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To cite this article: Diederik Coppitters *et al* 2026 *Environ. Res.: Energy* **3** 025009

ENVIRONMENTAL RESEARCH
ENERGY

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RECEIVED
10 November 2025

REVISED
27 February 2026

ACCEPTED FOR PUBLICATION
9 April 2026

PUBLISHED
20 April 2026

PAPER

Identifying dealbreakers and robust policies for the energy transition amid unexpected events

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Keywords: Whole-energy systems, transition pathways, energy modeling, optimization, uncertainty, unexpected events, myopic decision-making

Supplementary material for this article is available online

Abstract

Disruptions in energy imports, backlash in social acceptance, and novel technologies failing to develop are unexpected events that are often overlooked in energy planning, despite their ability to jeopardize the energy transition. Here, we explore the role of unexpected events and assess their impact on the energy transition pathway of a large-scale whole-energy system. First, we evaluate unexpected events assuming 'perfect foresight,' where the decision-maker is aware of the unexpected-event scenario from the start of the transition. This analysis allows us to identify dealbreakers, i.e. conditions that cause the transition to exceed cost or carbon limits. Then, we assess the unexpected-event scenarios under 'limited foresight' to evaluate the robustness of early-stage decisions when unexpected events arrive as a surprise, and the costs associated with managing them. Unlike the perfect-foresight benchmark, it reflects real decision-making conditions and helps policymakers identify which near-term policies reduce vulnerability to unexpected events and what cost penalties arise when early decisions are suboptimal. A case study for a national energy system demonstrates that the absence of carbon capture technologies and electrofuel imports in 2050 are the main dealbreakers, while accelerating the deployment of renewables is the most robust policy. Our findings help policymakers identify dealbreakers and implement targeted measures to address them. The method is adaptable to different regions and scalable to entire continents, enabling policymakers to understand the impact of regional disruptions on the broader energy transition and analyze the vulnerabilities of energy policies under varying modeling assumptions.

1. Introduction

Energy planning models involve numerous inputs that are inherently uncertain, such as technology and resource availability, energy commodity prices, and demand levels [1]. Modelers often represent this uncertainty—if they consider it at all—with probabilities or uncertainty ranges [2] and generate results following a predict-then-act approach [3]. However, this approach tends to underestimate the full spectrum of possible futures [4], leading to overconfidence in the selected course of action [5]. This underestimation occurs because uncertainty characterization focuses on the ordinary and predictable, and overlooks *unexpected events* [6]. In energy transition decision-making, such situations are often discussed as deep uncertainty, where probabilities—and sometimes even the set of plausible outcomes—are not known in advance (i.e. unknown unknowns) [7]. Here, we operationalize this idea by defining unexpected events as events that are largely mispredicted or unpredicted, substantially deviate from expectations, and persist long enough to influence strategic decisions, such as social resistance blocking wind power expansion [8], a disruption in resource supplies due to geopolitical tensions [9], or the failed breakthrough of anticipated technologies like nuclear small modular reactors (SMRs) [10]. Details about the terminology are provided in supplementary note 1. Although rare, unexpected events can substantially disrupt the course of action and transform dependencies into vulnerabilities [11]. For instance, if an anticipated resource like green hydrogen falls short, initial investments in hydrogen infrastructure could become obsolete [12]. Conversely, positive unexpected events—such as breakthroughs in technological learning—can accelerate the energy transition [13]. These unexpected events should, therefore, not be ignored in the decision-making process [14]. From a policy perspective, the objective is to strengthen the resilience of transition pathways, i.e. to reduce the risk that unexpected events derail progress toward climate targets and to preserve the ability to adapt when such disruptions occur [15]. Yet, their rarity and the limited data on their likelihood make them unsuitable for conventional risk-informed approaches, as the probability of unexpected events is deemed so negligible that standard uncertainty propagation techniques fail to recognize them as viable scenarios [16]. Therefore, alternative methods are needed to assess the role of unexpected events in energy system planning [17].

Existing studies primarily use story-and-simulation (SAS) approaches to assess the vulnerability of energy systems to a specific unexpected event [18, 19]. These assessments propose mitigation strategies in a specific context, such as adopting integrated energy markets to reduce risks related to supply disruptions [20] or deploying existing low-carbon technologies to avoid reliance on unicorn technologies that may never materialize [21]. Although valuable, SAS approaches rely on predefined scenarios [22], which limits their capacity to guide decision-making across a broad spectrum of unexpected-event scenarios [23].

In the context of decision-making across a broad spectrum of scenarios with unknown likelihoods, methodologies from decision making under deep uncertainty (DMDU) are gaining traction [24]. Unlike traditional predict-then-act approaches, where energy system planners typically agree on assumptions about the input parameter uncertainties, DMDU focuses on agreeing on decisions by exploring a variety of possible futures, identifying vulnerabilities, and proposing robust alternatives [25]. Despite its potential, the application of DMDU methods in energy system planning is scarce, applied only for uncertainties within predictable ranges [7, 26, 27], and seemingly unexplored in combination with unexpected events.

An additional gap in the literature is that nearly all the employed energy system models operate under perfect foresight [14, 28]. This unrealistic approach assumes complete knowledge of the future when optimizing investment decisions, allowing early-stage decisions in the energy transition to be tailored for a specific unexpected event predicted far in advance [29]. Myopic pathway optimization models are better suited for this context, as they enable sequential decision-making with limited foresight [30]. In this more realistic setting, early-stage investment decisions are made without knowledge of an unexpected event that may later arise. Yet, myopic decision-making models are relatively rare [31, 32], with only a handful applications incorporating SAS-based assessments [21, 33].

In this paper, we propose a method to assess the impact of unexpected events on energy system planning. We identify unexpected events based on the literature (detailed in supplementary note 2) and explore scenarios where these events occur in different combinations and with varying intensities across the stages of the energy transition. This time-varying representation is a central feature of our approach, as it allows capturing not only the scale of unexpected events but also their timing and sequencing.

The assessment method consists of two stages. First, we evaluate unexpected-event scenarios using a centralized, fully rational whole-energy-system optimization model to assess whether a successful transition is attainable under perfect foresight. This first stage establishes an idealized, best-case benchmark by indicating whether a successful transition is feasible at all when rational decision-makers can anticipate future events and adjust early decisions accordingly. From the scenarios that prove infeasible under perfect foresight, we use scenario discovery to identify dealbreakers, i.e. conditions that jeopardize the transition even if predicted. By highlighting such critical vulnerabilities, we make it clear where policymakers should concentrate efforts to prevent them from arising.

In the second stage, we analyze a more realistic setting with limited foresight. Early decisions are fixed, and the energy model optimizes in rolling timeframes using only near-term information, with unexpected events revealed in 5 year intervals during these optimizations. This second step of the method shows how different early policy choices—for example, accelerating renewable deployment or phasing out nuclear power—affect both the robustness of the transition to meet the carbon budget and the costs of doing so. Unlike the perfect-foresight benchmark, it reflects more realistic decision-making conditions and helps policymakers identify which near-term policies reduce vulnerability to unexpected events and what penalties arise when early decisions are suboptimal.

