, energy storage, and transmission investments and retirements (see for example [42,43]). Thus, the value function model used in this study captures regional electric sector dispatch in a stylized manner relative to more detailed systems operations or commercial production cost models [44]. In balancing detail and computational tractability, national capacity expansion models typically have greater geographical extents, longer time horizons, and sectoral interactions; production cost models often have unit-level resolution, greater temporal resolution, unit commitment costs and constraints, and detailed ancillary services markets [45,46]. Adding more production-level detail is an opportunity for future work but also requires outputs that EMF 37 models did not provide in the original analysis, including detailed spatial information on generation and energy storage capacity, operational parameters for power plants (e.g., minimum turn down limits), and time-series variables at appropriate temporal resolutions (e.g., hourly or subhourly load and variable renewable profiles). The optimization omits intra-annual energy storage dynamics, transmission constraints, and unit-level operations. Section 4 discusses how neglecting these features may bias cost results towards renewable-heavy pathways.

2.6. Parametric uncertainties: costs

This analysis considers uncertainties over technology capital costs and fuel costs. There are eight capital cost scenarios, consisting of combinations of low and high capital costs for variable renewables, CCS-equipped capacity, and nuclear (Fig. 4):

- Utility-scale solar PV, land-based wind, and offshore wind come from Bistline, et al. [47], which considers several sources in the literature for capital cost projections for U.S. solar, wind, and energy storage.
- High nuclear and CCS costs are based on US-REGEN assumptions [48], and low costs are based on a meta-analysis of expert elicitations from Verdolini et al. [49], using average annual cost reductions across studies and experts relative to 2020 levels. Many elicitations summarized in this meta-analysis are based on surveys that are over a decade old for nuclear and CCS, given how there have been few recent elicitations for these technologies. The lower nuclear costs in Fig. 4 align with the "Advanced" cost scenario in NREL's 2024 Annual Technology Baseline (ATB), which are about $3800/kW in 2035. The lower gas with CCS costs assumed below also align with the "Advanced" cost scenario in NREL's 2024 ATB, which are about

[1] REGEN features regional disaggregation and technological detail of the power sector and linkages to other sectors. Peer-reviewed articles can be found at https://esca.epri.com/models.html, and detailed model documentation is available at https://us-regen-docs.epri.com/.

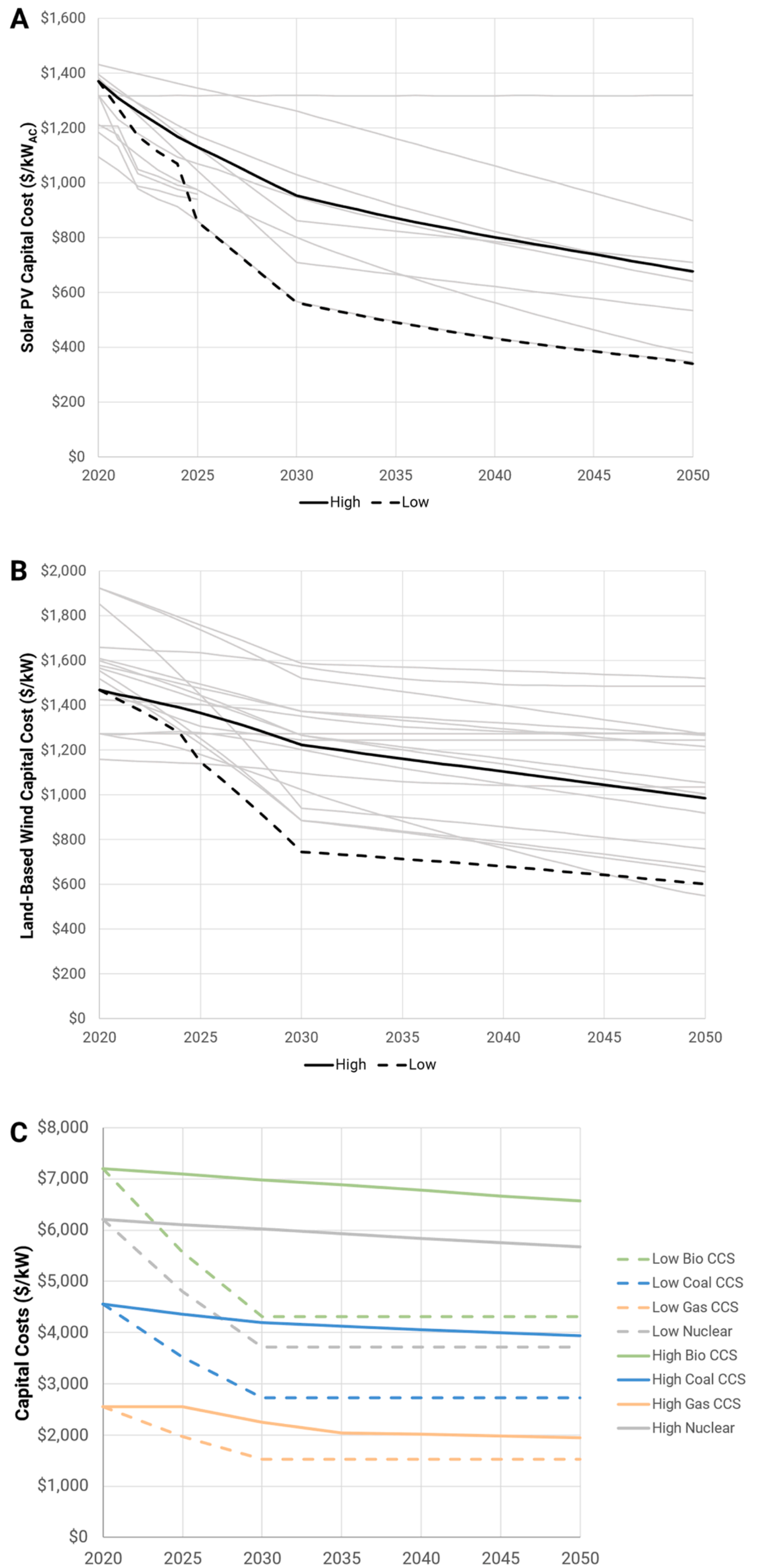

Fig. 4. Low and high capital cost assumptions over time. Values are shown for utility-scale solar PV (A), land-based wind (B), and CCS/nuclear (C).

