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Review article

Modeling disruptive events in renewable energy supply: A review

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ABSTRACT

The accelerating shift toward renewable energy necessitates robust planning frameworks that can accommodate unexpected disruptions. While various energy system modeling methods are widely used for planning and decision-making, they each have their own strengths and weaknesses in capturing uncertainty in the outcomes of disruptive event modeling. This review addresses a critical research gap by systematically analyzing how such methods quantify and mitigate the impact of disruptive events on renewable energy supply. It is the first to comprehensively assess modeling approaches specifically in this context. The study categorizes 108 disruptive events from 102 articles into four primary types: natural (e.g., floods, heatwaves), human-caused intentional (e.g., technological innovations), socio-political (e.g., wars, policy changes), and economic (e.g., interest rate shifts, carbon tax changes). Articles were selected using a PRISMA-compliant methodology from multiple sources, applying strict inclusion criteria: relevance to renewable energy, a clear focus on disruptive events, and use of modeling methods. Findings confirm the hypothesis that incorporating broader socio-economic and environmental criteria into modeling improves the robustness and realism of planning under disruptive conditions. The review shows that relying on one modeling objective such as cost often limits the ability to capture uncertainty and stakeholder concerns. Instead, models that integrate multiple criteria and generate a range of feasible solutions offer more resilient and adaptable planning outcomes. The study recommends combining complementary modeling strategies and tailoring criteria to stakeholder priorities. Such combined modeling approaches are well suited to future studies, enabling flexible, risk-informed, and context-sensitive modeling of disruptive events in renewable energy supply systems.

Introduction

Under the 2015 Paris Agreement, 195 countries pledged to limit global warming to below 2 °C above pre-industrial levels by reducing greenhouse gas emissions [1]. In the wake of the Fukushima nuclear accident in March 2011, countries such as Switzerland and Germany have accelerated the phase-out of nuclear power in light of the possibilities of nuclear accidents [2]. For such countries, it is therefore crucial to accelerate the deployment of renewable energy supply in order to comply with the requirements set out in the Paris Agreement.

In recent decades, several events such as the European heat waves of 2003 and 2022 [3], the Covid-19 Pandemic [4] and the Russian–Ukrainian War [5], have had adverse effects on daily human activities. Similarly, these types of disruptive events can have a huge impact on power generation. For example, nearly 2.3 GW of renewable energy installations in India were delayed due to lack of access to supply chains during the Covid-19 pandemic in 2020. [6]. As previously stated, accelerating the renewable energy supply is of paramount importance for countries. It is therefore essential that future power system planning considers the impact of such disruptive events on renewable power supply.

What is a disruptive event?

The simple definition of the term "disruptive event" implies that it has an extreme outcome. Broska et al. [7] note that an extreme event is a dynamic situation with a limited time frame that can affect the functioning of a system. Using the European Blackout of 2006 as a case study,

Abbreviations: PV, Photovoltaics; NPC, Net present cost; CO_2, Carbon dioxide; LP, Linear programming; MILP, Mixed integer linear programming; PSO, Particle swarm optimization; MGA, Modeling to generate alternatives.

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the authors explain how the removal of a high-voltage transmission line disrupted the functioning of the entire European electricity system for a period of two hours. The study further suggests that the impact of a disruptive event on a system is based on some characteristics of the affected system, such as its responsiveness to disruptive events. According to Aquino et al. [8], although disruptive events have significant consequences for the individuals experiencing them, these effects do not occur equally across the entire population. The study shows that severely limited financial, social, and cultural resources are likely reasons for the variations in the impact of disruptive events on people experiencing them. Mentges et al. [9] show that a disruptive event causes a loss of performance and, as a result, a system cannot fully absorb its impact. It shows that natural disasters, human or technical errors, intentional sabotage, or even organizational policy decisions, can induce a loss of performance in a system, making such activity a disruptive event.