We implement the two-stage assessment method using EnergyScope Pathway and apply it to Belgium as a case study, given its unique challenges related to limited renewable potential and high population density [29]. While the case study is specific to Belgium, the framework is transferable and can be adapted to different regions, events, and policies. The energy model and method are released as open-source and can be accessed on GitHub[5], while all our results are freely available on Zenodo[6].

2. Methods

2.1. Overview of the applied approach

We propose a two-stage method to assess the impact of unexpected events on the energy transition (illustrated in figure 1; boundary conditions, model-structural choices, and method settings are listed in table 1).

In the first stage, we build an ensemble of unexpected-event scenarios by sampling the unexpected-events space (see section 2.3 for the space definition; section 2.4 for scenario generation). Each scenario specifies the timing, magnitude, and persistence of unexpected events. For every scenario, we solve the whole-energy system pathway model with perfect foresight (see section 2.2 for details about the model). In this ideal setting, the planner knows the full future, including the unexpected events.

After evaluating each unexpected-event scenario, we classify it as feasible or not feasible using two criteria (detailed in section 2.5). First, a scenario is classified as not feasible if the corresponding optimized energy transition pathway exceeds the cumulative carbon budget by 2050. Second, it is classified as not feasible if the total transition cost required to meet the carbon budget is considered excessive.

To determine whether costs are excessive, we construct a cumulative cost-coverage curve. This curve ranks all carbon-budget-compliant solutions from lowest to highest cost and shows the share of scenarios that can be achieved at or below each cost level. We then compute the slope between adjacent points on the curve. When the slope exceeds a predefined threshold, additional spending yields only a small increase in covered scenarios at disproportionate cost. Costs beyond this point are considered unjustified, and scenarios requiring such expenditures are classified as not feasible.

This classification is a technical construct and should not be interpreted as a real-world failure of the energy transition. Rather, scenarios labeled as not feasible indicate conditions under which achieving the transition would likely require substantial changes, such as faster technological progress, stronger policy intervention, or shifts in market behavior. At the same time, the model assumes coordinated and rapid deployment once technologies become cost-effective, and therefore reflects an idealized planning benchmark that may overestimate real-world implementation speed. Although real-world systems may adapt to unexpected events in ways not fully captured here, this classification provides a structured way to identify combinations of conditions that exert the greatest pressure on the transition, highlight key vulnerabilities, and underline the importance of early policy decisions.

After labeling each scenario as either feasible or not feasible, we then apply scenario discovery to identify dealbreakers—combinations of unexpected events that render the transition infeasible even when the planner knows the full future (see section 2.6). As a method for scenario discovery, we adopt an interpretable classification tree that generates concise rules describing the infeasible region [34]. In the DMDU literature, the patient rule induction method (PRIM) is a common alternative method for scenario discovery [26]. We instead choose classification trees because they produce transparent rule lists, are straightforward to interpret, and can be applied consistently across both stages of our analysis.

In the second stage, we adopt limited foresight to better reflect real-world decision making. We define concrete early-stage decisions and fix the associated investments in 2030 for each early-stage decision in the model. As a reference, we define a myopic baseline in which the model makes cost-optimal investment decisions in 2030 based only on information available at that time, without unexpected events. This baseline corresponds to the cost-optimal decisions made by the model up to 2030 in nominal conditions, while decisions from 2035 to 2050 are optimized depending on the unfolding unexpected-event scenarios. We then contrast this baseline with several policies, in which specific early-stage decisions are imposed exogenously in 2030—regardless of their immediate cost-optimality. These cases are designed to reflect policymaking contexts in which decisions are guided by considerations other than near-term cost optimality, including political constraints and strategic objectives. The assumptions underlying these early-stage decisions are grounded in existing Belgian policy documents, including the

[5] https://github.com/DCoppitters/EnergyScope_pathway_unexpected_events/releases/tag/v2.0.0.
[6] https://doi.org/10.5281/zenodo.17256145.