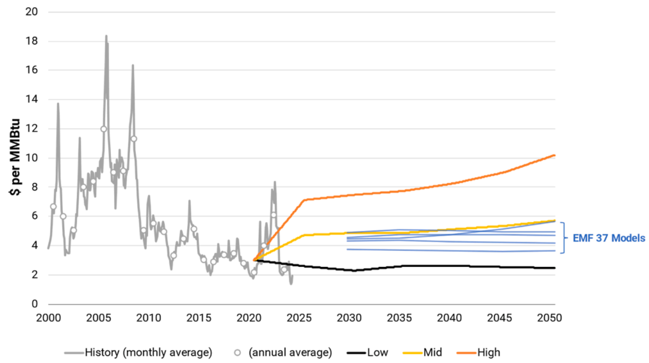

Fig. 5. Historical and projected natural gas prices over time. Values are shown for delivered prices to the power sector in real 2022 U.S. dollar terms. EMF 37 model natural gas price assumptions are shown in blue.

$1700/kW in 2035 for a 2-on-1 F-Frame combined cycle with 95 % capture.

Most EMF 37 models do not report capital cost assumptions for electric sector technologies in the scenario database. However, a recent multi-model analysis of power sector impacts of IRA, which includes several models in EMF 37, finds that many models assume capital costs based on NREL's Annual Technology Baseline [50], which are comparable to the "High" scenario in this analysis.

The analysis considers three fuel price scenarios, which are based on the U.S. Energy Information Administration's Annual Energy Outlook (AEO) scenarios (Fig. 5):

- The low price scenario is based on the high oil and gas resource scenario from AEO 2023.
- The middle and high price scenarios are based on the reference and low oil and gas resource scenario from AEO 2018, given that the low and high natural gas price scenarios in AEO 2023 have narrower range.

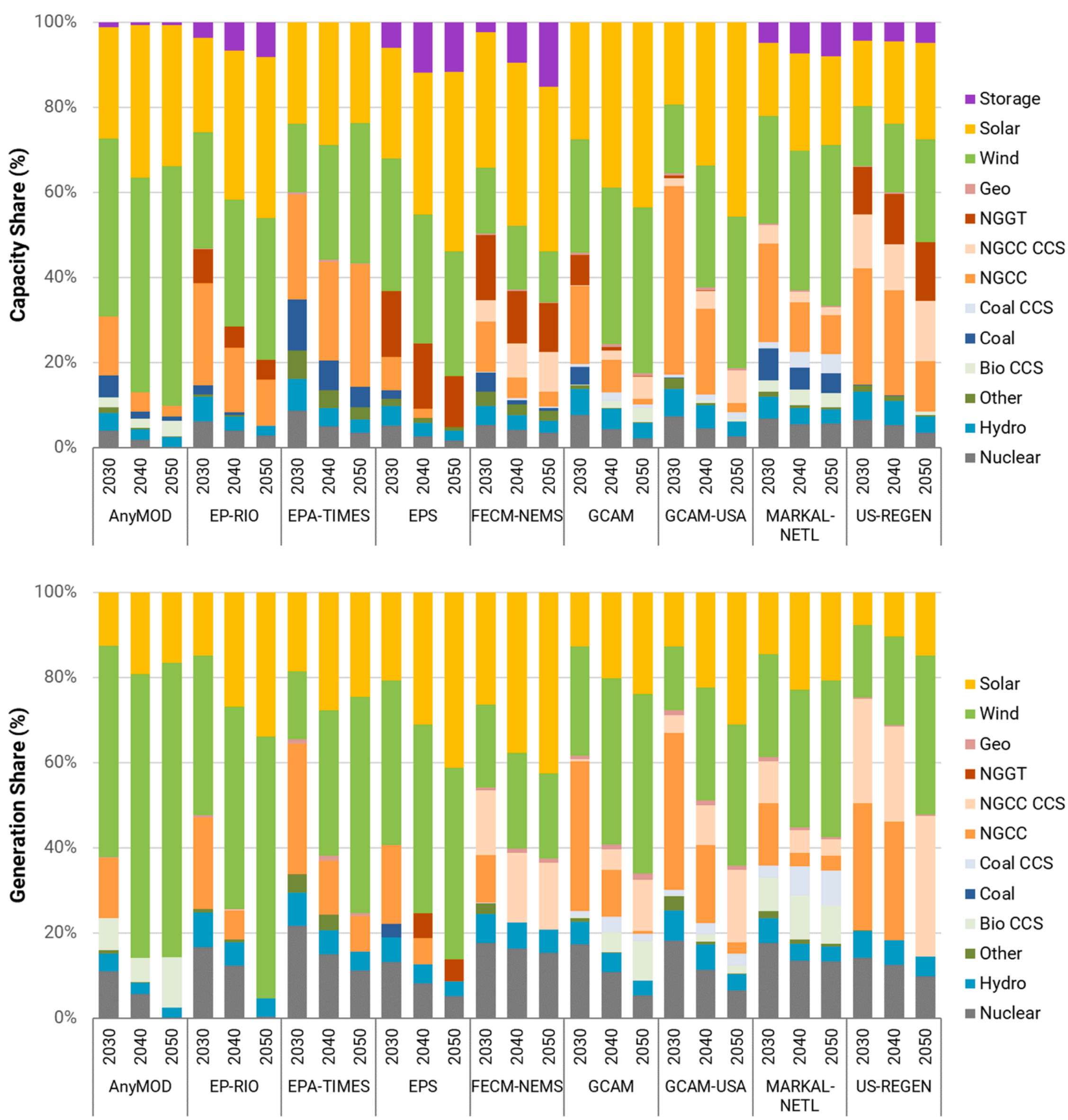

Fig. 6. Installed capacity share (top panel) and generation share (bottom panel) by technology and model over time. The top panel comes from EMF 37 results that reach economy-wide net-zero CO_2 in 2050 [2]. The bottom panel shows generation under the middle fuel cost scenario, which is an output of our analysis. Model descriptions are provided in Table 1.