Many disruptive events, particularly natural disasters, lead to negative consequences, such as infrastructure damage and service interruptions. However, not all disruptions are inherently harmful. Human-caused intentional events such as technological innovations can act as positive disruptions that improve system performance [10]. For instance, advancements in digital technologies, including artificial intelligence and the Internet of Things (IoT) have been pivotal in transforming renewable energy systems [11]. These innovations improve grid stability, optimize energy storage, and facilitate the integration of variable energy sources by enhancing the overall resilience of energy infrastructures [12]. Fig. 1 is a hypothetical illustration that shows the positive impact of technological innovation, using the cumulative solar PV electricity generation in a region as an example. It shows the difference in impact between a positive and negative disruptive event in a single figure. In a disruptive event such as a solar storm, photovoltaic cells can degrade significantly due to intense solar radiation [13]. As a result, solar PV generation will be negatively deviated compared to ordinary operation. In contrast, a disruptive event, such as the replacement of the PV modules with a more efficient one would have a positive impact due to the supply of more solar energy [14]. Therefore, it would have better outcomes compared to the ordinary operation.

Types of modeling techniques

Energy system modeling is an important tool that is being used not only to obtain future predicted values related to energy planning but also as a management tool for better decision-making [15]. Subramanian et al. [16] demonstrate that, based on the modeling approach, energy system models can be broadly classified into three categories: computational models, mathematical models, and physical models. Mathematical models employ either statistical techniques based on regression and optimization or theoretical and first-principle-based mechanistic models [16]. In the mathematical model based approach, optimization based modeling usually minimizes the total cost of an energy system over a selected time period based on demand and supply constraints [15]. Simulation-based modeling is another modeling approach that involves the solving of mathematical models with the intention of gaining an insight into how the system will function in response to different operational conditions [16]. This approach enables to investigate scenarios that may otherwise be too costly or otherwise infeasible in a real-world setting [16].

Research objectives

These different modeling approaches have their own advantages and disadvantages, and therefore it is important to analyze which approaches are more suitable when modeling disruptive events in the context of renewable energy supply. This review on modeling disruptive events in renewable energy supply was conducted to address this timely requirement. It primarily explores how the impact of different disruptive events on renewable energy supply can be quantified and mitigated through various modeling techniques. This review provides a comprehensive overview of the various disruptive events in the supply of renewable energy by conducting a systematic review of a wide range of disruptive events across diverse categories. Based on the research objective, this study is guided by the following hypotheses:

1. The integration of appropriate modeling techniques significantly enhances the resilience and sustainability of renewable energy systems when subjected to disruptive events.
2. Incorporating socio-economic factors into energy system modeling reduces uncertainties in planning for disruptive events and leads to more robust and context-sensitive outcomes.

To the best of the authors' knowledge, no review has yet been published on the modeling of disruptive events specifically in renewable energy supply. Hanna and Gross [17] conducted a review on disruptiveness based on the definitions given by Refs. [19] and [20] based on 30 articles. Their study focused on different model types (e.g., optimization and partial equilibrium models, simulation and agent-based models). Individual optimization methods such as Monte Carlo optimization and modeling to generate alternatives (MGA) have been discussed in the context of energy system modeling. However, less focus has been placed on individual simulation tools. Additionally, Hanna and Gross [17] investigated the importance of hybrid modeling methods through integration of general agent-based and differential equation models and soft-linking models. The present study investigated how the

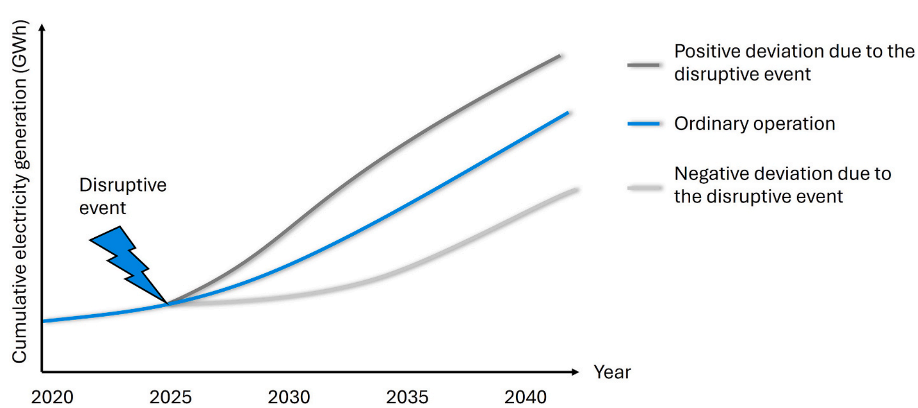

Fig. 1. Hypothetical illustration of the impacts of positive and negative disruptive events on ordinary operation of solar PV electricity generation. Disruptive events such as solar storms could have a negative impact while disruptive events such as using efficient solar PV modules have a positive impact. As this is a hypothetical representation, not all effects are included in the course of the curves, such as the time required to replace the PV modules.

combined individual optimization methods and combined general optimization-simulation models can be used for enhancing the resilience and sustainability of renewable energy systems in the face of disruptive events.