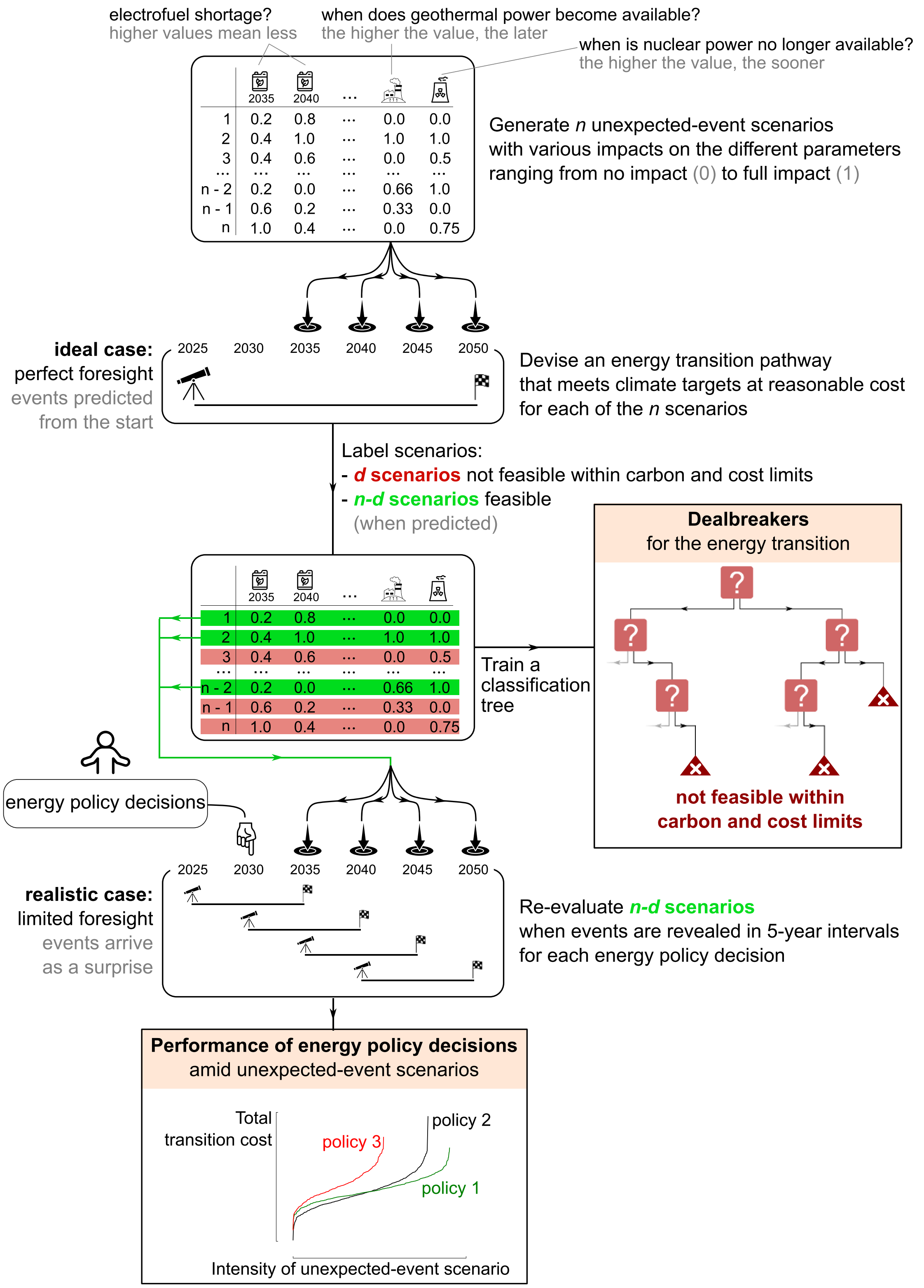

Figure 1. First, scenarios are generated by exploring the unexpected-events space and evaluated using an energy transition pathway optimization model with perfect foresight. This ideal setting optimizes the energy transition for each scenario starting with full knowledge on the future. In other words, if the pathway optimization model fails to find a solution, the scenario will inevitably lead to a transition that is not feasible within carbon and cost limits. By labeling the scenarios based on feasible or not feasible, a classification tree can derive the infeasibility conditions (i.e. dealbreakers). The $n-d$ feasible scenarios are then reassessed with limited foresight—a more realistic setting in which scenarios are revealed in 5 year intervals, and decisions are made without knowing future events. Thus, scenarios that are feasible with perfect foresight might become infeasible with limited foresight due to an early-stage decision that could hinder the ability to address unexpected events that arise later. By starting from specific energy policy decisions (e.g. accelerated deployment of renewables, early phase-out of nuclear power), these scenarios are evaluated to determine how many unexpected-event scenarios are managed and the associated costs. This approach allows policymakers to assess the performance of energy policy decisions in relation to unexpected events.

Table 1. Overview of main boundary conditions, model-structural choices, and methodological settings.

Category	This study
Boundary conditions	• Belgium case study; single-node national representation • Exogenous energy-service demands; no endogenous demand response • Exogenous resource availabilities, domestic renewable potential limits, and technology capacity bounds • Constrained imports (electrofuels, biofuels, electricity); no endogenous trade-price feedback • National carbon budget (CO_2 energy-related emissions only); fixed allocation rule
Model structure	• Linear whole-energy-system cost-minimization with social discount rate; annualized CAPEX, OPEX, fuel, and import costs included • Centralized social planner model; no strategic behavior • Endogenous technology choice from a technology-rich portfolio (multi-sector coverage) • Five-year investment steps to 2050; existing assets subject to technical lifetimes; no explicit growth-rate constraints • Exogenous technology cost trajectories (no endogenous learning)
Method settings	• Unexpected events represented as time-varying parameter changes (46 parameters); parameters sampled independently • Space-filling Sobol sampling mapped to discrete impact levels; fixed sample size • Stage 1: perfect-foresight feasibility screening • Stage 2: rolling-horizon limited foresight; events revealed in five-year steps; 2030 decisions fixed • Feasibility criteria based on carbon budget and cost-coverage cutoff • Scenario discovery using classification trees with cross-validation

REPowerEU chapter of Belgium's recovery and resilience plan [35], the federal hydrogen strategy [36], and the Belgian nuclear phase-out law [37]. These decisions include: (1) accelerating the expansion of renewable energy technologies to their maximum potential; (2) phasing out nuclear power; and (3) making upfront investments in hydrogen-powered technologies. Additionally, we include a decision related to (4) delaying the deployment of renewable energy technologies, i.e. no changes to the energy system are made between 2025 and 2030 in this sector. Although such inertia does not correspond to a formally stated policy objective, it reflects a plausible outcome of political short-termism, public misunderstanding, and competing economic interests, which have been widely observed in practice [38]. This scenario, therefore, serves as a stylized representation of self-interested or irrational policy making, and allows exploring the potential consequences of continued inaction in the context of unexpected events. Detailed descriptions about the early-stage decisions are available in supplementary note 8.

After the early-stage decision made in 2030, each unexpected-event scenario is revealed in five-year intervals, and decisions from 2035 to 2050 are optimized depending on the unfolding unexpected-event scenario. Scenarios that were infeasible under perfect foresight are excluded, since they are inevitably infeasible under limited foresight as well. Among the remaining scenarios, some that were feasible with perfect foresight become infeasible under limited foresight because early-stage decisions can restrict the ability to respond to later unexpected events.

Similar to the first-stage analysis, we sort the feasible unexpected-event scenarios by the cost increase they cause, producing a cumulative cost curve. This curve provides a basis for assessing both cost-effectiveness and robustness. We define robustness as the number of scenarios that still meet the carbon budget under limited foresight while remaining within the justifiable cost range. The cost increase, measured relative to the perfect-foresight benchmark, serves as a proxy for the intensity of the unexpected event and indicates how well a given early-stage decision can accommodate unexpected events when subsequent decisions are made myopically by managing the additional induced total transition cost. In this way, we evaluate the severity of performance degradation (i.e. cost increase) rather than the magnitude of parameter deviations. Conceptually, this resembles a regret-like metric [39], which measures performance loss relative to an ideal reference.

Finally, to explain why some scenarios that are feasible under perfect foresight become infeasible under limited foresight, we divide the feasible perfect-foresight scenarios into two groups: those that remain feasible under limited foresight and those that become infeasible when the transition is optimized myopically from a given early-stage decision as the unexpected event unfolds. We then fit a second classification tree to this labeled set to identify which characteristics of unexpected events drive failures under limited foresight.

While our method aligns with the structure of robust decision making within the broader DMDU tradition—vulnerability analysis, policy screening, and robustness analysis [26]—it extends this framework by embedding a detailed optimization model of energy transitions and explicitly contrasting outcomes under perfect and limited foresight. These extensions link exploratory scenario analysis to the path-dependent dynamics of long-term energy transitions.

2.2. Whole-energy-system pathway model

To identify technology- and resource-driven vulnerabilities in long-term energy transitions under unexpected events, we use EnergyScope Pathway [29], a linear, technology-rich whole-energy-system optimization model that determines cost-optimal investment pathways subject to a carbon budget over a multi-decade horizon. The model is formulated as a centralized social planner optimization problem, providing a best-case planning perspective that is well suited for stress-testing under unexpected-event scenarios: if infeasibility with respect to the carbon budget or total transition costs arises even under coordinated, system-optimal assumptions, it points to fundamental vulnerabilities that are unlikely to disappear—and may be amplified—under more fragmented real-world decision-making.

The model covers all major sectors, including electricity, heating, transport, and non-energy demand. Energy service demands are specified exogenously, while the technology portfolio used to meet these demands is selected endogenously by minimizing total system cost. The model represents six demand categories and 112 technologies across supply, conversion, and storage, as well as 23 resources, including imported electricity, biofuels, and electrofuels (i.e. fuels produced abroad from electricity, such as hydrogen, ammonia, methanol, and synthetic methane [40]). The technology scope broadly reflects the range of options emphasized in European decarbonization strategies, including those highlighted in the Strategic Energy Technology (SET) Plan [41], allowing the analysis to complement policy planning by identifying vulnerabilities within this shared technology space.