The EMF 37 models vary in their default assumptions for natural gas prices over time, but many models have values that are consistent with the “Mid” case in this analysis or a trajectory between the “Mid” and “Low” cases.

The analysis considers all combinations of technology and fuel cost uncertainties, which leads to 24 total cost scenarios.

3. Results

We evaluate a set of nine pathways derived from the EMF 37 study, illustrated in Fig. 6 [2].

Models suggest that wind and solar play larger roles in the generation mix over time for net-zero CO_2 energy systems (Fig. 6), though the extent varies by model [51].[2] There is also variation in the pace of fossil fuel capacity declines over time, with some models retaining coal- and natural-gas-fired capacity over time to provide dispatchable capacity. Models also indicate different levels of clean firm capacity, including carbon capture and storage (CCS), nuclear, firm renewables, and long-duration energy storage.

These differences in capacity mixes and scenario-dependent generation lead to variation in CO_2 and co-pollutants over time (Fig. 7). Higher fuel costs for natural gas generally lead to increases in generation from coal and biomass (see Fig. 11 in Additional Analyses), which increase emissions during the transition.[3] Although emissions decline over time, electricity CO_2 intensities are greater than zero along the transition and even when net-zero CO_2 across the economy is reached, where residual emissions are balanced by carbon removal.[4] These residual emissions are due in part to the prominent role that electrification and electricity-derived fuels play in displacing fossil fuel use in decarbonized systems [52], which leads to different levels of electricity demand increases across models.

3.1. Non-Dominated pathways

Table 2 highlights the non-dominated pathways using our value function model, under the 24 cost and price scenarios and four sets of objectives—minimizing cost only, CO_2 emissions only, co-pollutants only, and combined cost and emissions. Note that pathways with high variable renewable shares may appear less costly than they would in more detailed simulation models, given that the value function model omits operating reserve requirements, endogenous energy storage, and unit-level cycling.

Fig. 8 illustrates how the six pathways that are non-dominated across all three criteria compare under the 24 cost and price scenarios. Each criterion has been normalized so that 1 is the worst outcome of that criteria across all non-dominated pathways and scenarios. Note that CO_2 and co-pollutants do not vary across capital costs, due to the fixed capacity pathways across scenarios; thus, panels (b) and (c) have only the three fuel scenarios.

If we look only at Fig. 8a, this shows that across the 24 scenarios, only two alternatives are non-dominated when cost is the sole criteria. EP-RIO is the lowest cost in 16 scenarios and dominates all other pathways except US-REGEN, which has the lowest cost in 8 scenarios. EP-RIO is almost entirely renewable generation in 2050, so system costs are sensitive to wind and solar capital costs. US-REGEN has a more balanced pathway of low-emitting technologies and is lower in cost when wind and solar are expensive. We note that each pathway is the least cost solution within its own model. However, some pathways are not the lowest cost of all models considered for the input cost assumptions in this analysis.

If we look only at Fig. 8b, this shows that if we consider only CO_2, then only two models are non-dominated: AnyMod and MARKAL-NETL. We note that all of the pathways are part of economy-wide pathways that meet an economy-wide net-zero CO_2 constraint in 2050. Here, we are focusing on power system CO_2 and cumulative emissions along the time path. This leads to many of the pathways being dominated. The non-dominated models have the lowest electricity sector CO_2 due to their negative emissions from biomass with CCS (BECCS) deployment.

Fig. 8c shows that five models are non-dominated when we consider co-pollutants only: AnyMod, EP-RIO, FECM-NEMS, GCAM, and US-REGEN. This highlights the importance of considering a range of criteria. Most modeling exercises focus on costs and CO_2, to the exclusion of other criteria, which may be important to decision-makers and communities [53]. This result starkly illustrates the weakness with such an approach. Using a narrow set of criteria to determine candidate pathways may miss important compromise alternatives. In this case, the FECM-NEMS pathway is a particularly interesting compromise. While it is dominated across cost alone and across CO_2 alone (but not when the two criteria are considered together), it is close in both cases, with the third lowest costs when renewables costs are low, and very close to the lowest CO_2 in each case. It is non-dominated under co-pollutants and is steady across the three fuel cost scenarios. Compared to EP-RIO and US-REGEN, this pathway has less wind capacity and more energy storage, solar, and nuclear than the other pathways. Moreover, it is between EP-RIO and US-REGEN in overall renewables generation.

If we consider all three criteria combined, six models are non-dominated: AnyMOD, EP-RIO, FECM-NEMS, GCAM, MARKAL-NETL, and US-REGEN. The three dominated models are not shown: EPA-TIMES is dominated by EP-RIO, EPS is dominated by EP-RIO and GCAM, and GCAM-USA is dominated by FECM-NEMS, GCAM, and US-REGEN. EPA-TIMES retains considerable existing coal and biomass capacity, which leads to higher emissions, especially under higher fuel price scenarios. EPS has greater combustion turbine capacity and generation, which has higher emissions intensities and higher costs under high fuel price scenarios. GCAM-USA has the highest near-term gas-fired generation, increasing emissions and costs.