The remainder of this review focuses on the review methodology used, categorization of the results obtained, a discussion regarding the evaluation of the modeling techniques that have been used in the results, and, finally, the conclusions.

Review methodology

In order to answer the primary research question and test the two research hypotheses, it is paramount that literature relevant to disruptive events in renewable energy supply is identified as much as feasible. To identify the relevant literature for review, a keyword-based search related to the modeling of disruptive events in renewable energy supply was first conducted in the Scopus literature database [18]. Scopus was used for the primary literature search because it covers a wider range of journals [19] and more recent sources [20] than other databases. The following search string for this keyword-based search was used:

TITLE-ABS-KEY ((“renewable”) AND (“energy system*”) AND (“disruptive” OR “disorder*” OR “uncontrollable” OR “conflict” OR “war” OR “clash” OR “invasion” OR “disaster” OR “catastrophe” OR “calamity” OR “pandemic” OR “crisis” OR “upheaval” OR “extreme weather” OR “geo politic*” OR “innovation” OR “novel technology”) AND (“generation” OR “capacity” OR “supply”) AND (“simulation” OR “modeling ” OR “optimization” OR “analysis”)) AND (LIMIT-TO (DOCTYPE, “ar”)).*

The idea was to include as many keywords related to disruptiveness as possible. Therefore, synonyms relating to disruptiveness were used (e.g., disorder, disaster, catastrophe) based on exploratory testing. At the same time, the most prominent keywords related to disruptive events occurred during the past few years (e.g., pandemic, crisis, war) and their synonyms (e.g., clash, upheaval) were included in order to increase the search range. Furthermore, key words such as innovation and novel technology were deliberately incorporated to encompass positive disruptive events. The search was then narrowed only to articles related to renewable energy supply. This keyword-based search yielded 395 relevant research articles.

A systematic literature review method corresponding to the “Preferred Reporting Items for Systematic review and Meta-Analyses” (PRISMA) [21] was used in order to filter and identify the most relevant literature for this review (see Fig. 2). Initially, all the 395 articles were screened based on the title and abstract. Based on the title and abstract, articles which were in a language other than English (e.g., Ref. [22]) and articles that had a study focus outside a modeling of disruptive event in renewable energy supply (e.g., Refs. [23,24]) were excluded. During the next step of the screening process, articles that did not have a clear focus on a disruptive event (e.g., Refs. [25,26]) or did not follow a modeling approach (e.g., Refs. [27,28]), or the focused technology in the article was not related to renewable energy (e.g., Refs. [29,30]) were excluded based on the full content of the articles. In addition to the search results obtained from the keyword-based search in Scopus, 24 additional scientific articles obtained from Google Scholar and through citation tracking have been included. The same exclusion criteria that applied to the articles obtained from the keyword-based search were also applied to these additional articles. Importantly, none of these 24 articles met any of the aforementioned exclusion criteria, meaning that all of them were ultimately included in this review, except for one article that was not peer-reviewed at the time of this study [31].

Based on these filter criteria, a total of 102 relevant articles for this review were obtained. Exclusion or inclusion criteria applicable to all 419 articles and the summary of the data extracted from the selected 102 articles is available for download on Jülich Data [32] in Microsoft Excel format. This study and the results outlined in the following sections of this review are based on the results of these 102 selected articles presented in this Excel document.