The transition is segmented into five-year steps (seven representative years), and the model optimizes technology investment in each period with linking constraints to form a consistent pathway. To optimize the transition, the model supports both perfect foresight and myopic evaluation approaches. In the perfect-foresight setting, the model optimizes the entire transition from start to finish with full knowledge of future conditions. A carbon budget is applied for the whole period, leaving the emissions pathway flexible as long as the carbon budget is respected. We adopt an acquired-rights principle to allocate the CO_2 budget to Belgium, based on the method proposed by Rixhon [42]. The budget (1.5 $GtCO_2$eq) corresponds to Belgium's share of global energy-related emissions in 2020 (124 $MtCO_2$eq out of 34.8 $GtCO_2$eq) applied to the global carbon budget of 420 $GtCO_2$eq, which yields a 66% chance of limiting warming to 1.5 °C. In contrast, the myopic approach optimizes the transition sequentially using a rolling-horizon method, where decisions are made based only on currently available information. Because a cumulative carbon budget cannot be enforced directly in this setting, we impose intermediate emission limits for each time window that are calibrated to reproduce the same overall carbon budget. Temporary overshoots are allowed but heavily penalized and carried forward to subsequent periods, ensuring that the total budget is respected. The final-year (2050) emission limit is enforced as a hard constraint. Details on the calibration of intermediate limits are provided in the supplementary note 3 and we refer to Limpens *et al* [29] for additional details on the modeling setup.

Using the above framework, the model was applied to Belgium based on the reference dataset of Limpens *et al* [29]. Intermediate emission constraints in the myopic formulation and all country-specific data updates (e.g. import availability and technology potentials) are documented in supplementary note 3.

The model is released as open-source and is available on GitHub[7], along with an installation guide and documentation.

[7] https://github.com/DCoppitters/EnergyScope_pathway_unexpected_events/releases/tag/v2.0.0.

2.3. Space of unexpected events

The parameters representing unexpected events are selected based on categories repeatedly highlighted in the literature as critical sources of disruption in long-term energy transition planning and are presented in table 2. We focus on geopolitical supply disruptions affecting imported energy carriers (electricity, electrofuels, and biofuels) [43], non-arrival or delayed maturation of emerging low-carbon technologies [21], socio-political resistance to behavioral change (e.g. renovation of low-temperature heating technologies) and renewable deployment [43, 44], macroeconomic shocks such as exchange-rate deterioration that increase the cost of imported technologies [45], structural demand surges linked to economic or demographic change [45], and policy-driven or socially induced nuclear phase-outs [46]. These categories were translated into model parameters that directly affect resource availability, technology deployment limits, capital costs, demand levels, or technology availability timing within EnergyScope Pathway, focusing on technologies and system components that play a structural role in Belgian decarbonization pathways and whose disruption can materially affect feasibility or cost. A detailed discussion of each unexpected-event category and its mapping to model parameters is provided in supplementary note 2.

The parameters are organized in 10 groups: the availability of imported electrofuels, biofuels, and electricity; societal resistance to deploying PhotoVoltaic (PV) arrays, onshore wind and offshore wind, to low-temperature heating renovations, and to mobility changes; increased demand and rising import costs for specific technologies. Each group is assessed independently for the years 2035, 2040, 2045, and 2050, resulting in four parameters per group and a total of 40 parameters. These parameters are treated as discrete variables, each assigned values of 0%, 20%, 40%, 60%, 80%, or 100% of the maximum potential impact. The values vary independently across phases, enabling diverse scenario representations. For example, in one scenario, electrofuel supply might face a 60% shortfall in 2035, no shortfall in 2040, a complete disruption in 2045, and a 40% shortfall in 2050, reflecting potential geopolitical instability during the energy transition.

Technology availability impacts are modeled using six additional parameters. For each unicorn technology, a parameter indicates when the technology becomes available: 2040 (0% impact), 2045 (33%), 2050 (67%), or not at all (100%). Similarly, nuclear power availability may be phased out by 2035 (100% impact), 2040 (75%), 2045 (50%), or 2050 (25%), or remain available throughout the energy transition pathway (0%). Once phased out, the availability cannot be reversed. Finally, carbon capture and storage (CCS), including point-source capture and direct air capture, is treated differently because its deployment trajectory is highly binary in nature: either large-scale capture infrastructure becomes available and rapidly deployable after 2040, or it remains unavailable altogether. Unlike nuclear or other unicorn technologies, where gradual phase-in or phase-out is plausible, CCS requires coordinated pipeline infrastructure, regulatory approval, and public acceptance, which make partial or staggered adoption unlikely [47]. For this reason, we assign a binary impact: either available during the transition from 2040 onwards (0% impact) or not at all (100%).

In total, 46 parameters are considered: 40 for availability, resistance, demand and cost issues across the four phases (from 2035 to 2050 in five-year intervals), and six for technology-specific disruptions. These include nuclear SMRs, CCS, geothermal power, ammonia-fired combined cycle gas turbines (CCGT), ammonia cracking, and conventional nuclear power phase-out.

2.4. Space exploration

The unexpected-event space defined in section 2.3 is extremely large. With 46 parameters that can each take multiple values across several transition phases, the number of possible combinations is on the order of 10^{35}. Evaluating all combinations is therefore computationally intractable. Therefore, we generate a representative ensemble of scenarios that systematically covers this space. To do so, we use a Sobol low-discrepancy sequence to sample the 46-dimensional parameter space [48]. A Sobol sequence distributes points evenly across a high-dimensional space and each sampled point corresponds to one unexpected-event scenario, represented as a vector of normalized values between 0 and 1.

Each scenario is then evaluated independently and the feasibility of the resulting energy transition pathway is evaluated (detailed in section 2.5). A convergence analyses show that 1000 scenarios yields stable classification results and cumulative cost curves (shown in supplementary note 6).

The detailed space exploration and mapping procedure is described in supplementary note 4.

2.5. Criteria for a successful energy transition

In this work, the energy transition is considered not feasible when the carbon budget is breached, or when the total transition cost to meet the carbon budget is excessive.

Table 2. Parameters subject to unexpected events, their potential impacts on expected values, and the years when these impacts occur. For example, the expected availability of imported electrofuels may be affected in 2035, 2040, 2045, and 2050 by reductions of 0%, 20%, 40%, 60%, 80%, or 100%, with each year potentially experiencing a different level of impact. For unicorn technologies, a single parameter per technology indicates their availability, with possible scenarios being: available in 2040 (0% impact), 2045 (33% impact), 2050 (67% impact), or unavailable (100% impact). Similarly, nuclear power may be phased out in 2035 (100%), 2040 (75%), 2045 (50%), or 2050 (25%), or it may remain available throughout the transition (0%). Once phased out, nuclear power cannot be reinstated. Carbon capture and storage (CCS) technologies (point-source capture and direct air capture) are modeled as a binary outcome, either available from 2040 onwards (0% impact) or not available at all (100% impact). A detailed discussion of each unexpected-event category and its mapping to model parameters is provided in supplementary note 2.