Overall, we see that the robust decarbonization paths vary depending on which criteria are emphasized. If cost is the only criterion (subject to the net-zero CO_2 constraint), the pathways from US-REGEN and EP-RIO are preferable. If CO_2 is only criteria, then AnyMOD and MARKAL-NETL are best. For co-pollutants under lower fuel costs, AnyMOD is best, but when we consider high fuel costs, the most robust pathways are FECM-NEMS, US-REGEN, and GCAM.

Fig. 8 shows that costs across models and scenarios are generally within a relatively tight range (with the range from high to low about 85 % of the mean), whereas the CO_2 varies more, and the co-pollutants vary considerably (with the range being more than twice the mean). However, co-pollutants in these net-zero systems are much lower than current levels of co-pollutants, and marginal abatement costs of moving to pathways with lower co-pollutants can be expensive. For example, moving from the US-REGEN to AnyMOD pathway implies a co-pollutant abatement cost of between $50,000 and $120,000 per ton in the lower fuel cost scenarios. It is important to note that remaining co-pollutants in the system will be concentrated at the remaining fossil plants, and not spread evenly across the system. This means that there may be important implications of the higher polluting pathways, particularly for environmental justice communities, who tend to bear a larger proportion of pollution from all industries [54,55].

We can also examine tradeoffs between other criteria. The tradeoff between MARKAL-NETL, which has lower CO_2 due to its higher carbon

[2] Gao, et al. [51] discuss differences across model structures and input assumptions that can influence modeled outputs.

[3] Although prices for all fuels increase in the high-cost scenario, the relative price increase is highest for natural gas. Models with more pronounced gas-to-coal switching—AnyMOD, EP-RIO, and EPA-TIMES—generally retain more coal capacity and have larger gas generation shares without CCS in the middle fuel cost scenario.

[4] These removals may be inside the power sector—through biomass with CCS (BECCS) for electricity generation—or outside of the power sector—though afforestation, direct air capture, or BECCS for liquid fuels

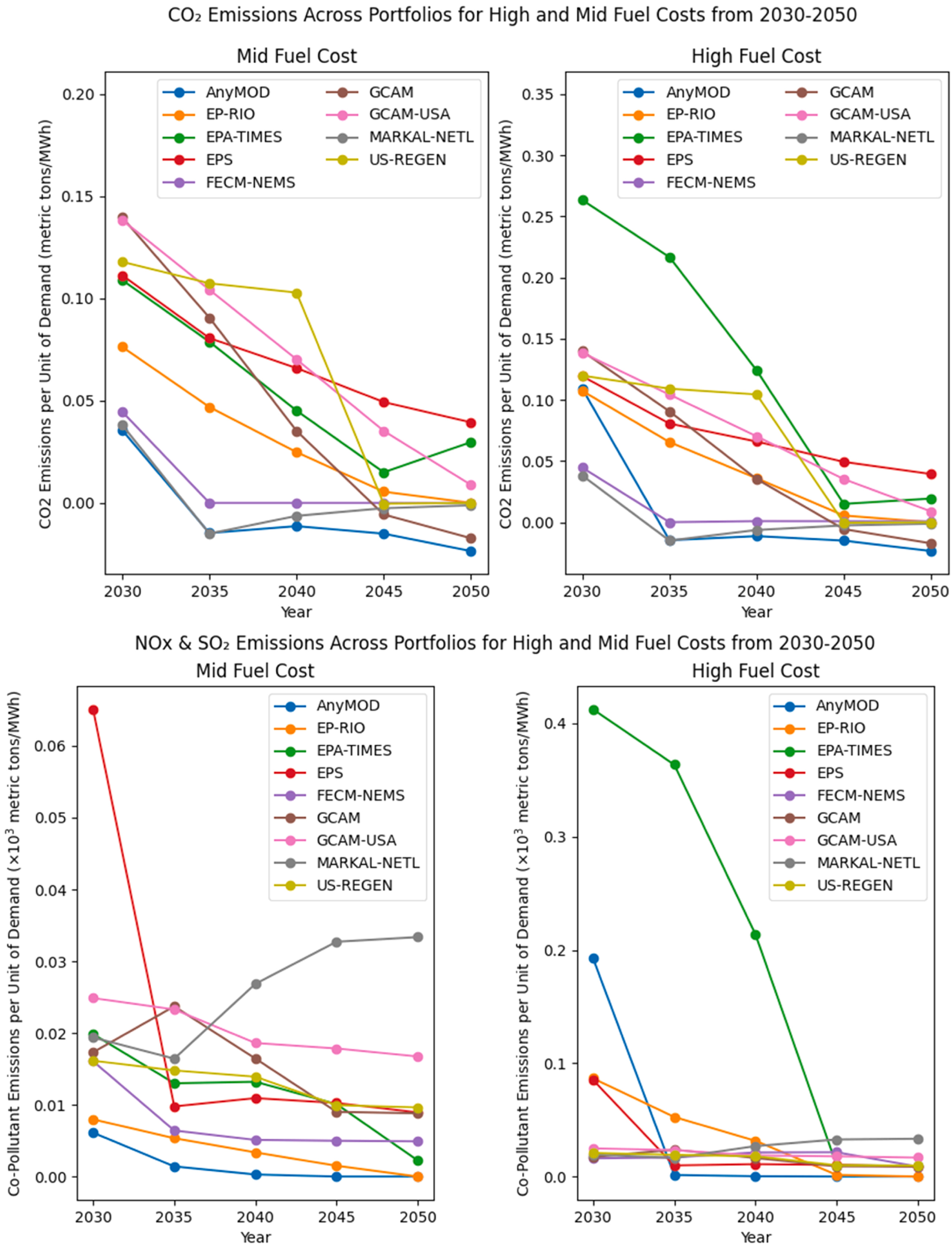

Fig. 7. Electric sector emissions intensity for CO_2 (top panels) and co-pollutants (bottom panels) per unit of demand over time. Lines represent outputs under different pathways. Emissions are normalized by electricity demand for comparability across models with different levels of electrification and service demand (in units of metric tons per MWh). Emissions intensities are shown for the middle fuel cost scenario (left panels) and high fuel cost scenario (right panels).