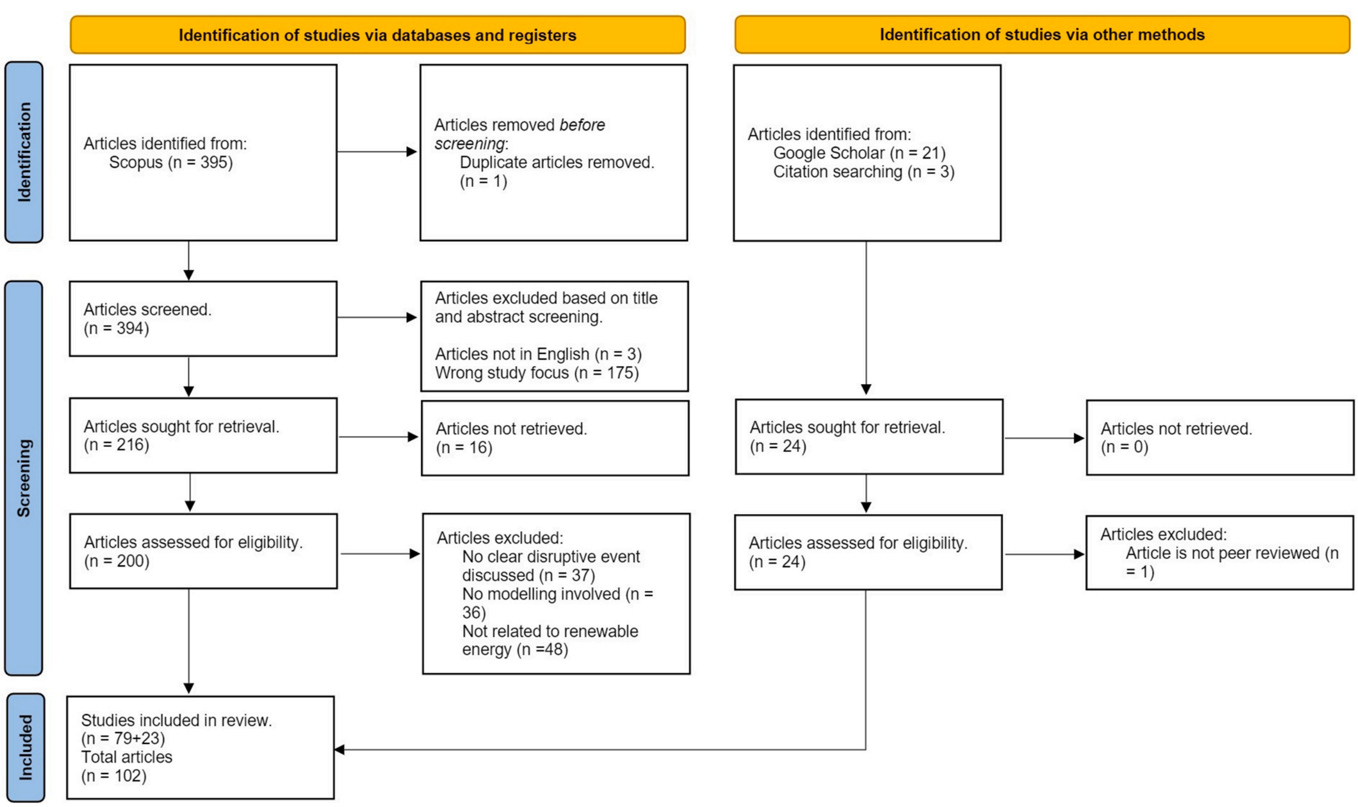

Fig. 2. Flow diagram representing the systematic literature review process as per the guidelines set out by PRISMA.

Results

This section presents the main findings of the analysis of the 102 studies. Section "category of disruptive events and impacts" shows the categorization of the disruptive events and their impacts and Section "system boundaries" the system boundaries of the reviewed studies. In Section "considered criteria", the criteria that have been used to model the disruptive events in the reviewed articles are analyzed to test the research hypothesis on the role of socio-economic factors in the modeling of renewable energy systems. The different types of models and methods used by the studies are analyzed in section "models and methodologies". These modeling techniques will be used to assess how the impact of different disruptive events on renewable energy supply can be quantified and mitigated.

Category of disruptive events and impacts

The reviewed articles contain a total of 108 disruptive events related to renewable energy supply, including similar types of disruptive events. First, these 108 events were categorized based on the cause of the event. From an organizational perspective, disruptions can be classified into three main categories, namely natural, negligent, or intentional [33]. However, based on the reviewed disruptions in renewable energy supply, this categorization was further extended into events related to natural, human-caused intentional, socio-political, and economic factors (see Table 1). The articles that were obtained for this review using the methodology described in Section "review methodology" were published between 2003 and September 2023, with the publication trend shown in Fig. 3a. A significant increase in the number of studies after 2018 in almost all categories of disruptive events can be observed.