Category	parameters (46 in total)	Parameter values	Years of impact
Availability imports:			
electrofuels	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
biofuels	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
electricity	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
Resistance to change:			
private mobility	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
low-temperature heating	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
PV deployment	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
wind onshore deployment	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
wind offshore deployment	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
Exchange rate deterioration	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
Energy demand increase	4 (one per year)	[0, 20, 40, 60, 80, 100]	2035, 2040, 2045, 2050
Unicorn technologies			
Ammonia-fired CCGT	1 (sets arrival)	[0, 33, 67, 100]	2040, 2045, 2050
Ammonia cracking	1 (sets arrival)	[0, 33, 67, 100]	2040, 2045, 2050
Nuclear SMR	1 (sets arrival)	[0, 33, 67, 100]	2040, 2045, 2050
Geothermal power	1 (sets arrival)	[0, 33, 67, 100]	2040, 2045, 2050
Carbon Capture	1 (sets availability)	[0, 100]	2040, 2045, 2050
Nuclear phase-out	1 (sets timing)	[0, 25, 50, 75, 100]	2035, 2040, 2045, 2050

To assess when transition costs become excessive, we sort costs from low to high and normalize them against the optimal total transition cost achieved under perfect foresight, without any unexpected events. This creates a cumulative curve that tracks the total transition cost relative to the number of unexpected-event scenarios, arranged from the cheapest to the most challenging, resembling a rotated *S*-curve. For each point on the curve, we calculate the gradient. The cut-off point corresponds to where the gradient exceeds 5, meaning there is a cost increase of $5\%_{\mathrm{abs}}$ for a $1\%_{\mathrm{abs}}$ increase in the number of scenarios covered. Beyond this point, any further increase in costs is considered excessive. Note that the evaluation of the gradient begins when the percentage of unexpected-event scenarios covered reaches 10%, starting sufficiently far along the plateau of the rotated *S*-curve, neglecting the rapid increase (with high gradients) at the beginning of the curve.

2.6. Classification tree

We use a classification tree to identify the key features of the unexpected-event scenarios leading to an energy transition that is not feasible [34]. After evaluating the unexpected-event scenarios in the pathway optimization model using perfect foresight, the scenarios are labeled with a binary target variable to indicate whether they resulted in a feasible or infeasible energy transition. For this dataset of evaluated scenarios, we apply a supervised machine learning technique using decision tree classification with the classification and regression trees algorithm [49]. The tree is trained using the *scikit-learn 1.3.0* package in Python [50].

The dataset, including the 46 parameters subject to unexpected events, is supplemented by four cumulative measures: resistance to PV deployment, onshore wind deployment, offshore wind deployment, and the rise in energy demand. Each cumulative measure is calculated as the sum of its values across the affected phases (2035, 2040, 2045, 2050). These cumulative measures matter because the energy transition is not only determined by single impacts in isolation but by their persistence and accumulation across phases. A one-time shortfall in PV deployment might be compensated later, but sustained resistance compounds into a structural barrier. Similarly, demand growth that is modest in one phase can become critical when aggregated over multiple phases. By including these cumulative indicators, the classification tree can detect systemic vulnerabilities that only emerge when impacts accumulate, providing a more realistic assessment of transition risks.

To prevent overfitting and maintain interpretability, we limit the number of tree leaves by balancing interpretability and coverage scores [51]. The Interpretability score measures the number of unique features in the tree, while the coverage score reflects the proportion of data points correctly assigned. We also conduct *k*-fold cross-validation to assess the performance of the model on data not included in the training set [34]. The classification tree scores are detailed in supplementary note 5.

3. Results

3.1. Dealbreakers for the energy transition

In a first phase, we evaluate the unexpected-event scenarios under perfect foresight—an ideal case where the decision-maker knows the unexpected-event scenario from the start of the transition. Following the evaluation, the scenarios are labeled as either feasible or not feasible, depending on whether the carbon budget is met without an excessive cost increase. The perfect foresight method ensures that if the pathway optimization model fails to identify a solution for a given scenario, no solution exists within the decision space, even when the unexpected-event scenario is known from the beginning of the transition. Finally, we train a classification tree to identify the key scenarios that do not meet the carbon and cost limits and to determine which unexpected events most strongly drive this infeasibility.

The classification tree identifies the combinations of unexpected events that lead to a transition that does not meet the carbon or cost limits (figure 2). The results illustrate that the tree mainly splits on whether electrofuel imports and low-carbon technologies are available in 2050. Although unexpected events can occur in any transition phase (2035–2050) and early disruptions can have substantial impacts on costs or emissions, the transition still has several remaining phases to adjust when they occur early. An early disruption, therefore, leads to infeasibility only if recovery remains impossible or too costly in all subsequent phases. Such combinations are less frequent than cases where flexibility is no longer available by 2050. For this reason, features describing the availability of key options in 2050 provide the clearest separation between feasible and infeasible pathways and therefore appear most prominently in the tree.

When CCS technologies are available, the perfect-foresight model almost always succeeds (99.9%) in realizing a transition within the carbon budget at acceptable costs. Across these successful pathways, CCS costs remain limited, ranging from 0% to 6% of the total transition costs. However, this also exposes a first critical dealbreaker: although CCS could, in principle, enable a successful transition, the apparent success of the energy transition depends heavily on the assumption that large-scale CCS deployment becomes feasible at precisely the required time.

Without CCS available, the transition does not meet cost and carbon limits if electrofuel supply (i.e. imported synthetic fuels produced from electricity) is eliminated by 2050, or if imports are very low ($<110\,\mathrm{TWh\,yr^{-1}}$) while final energy demand rises substantially ($>14\%$). If electrofuel imports remain partially available, the transition can still become infeasible when final energy demand rises sharply ($>43\%$) and conventional nuclear power is unavailable by 2050. Even with moderately high demand growth (between 35% and 43%), the transition can still not meet the carbon and cost limits if either nuclear SMRs or geothermal power stations are not yet available by 2050, as these technologies provide the low-carbon power generation needed to overcome the absence of conventional nuclear power.

To make the results more interpretable, we present a heatmap that illustrates the proportion of scenarios leading to not meeting the cost and carbon limits with respect to two key parameters influencing the prediction accuracy of the classification tree: the availability of electrofuel imports in 2050 and the rise in total final energy demand (figure 3). We focus on the subset of scenarios where CCS technologies are not available. When neither CCS nor electrofuel imports are available in 2050, an energy transition that does not meet the carbon or cost limits is inevitable without our modeling context. However, as electrofuel availability increases, this likelihood declines sharply. The rate of scenarios not meeting the limits is roughly half when the electrofuel import availability and the rise in total final energy demand increase proportionally, ranging from 20% electrofuel import availability with no demand growth to 80% import availability with 60% demand growth.