Table 2
Comparison of non-dominated pathways for each objective. "Pathway" refers to the model-specific path of capacity illustrated in Fig. 6. Checkmarks indicate that the pathway is non-dominated under the objective at the top of the column; an X indicates the pathway is dominated.

Pathway	Cost Only	CO_2 Emissions Only	Co-pollutant Emissions Only	Cost and Emissions
AnyMOD	�	✔	✔	✔
EP-RIO	✔	�	✔	✔
EPA-TIMES	�	�	�	�
EPS	�	�	�	�
FECM-NEMS	�	�	✔	✔
GCAM	�	�	✔	✔
GCAM-USA	�	�	�	�
MARKAL-NETL	�	✔	�	✔
US-REGEN	✔	�	✔	✔

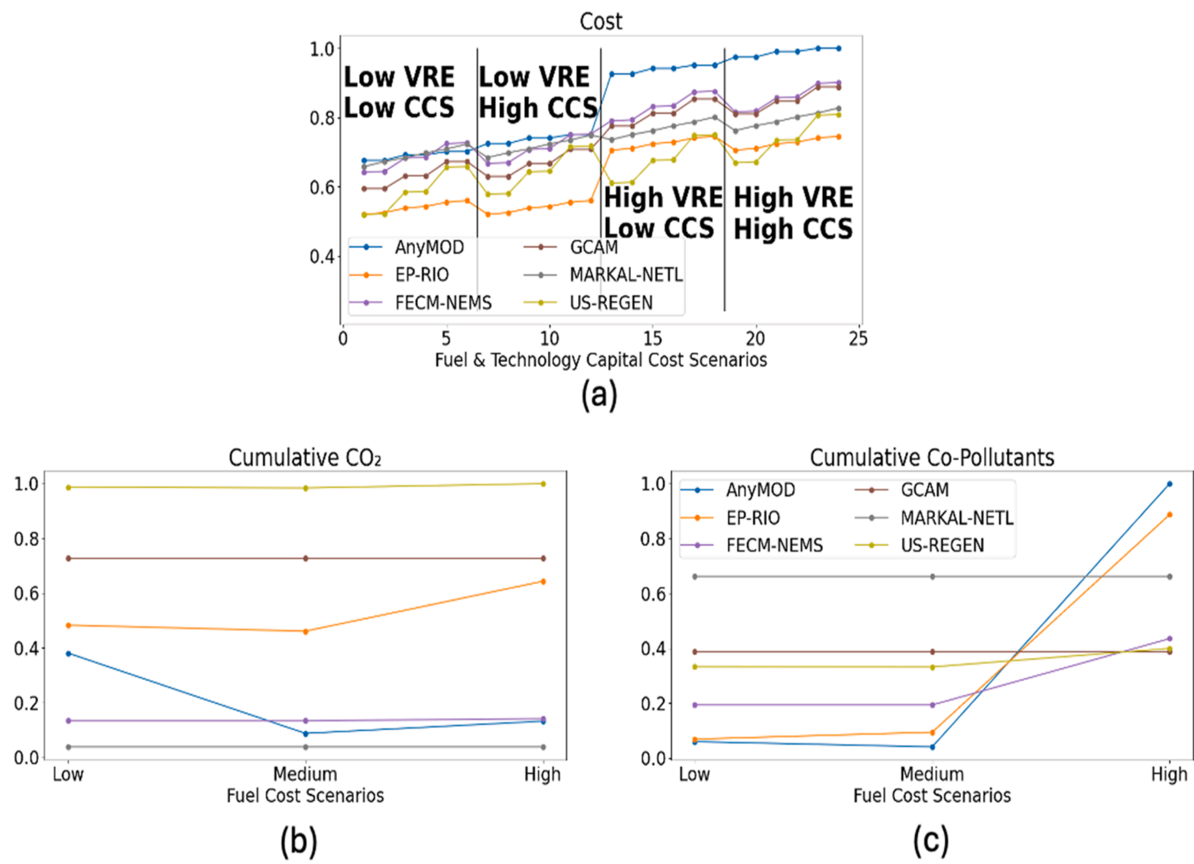

Fig. 8. Normalized costs (a), CO_2 emissions (b), and co-pollutant emissions (c) over scenarios with varying fuel and technology capital costs for pathways that are non-dominated over the joint cost and emissions criteria. For costs, the 24 scenarios are composed of combinations of fuel costs (low, mid, and high) and technology capital costs. Each criteria represents cumulative values from 2030 through 2050 and has been normalized so that 1 is the worst outcome of that criteria across all pathways and scenarios. For emissions, the scenarios are independent of capital costs. Panel (c) considers the sum of cumulative SO_2 and NO_x emissions.

removal via BECCS,[5] and EP-RIO, which has low co-pollutants in the lower fuel cost scenarios, implies a tradeoff of about 1300 tons of CO_2 for every ton of co-pollutants. The tradeoff between AnyMOD, which has low CO_2, and EP-RIO, which has low costs, implies a cost of between \$25–250 per ton of CO_2.

When it comes to co-pollution, a key tradeoff occurs between the lower and higher fuel costs. For example, both EP-RIO and AnyMOD have low co-pollutants in the lower fuel cost scenarios, but jump up when fuel costs are high. This implies a lack of robustness in the face of uncertain fuel costs. GCAM, for example, would be dominated except for the high fuel price scenario, and US-REGEN would be dominated when considering only CO_2 and co-pollution due to its lower carbon removal and higher CCS. Pathways that retain higher-emitting coal capacity are risky from an emissions perspective if there is uncertainty about fuel costs, especially if high gas prices obtain.[6]

In summary, these scenarios illustrate tradeoffs between several criteria and pathways. Although some pathways are dominated when looking at specific economic and environmental criteria (Table 2), there is a tension between lower emissions and higher costs and vice versa.