3.2. Robust energy policy decisions amid unexpected events

The second stage of the method shifts from perfect foresight to myopic foresight to assess unexpected-event scenarios in a more realistic setting. Here, scenarios are revealed in 5 year intervals, and decisions

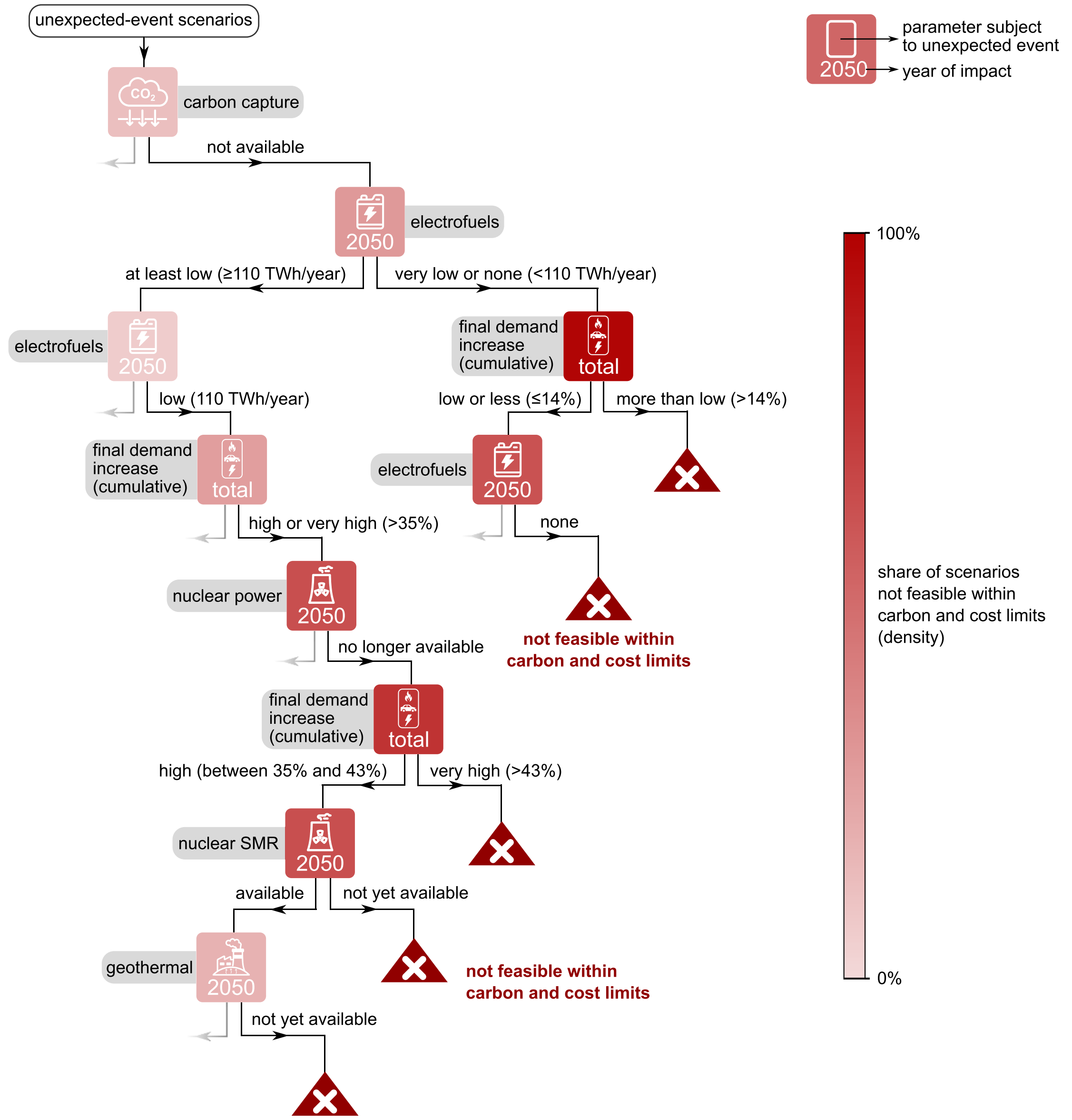

Figure 2. Classification tree of unexpected-event scenarios, labeled as either feasible or not feasible within carbon and cost limits under perfect foresight, and used to identify the main dealbreakers. The tree is post-pruned to remove branches that never lead to infeasibility. Carbon capture availability is the decisive factor: when available, the transition almost always remains feasible (99.9%). Without carbon capture, infeasibility arises if electrofuel supply (i.e. imported synthetic fuels) is eliminated by 2050, or if imports are very low while final energy demand increases substantially (>14%). If electrofuel imports remain partially available (110 TWh yr^{-1}), infeasibility occurs when demand rises sharply (>43%) and conventional nuclear power is unavailable by 2050. Even under moderately high demand growth (35%–43%), the transition can become not feasible if either nuclear SMRs or geothermal power are unavailable by 2050. The shading of the nodes represents class density: the share of scenarios not feasible within carbon and cost limits at each node. Nodes become darker red as this share increases, with each split raising the proportion in the right-hand node.

are made without knowledge of events that will occur later in the transition. We introduce early-stage decisions in 2030 into the pathway model and evaluate, from a myopic perspective, how these initial choices affect the ability to handle unexpected events that emerge later in the transition (up until 2050). This approach better reflects reality, as energy policy decisions are often made early in the transition process with limited foresight, and pathways evolve as the future gradually unfolds. For the scenarios that achieve a successful energy transition, we arrange the transition costs in ascending order. This produces a cumulative curve of total transition cost relative to the share of unexpected-event scenarios that can be successfully managed when starting from a specific early-stage decision. We use this curve to assess cost effectiveness and robustness, where robustness is defined as the share of scenarios that meet the carbon budget under limited foresight while staying within a justifiable cost range.

An early-stage decision favoring accelerated renewable deployment—reaching the maximum potential of wind and PV capacities by 2030 (onshore wind at 20 GW, offshore wind at 8 GW, and PV at

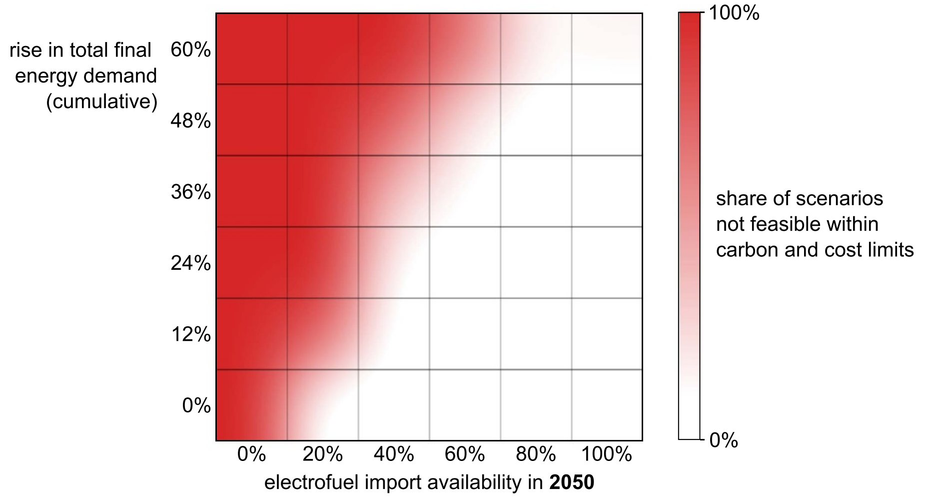

Figure 3. Heatmap illustrating the impact of electrofuel import availability in 2050 and the rise in total final energy demand on the likelihood of an energy transition not meeting the carbon or cost limits when no carbon capture and storage technologies are available. Not meeting the limits is certain with no imports, and the likelihood remains stable when higher import availability coincides with stronger demand growth. The cells are interpolated using a quadratic method to create a smooth transition between values.

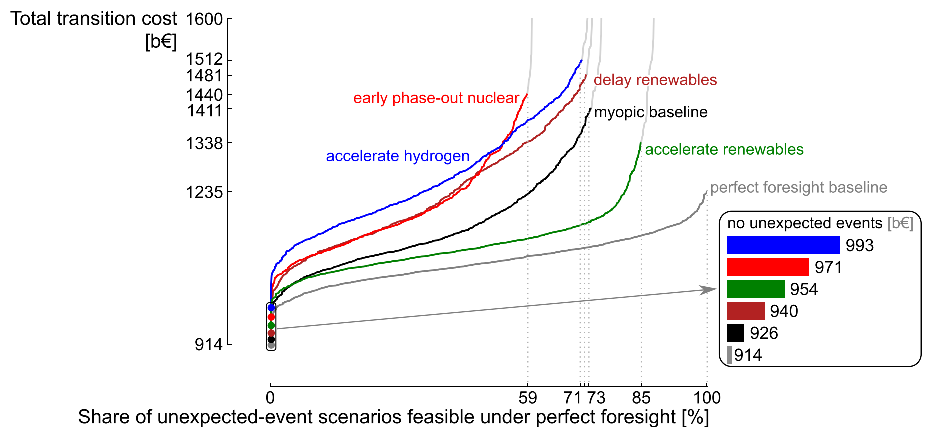

Figure 4. The cumulative transition cost curves for different energy policy decisions made in 2030 show that accelerated deployment of renewables by 2030 yields higher robustness to unexpected events (85% feasible scenarios vs 73% for the myopic baseline) and tracks the perfect-foresight benchmark more closely, at the cost of only a small premium in total transition costs when no or low-impact unexpected-event scenarios arrive. In contrast, delayed adoption, nuclear phase-out, or accelerated hydrogen deployment increase costs and reduce robustness. The perfect foresight approach (gray curve) represents the theoretical lower bound for these curves, as perfect foresight allows managing unexpected events at the lowest possible cost. The colored lines represent the cumulative cost curves, where the costs for managing unexpected-event scenarios remain within a reasonable range. The gray continuation of these curves illustrates how the costs further evolve at unreasonable rates.

104 GW_p)—is more robust to unexpected-event scenarios than the myopic baseline (figure 4), which installs only moderate renewable capacity by 2030 (onshore wind at 20 GW, offshore wind at 4.7 GW, and PV at 28 GW_p). The accelerated renewables pathway yields 85% feasible scenarios, compared to only 73% when starting from the myopic baseline early-stage decision. In addition, the accelerated renewables pathway tracks the perfect-foresight benchmark more closely, indicating that unexpected events can be absorbed with minimal additional transition costs when starting from the accelerated renewables policy. However, if no unexpected events occur, the accelerated pathway yields a total transition cost of 954 b€, compared to 926 b€ under the myopic baseline—equivalent to annual investments of 6% of Belgium's GDP (2024) [52]. This premium of 28 b€ can be interpreted as an insurance cost: accelerating the deployment of renewables secures a transition that remains feasible across a much larger share of unexpected-event scenarios, while keeping overall costs close to the perfect-foresight benchmark, at the expense of slightly higher costs if no or low-impact unexpected events occur.

Delaying the adoption of renewable technologies until after 2030 slightly increases the total transition cost to 940 b€ when no unexpected events occur. Moreover, the cumulative cost curve diverges more strongly from the myopic baseline, indicating that delaying renewable deployment raises the transition cost of handling unexpected-event scenarios compared to starting with moderate deployment in 2030 (i.e. the myopic baseline curve). The robustness remains similar, with 72% of unexpected-event scenarios feasible, compared to 73% under the myopic baseline. The two other pathways are substantially more expensive than the myopic baseline: phasing out nuclear power by 2030 (971 b€) and accelerating the deployment of hydrogen technologies (993 b€). The nuclear phase-out pathway also proves to be the weakest, with only 59% of scenarios feasible. This reflects Belgium's already limited low-carbon power options and the increased reliance on imports in the absence of nuclear capacity. The hydrogen pathway produces the highest transition cost because it depends on expensive technologies such as electrolysis and advanced hydrogen cogeneration throughout the transition. Its robustness (71%) remains close to that of the myopic baseline and the delayed renewables pathway, since no major technology option is excluded, unlike in the nuclear phase-out case.

An additional analysis, detailed in supplementary note 11, explores why the myopic pathways do not meet the limits in scenarios where perfect foresight succeeds. Using classification trees on the evaluated scenarios for each early-stage policy under myopic foresight, it identified three main drivers: availability of CCS, electrofuel imports in 2045 and resistance to PV deployment.

4. Discussion

Our method introduces three novelties in assessing unexpected events in energy system planning: First, unlike traditional SAS analyses that rely on predefined scenarios focused on ordinary and predictable events [14], this method systematically explores the unexpected-events space through an ensemble of time-varying scenarios that capture both the scale and timing of disruptions. Second, while decision-making under deep uncertainty has been applied only to predictable ranges of parameters, this work extends it to unexpected events that are largely mispredicted or unpredicted. Third, by considering both perfect and myopic foresight, the method provides infeasibility conditions (i.e. the dealbreakers) and considers the importance of early-stage decisions in sequential decision-making—features that conventional perfect-foresight studies neglect. Specifically, the perfect foresight approach helps identify the infeasibility conditions which are visualized and interpreted using a classification tree. The more realistic myopic foresight approach introduces the element of surprise, with decision-makers gradually becoming aware of future events over time when starting from a specific energy policy decision. By combining these approaches, decision-makers gain clear insights into critical vulnerabilities and robust early-stage policy decisions for managing unexpected events.

In the illustrative application to Belgium, using the adopted carbon-budget and cost-feasibility criteria, the first stage identifies the unavailability of carbon capture and the loss of electrofuel imports in 2050 as the primary dealbreakers under perfect foresight. Even when electrofuels remain partially available, the transition does not meet the carbon and cost limits if cumulative demand rises strongly, conventional nuclear power is phased-out by 2050, and either nuclear SMRs or geothermal power are not deployable by 2050.