[5] Although the MARKAL-NETL portfolio has among the lowest net CO_2 emissions intensities, it relies heavily on negative emissions from BECCS, which allows some fossil-fuel-fired generation in mix. This leads to higher co-pollutants because of the remaining coal, natural gas, and biomass generation, especially when fuel costs are high. On the other hand, EP-RIO has a notable lack of BECCS, leading to higher CO_2.

[6] We note that this response to high fuel costs is driven entirely by early co-pollutants, in 2030, and thus the tradeoff is most important in the mid-transition.

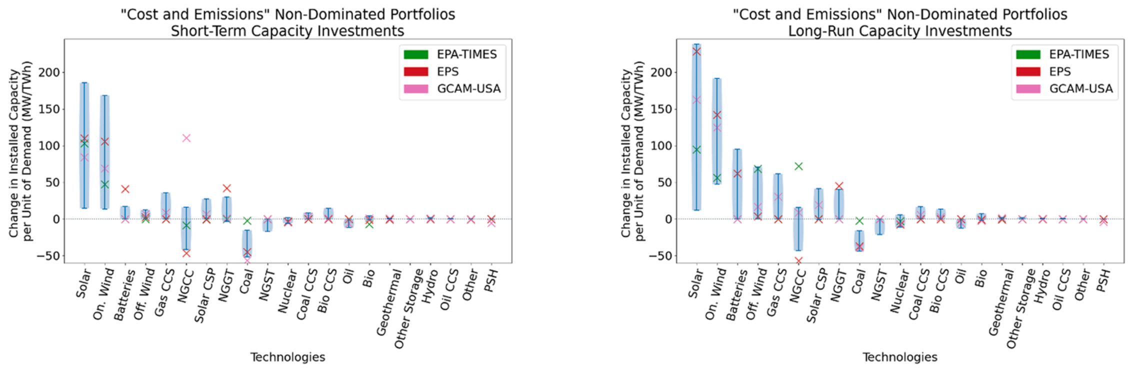

Fig. 9. Range of net changes in installed capacities by technology. Bars show range for the six non-dominated pathways (AnyMOD, EP-RIO, FECM-NEMS, GCAM, MARKAL-NETL, US-REGEN) for near-term investments through 2035 (left) and long-run investments through 2050 (right). Values are shown as changes relative to current levels and are normalized by electricity demand for comparability across pathways/models. Dominated pathways investments are marked with X's (EPA-TIMES, EPS, GCAM-USA). NGGT = natural gas combustion turbines; NGCC = natural gas combined cycle; CCS = carbon capture and storage; CSP = concentrating solar power; NGST = natural gas steam turbines; PSH = pumped storage hydro. Refer to Fig. 12 for a zoomed view of the technologies on the right tails of these figures with smaller variations.

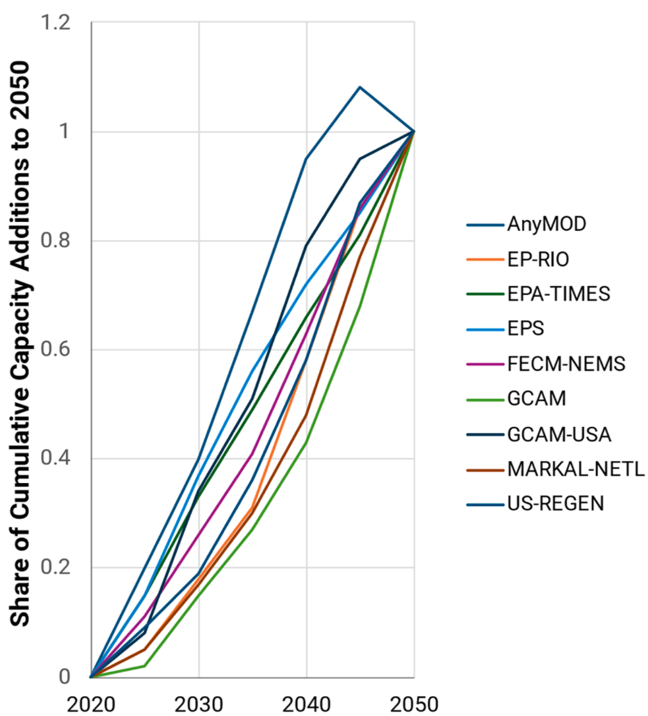

Fig. 10. Share of cumulative electricity generation capacity additions over time by model. Values are shown as a share of their cumulative 2050 values. Results are from the EMF 37 study for pathways that reach economy-wide net-zero CO_2 in 2050.

3.2. Insights into individual investments

Fig. 9 shows technology-specific installed capacity for the non-dominated pathways when all three criteria are considered. The range represents the full set of non-dominated pathways. Many technologies have relatively narrow and limited deployment ranges, meaning the pathways of these technologies are robust across non-dominated pathways. Other technologies have wide ranges, such as solar, wind, batteries, and gas-fired capacity. This variation implies more uncertainty about the extent of new investments in these technologies across models. Note, however, that wind and solar are both strictly positive, meaning that all non-dominated pathways show an increase in these capacities. Similarly, coal is always strictly negative, meaning all non-dominated pathways show a decrease in this capacity.

Natural gas combine cycle (NGCC) capacity, on the other hand, ranges between significant capacity reductions to capacity increases, which reflects uncertainty about this technology's role as a capacity and generation resource [56]. We note that some of the dominated pathways have too much NGCC, falling above the range for the non-dominated pathways, and some have too little; this aggravates the lack of clarity around this technology.

We note that it is important to consider the technologies that are present in all non-dominated pathways; but these are less interesting if they are also present in all dominated pathways. If the investments in the dominated pathways for an individual technology fall within the ranges in Fig. 9, this implies that guidance on investments and retirements are more uncertain for such options.

We find that for most of the technologies, the capacities in the dominated pathways fall within the range of capacities of the non-dominated (solar, onshore and offshore wind, natural gas with CCS, nuclear, coal with CCS, biomass with CCS, oil with CCS, hydropower, and other storage). For these technologies, the ranges are not very informative, since all models, whether dominated or non-dominated, fall in the same range. For a few technologies, some of the capacities in the dominated are higher while some are lower (natural gas combined cycle, pumped storage hydropower; geothermal and coal in 2035). For these technologies, the ranges tell us something, but don't imply a preferred direction, in terms of whether more or less capacity in these technologies is consistent with a robust pathway. For a couple of technologies – biomass in both timeframes and geothermal in 2050 – we find that all of the capacity investments in the dominated pathways are below the top of the range for the non-dominated and at least one is strictly below the range, implying that the dominated pathways have weakly too little biomass and geothermal. Similarly, for natural gas combustion turbines and oil, as well as for coal in the long run, we see the opposite: all of the capacity investments in the dominated pathways are above the bottom of the range of the non-dominated, and at least one is strictly above the range; implying that the dominated pathways have weakly too much NGGT, oil, and coal.

4. Discussion

4.1. Conclusions

This analysis provides a proof-of-concept framework for considering uncertainty and conflicting objectives in electric sector decarbonization decisions. The analysis provides numerical modeling of U.S. electricity investments under net-zero economy-wide emissions by 2050. The

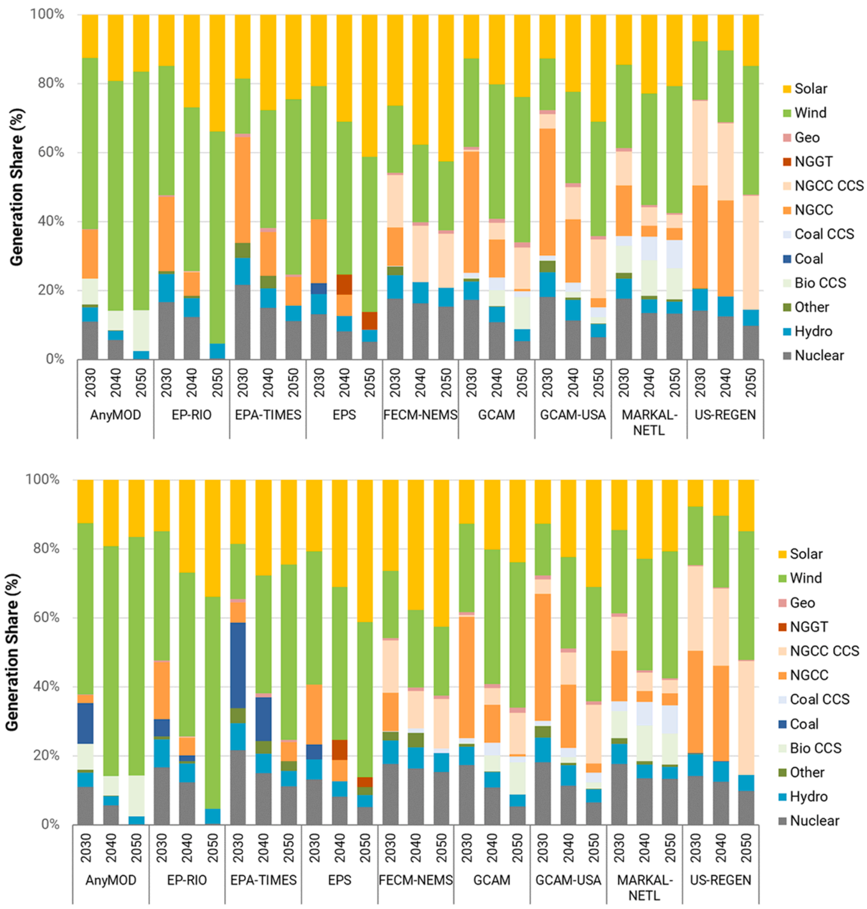

Fig. 11. Generation shares by technology and model over time under the middle fuel cost scenario (top panel) and high fuel cost scenario (bottom panel). Model descriptions are provided in Table 1.

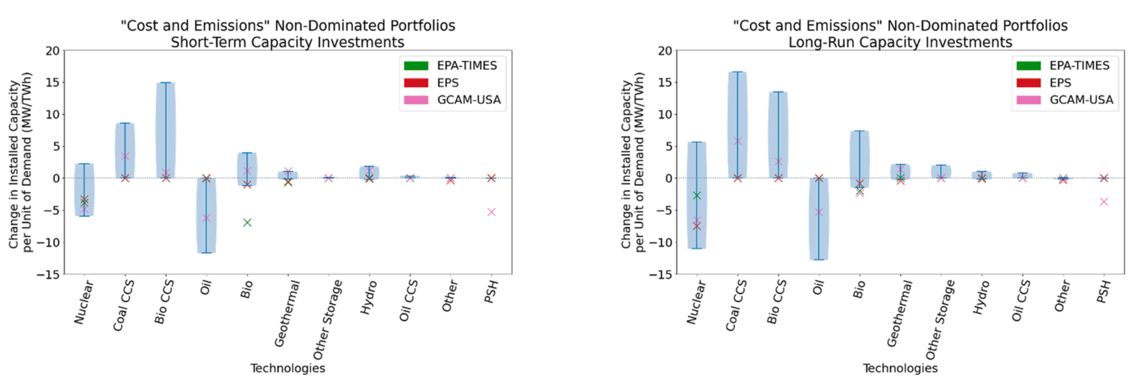

Fig. 12. Range of net changes in installed capacities across technologies with smaller variations. Refer to Fig. 9 for description of the meaning of the bars and X's.

methodological framework has the potential to reduce the number of pathways for utilities to choose from, provides insights into the range of investments into individual technologies, and highlights tradeoffs between different criteria. A particular strength is that, in combining belief dominance with Pareto dominance, it can uncover interactions between parameter uncertainty and specific criteria. Given the limitations of the study (which are summarized in Section 4.2), these results should be interpreted as illustrative rather than prescriptive.