Our method does not model the underlying causes of these dealbreakers directly; instead, they can be interpreted as socio-technical branching points [53, 54], where wider processes could trigger these dealbreakers. Such processes could include geopolitical conflicts or trade disputes restricting electrofuel imports [55]; political opposition or institutional shifts blocking nuclear power deployment [56]; and weak policy feedback or economic restructuring driving higher demand [57]. Based on this analysis, targeted responses for policymakers can be constructed. In the case of electrofuel imports, possible mitigation actions are long-term trade agreements with key exporting countries and employing a contractual framework similar to early liquefied natural gas markets—featuring bilateral agreements, long-term commitments and take-or-pay clauses [58]. Additionally, diversifying suppliers, routes, and carriers should be prioritized to mitigate supply security issues, despite potential higher costs [59].

Under limited foresight, the Belgian application with the adopted carbon-budget and cost-feasibility criteria shows that policies accelerating renewable deployment are more robust to unexpected events, as they can manage a larger share of scenarios while remaining within the carbon and cost limits. By contrast, delaying renewable rollout and phasing out nuclear power early increase vulnerability to unexpected events and raise the associated management costs. While previous studies have highlighted the cost benefits of accelerating the transition [60, 61], our results strengthen this direction by focusing on unexpected-event management. The relative performance of these early-stage decisions is case-specific and depends on the Belgian energy system and feasibility assumptions. At the same time, the analysis reveals a structural insight: early-stage decisions shape the range of response options available later in the transition, thereby influencing robustness when unexpected events unfold.

The proposed framework can be applied to different regions and model scopes, from single-country studies to multi-region energy systems, by adjusting the boundary conditions and repeating the same two-stage evaluation and scenario-discovery workflow. Applying the method to larger energy transition models that explicitly represent cross-border interactions, such as multi-region systems linking European Union member states [62], could help identify how vulnerabilities and infeasibility conditions arise from interdependencies between regions. In such settings, the approach can be used to examine risks related to shared infrastructure and import dependencies, including fossil gas reliance, and to assess how disruptions in one region may affect others [63]. In this sense, what transfers across cases is the analytical approach, not the specific dealbreakers identified in the Belgian application, which would need to be reassessed under local system characteristics and feasibility assumptions.

Nevertheless, our work has several limitations. Due to the extensive number of unexpected events considered and the different stages at which they could occur during the transition, exploring all combinatorial combinations ($\approx 10^{35}$) is infeasible. Therefore, we rely on exploration approaches to generate a representative set of scenarios to represent the space, as is commonly done in DMDU [26]. Despite the sufficient accuracy of the exploration approach in the classification tree and cost curves (detailed in supplementary note 6), it remains an approximation of the entire space. In addition, we do not assign joint probabilities or correlations between events. In settings of deep uncertainty, such assumptions can give a misleading sense of precision [26]; instead, we examine outcomes through transparent stress tests across a wide set of independent combinations. Moreover, only negative unexpected events are considered, while the energy transition could potentially benefit from positive unexpected events (e.g. abundant electrofuel supply) or radical demand-side transformations [18]. Combining the analysis of both negative and positive unexpected events in the analysis opens the door to evaluating the antifragile nature of energy policy decisions, where certain decisions not only remain robust against negative events but also take advantage of positive ones [6], providing a basis for future work.

Another limitation is the assumption of a fully rational, centrally optimizing decision-maker. In practice, decisions are made by decentralized actors with different objectives, priorities, and constraints, which can delay investments and shift capacity away from system-optimal locations. Our results should therefore be interpreted as a best-case stress test: if dealbreakers arise even under idealized centralized decision-making, they are likely to persist or intensify under more realistic decision-making structures. Future work could relax this assumption by incorporating heterogeneous policy actors and by examining incentive-based mechanisms that help redirect self-interested behavior toward socially favorable transition outcomes [64–66]. Recent work shows how such settings can be modeled, albeit at the expense of a more technically simplified representation of the energy system, using bilevel and game-theoretic approaches [67]. In these formulations, actors optimize individual investment objectives at an upper level and market clearing determines prices, dispatch, and emissions at a lower level, with equilibrium outcomes emerging from their interaction rather than from a single system-wide optimum [67]. Robustness to unexpected events could then be assessed by applying the same time-varying unexpected-event scenarios in a rolling-horizon, decentralized setting.

Relatedly, the framework assumes fixed expectations and does not endogenously represent financial-market dynamics or expectation updating, which in practice could help actors respond to unfolding unexpected events and still remain within carbon and cost limits. This is a common simplification in large-scale, technology-rich energy system optimization models [68], even though expectation formation and financing conditions can influence investment timing and adjustment to unexpected events [69]. Approaches such as real options explicitly capture such adaptive investment behavior under uncertainty, while backcasting perspectives emphasize how long-term net-zero targets can discipline near-term decisions despite uncertainty [70]. These approaches are complementary: our framework first identifies structural vulnerabilities and fragile early decisions in a fully specified energy system, which can then be used as inputs to more adaptive or forward-looking decision analyses.

Navigating the decision space to manage unexpected events while staying within climate targets is only possible by increasing the total transition costs. Although higher transition costs can be justified to achieve climate goals, this tolerance is limited [71]. Eventually, a tipping point will be reached where excessive costs are no longer justifiable, forcing governments to accept higher GHG emissions to keep costs manageable. Determining when transition costs become excessive is subjective, and defining a precise threshold involves significant assumptions. In our study, this threshold is identified by the sharp increase in the cumulative cost curve, which results in feasible solution within cost tolerances in line with the 10%–30% relaxation range commonly used in modeling to generate alternatives (MGA) approaches [72–74]. MGA could also provide predefined policy decisions in the model. By exploring the decision space, MGA could generate diverse, near-optimal early-stage decisions that may outperform the user-defined starting conditions considered in the current study. A related approach is Direct Policy Search (DPS), which develops adaptive, state-responsive policies and has been shown to improve robustness under deep uncertainty in other domains [75]. Alternatively, a combination of the pathway optimization model and reinforcement learning could be considered, where an agent is trained through interactions with its environment and repeats the entire transition with different sequences of actions and states to develop an optimized policy [76]. These approaches, combined with positive unexpected events and antifragility metrics to reward the agent as mentioned earlier, will be considered in future work.

Even in its current state, our method facilitates an open exploration of possibilities, identifies infeasibility conditions, and assesses the performance of energy policy decisions in the context of unexpected events. The results provide policymakers with clear insights into critical vulnerabilities, helps formulate robust energy policies to address these events, and reveals any extra costs involved.

Acknowledgments

D C acknowledges the support of the Fonds de la Recherche Scientifique—FNRS [CR 40016260]. S M and G W acknowledge support from the Swiss National Science Foundation (SNSF) under Grant No. PZ00P2_202117. S M acknowledges funding from the European Union's European Research Council (ERC), Grant Project No. 101164071 (UNITES). A B acknowledges the support of the Swiss Federal Office of Energy through the SWEET consortium PATHFNDR under Grant No. SI/502259.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.17256145 [77].

Supplementary Information available at https://doi.org/10.1088/2753-3751/ae5d4c/data1.

Conflict of interest

A B served on review committees for research and development at ExxonMobil and TotalEnergies. A B and S M have ownership interests in firms that render services to industry, some of which may provide energy planning services. All other authors have no competing financial interests.

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