The analysis highlights that focusing only on cost may eliminate plausible alternatives before conversations are even started on other criteria, especially justice-relevant criteria such as co-pollutants. We see that when cost is the only optimization objective, the candidate pathways are narrowed down to two. When, however, we consider co-pollutants as an objective, there is a wide range of candidate pathways that are non-dominated. Thus, the analysis confirms that there is broad variation in technology investments depending on how uncertainties resolve and which decision-making criteria are considered: there are many pathways that can achieve these goals.

The EP-RIO pathway, which has high renewables and energy storage shares over time along with low-utilization gas-fired capacity, seems to have the most consistent results across cost scenarios and criteria. It has the lowest or nearly lowest cost in all scenarios and only scores poorly in emissions when fuel prices are high due to greater near-term coal generation. We note, however, that the cost results are driven by the particular value function model we used; costs associated with the integration of variable renewable energy have a particularly strong impact.

While there are a number of plausible pathways, we note that when looking at the range of investments into individual technologies, we see that the investment into NGCC provides the clearest decision point differentiating among the non-dominated pathways. This technology sees significant disinvestment in some pathways and positive investment in others. We see a pattern where higher NGCC is associated with lower costs but higher electricity-sector CO_2. Thus, an important aspect is that the presence of NGCC in a pathway implies the presence of negative emissions technologies; in some cases, these may be from outside the electricity sector. This underlines a tension in planning and policy: utilities are focused on power system investments; policies would need to be carefully crafted to line up incentives for negative emissions technologies outside the electricity sector with investments within the electricity sector.

Our framework uncovered a lack of robustness to fuel prices, especially for the non-cost criteria. There is potential for higher CO_2 and co-pollutants in higher fuel price scenarios, especially for pathways that retain existing coal and biomass capacity. Dispatchable resources play important functional roles in power systems, including so-called "clean firm" options that "can be counted on to meet demand when needed in all seasons and over long durations" [57]. What we find is that when natural gas prices are high, pathways that do not build as much CCS, nuclear, and long-duration storage (clean firm options) may be forced to rely on resources such as coal and biomass capacity that have much higher CO_2 and co-pollutant levels. The importance of fuel costs in these results underscores how future work should quantify uncertainty around different fuel prices and evaluate their potential impacts on planning. This implies that in a world where there is a chance of high fuel prices and co-pollution is of significant concern, caution should be applied to results using central assumptions about fuel costs.

4.2. Limitations and future research

While this analysis has provided key insights in the face of deep parametric uncertainty and multiple criteria, it did not fully address structural uncertainty. Our analysis takes EMF 37 pathways as given and uses a single value function model with a relatively simple framework for system dispatch. Future work can investigate adaptive investments and pathways with high option value based on uncertainties in policies, technologies, and markets, which would complement the approach taken here. A more detailed operational model as part of the value function model could influence the questions in this study. To more fully investigate structural uncertainty, an analysis would require a full model intercomparison exercise, in which each model evaluates each portfolio under a set of criteria.

Limitations in the analysis suggest other fruitful directions for future work:

1. We only consider three planning criteria (cost, CO_2, and co-pollutants) in our analysis. However, other objectives are also important to decision-makers, including system reliability, resiliency, distributional outcomes, and others.
2. It would be ideal to conduct a multi-model analysis with internally consistent, harmonized scenarios instead of running an ex-post value function model.
3. The analysis examines the sum of co-pollutant emissions. Future work could examine spatially explicit pollutant modeling with damage-weighted estimates.
4. We consider uncertainties associated with technology and fuel costs only. Future work can look at other uncertainties in the decision-making environment, including state and federal policies, load growth (e.g., from end-use electrification and data centers), and demand-side flexibility.
5. The analysis focuses on national-level outcomes, but given the heterogeneity of regional decarbonization strategies, future work can examine more localized robust decision analysis.

Glossary of key terms

- **Belief dominance:** Pathway A is belief dominant over pathway B if A outperforms B on a given metric (e.g., cost) under all model or parameter assumptions. In other words, no plausible input set makes B better than A on that metric.
- **Co-pollutants:** Pollutant species, sulfur dioxide (SO_2) and nitrogen oxides (NO_x) in this analysis, emitted alongside CO_2 when fossil fuels are burned.
- **Energy Modeling Forum (EMF) 37:** This coordinated model intercomparison project focuses on U.S. economy-wide net-zero pathways, which gives rise to the electric sector portfolios used as part of this analysis.
- **Pareto dominance:** Pathway A is Pareto dominant over pathway B if A is at least as good as B on every metric (e.g., cost, CO_2, co-pollutants) and strictly better on at least one metric for a fixed assumption set.
- **Robust portfolio decision analysis (RPDA):** RPDA is a method for screening multiple candidate scenarios (or "pathways") by combining belief and Pareto dominance. RPDA operationalizes belief dominance as a prescriptive decision rule, applies this concept to portfolios of individual alternatives, and then identifies robust individual alternatives among the non-dominated set.
- **Value function model:** A simplified optimization tool that translates exogenous capacity investments into output metrics (e.g., system cost, emissions). Unlike a full operations simulation (which considers unit commitment, ramp rates, and reserves), the value function model uses simplified operational dynamics to provide rapid cost comparisons across dozens of EMF 37 pathways and scenarios but does not capture many operational constraints.

Additional analysis

Fig. 10 illustrates the time trend of cumulative capacity additions for pathways in the EMF 37 study.

Generation shares by technology across pathways are shown in Fig. 11, which compares middle and high fuel cost scenarios.

CRediT authorship contribution statement

Erin Baker: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **John Bistline:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Nexus Attiogbe:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare no conflict of interest.

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