Furthermore, the different types of disruptive events have an impact on different demand sectors. In the reviewed studies, four types of demand sectors to which the generated renewable energy is coupled could be identified, namely *electricity*, *fuel*, *hydrogen,* and *heat*. Fig. 3b shows which disruptive event category had an impact on which demand sector in the reviewed articles. In each disruptive event category, the primary demand sector focused on was electricity. The reason for this could be that the term renewable energy supply is mainly associated with electricity generation. The following is an analysis of the impact of the various categories of disruptive events on the various demand sectors.

In the natural category, all the natural hazards or disruptive events that were caused by a natural effect were included. Strong winds from hurricanes or tornadoes can cause damage to wind turbines, resulting in the breakage of blades or the collapse of entire turbines or wildfire smoke and particulates can block sunlight, significantly reducing solar panel output. In the natural category, there has been a focus during the recent half-decade on the impact of extreme weather events [38,41,43,45,49], global warming-related ones such as heat waves [37,39,52], and droughts [51], which can critically affect renewable energy supply. A low focus, with only one study, was in the case of natural disruptive events affecting hydrogen production [43]. Nevertheless, more attention should be paid to this issue, as future energy systems will have a larger share of green hydrogen, while natural disasters continue to increase.

Table 1
Categorization of disruptive events in this literature review.

Category	Example disruptive events	Studies	No. of studies
Natural	Hurricanes, floods, heat waves, droughts	[34–53]	20
Human-caused intentional	Invention of high efficiency solar cells, novel hybrid energy systems	[47,54–92]	40
Socio-political	Wars, oppositions by society, new energy policies	[35,37,93–122]	32
Economic	Increase in interest rates, reduction in carbon tax	[70,102,120,123–135]	16

In the human-caused intentional category includes the disruptive events caused due to a new technological innovation. For example, innovations in solar panel materials can significantly increase the efficiency of the conversion of sunlight into electricity [14]. Higher efficiency means that more electricity can be generated from the same amount of surface area, making solar energy more viable in regions with less sunlight. A more stable and reliable energy supply can be achieved through innovations in hybrid systems that combine different renewable energy sources (e.g., solar and wind) with storage [136]. In the human-caused intentional category, the number of studies increased continuously due to new technical improvements in the renewable energy supply. These improvements include the use of hybrid energy technologies [39,67], improved wind turbine selection process for new wind plants [61], and novel wind turbine foundation design [91]. The category human-caused intentional includes most disruptive events, mainly due to a high proportion of studies focusing on new inventions in the field of renewable energy supply. In particular, there was a higher focus on green hydrogen production in articles [65,85,88,89] published during the last four years. In contrast, there was little focus on the fuel sector, which has primarily emphasized biofuel production (e.g., Ref. [98]).

The socio-political category includes events caused by social activities or political decisions. Investors may view politically unstable regions as high risk, resulting in reduced investments for renewable energy projects [137]. The result can be a slowdown in the deployment of renewable energy even in regions with significant potential. Local opposition due to concerns about visual impact (e.g., Ref. [138]), noise, land use, or environmental impacts can arise for renewable energy projects such as wind farms or large solar installations [139]. This can cause projects to get delayed, cost more, or even cancelled [140]. After 2021, a steep increase in the number of articles written in the socio-political category could be observed, mainly due to the impact of renewable energy supply as a result of the Covid-19 pandemic [111,113,118] and the Russian–Ukrainian war [115]. The energy crises due to the war between Russia and Ukraine was a major reason for disruptive events regarding heat demand in the socio-political category (e.g., Ref. [115]).

The events related to economic reasons are included in the economic category. The occurrence of economic problems can result in the imposition of higher interest rates, which can consequently elevate the financial burden associated with the procurement of capital for renewable energy projects [141]. Subsidies, tax credits and other incentives that support renewable energy may be reduced or eliminated by governments facing economic difficulties [142]. Without this financial support, the viability of renewable energy projects may be reduced. Comparatively, only a small number of studies have focused on economically-related disruptive events. However. the number of articles in this category increased in the last few years due to the effects of changes in carbon emission trading [70,130,132] and carbon tax related to renewable energy supply [125,126,133].

System boundaries

This section outlines the system boundaries that have been considered by the reviewed studies. Section "considered technologies" includes the types of different energy technologies that were considered, whereas section "spatial resolution and location" shows the geographical scope related to the case studies.

Considered technologies

The reviewed articles considered different renewable energy technologies. 19 of the 102 studies focused on a single energy technology, while [38,103,105,127] did not specify the technology they focused on.

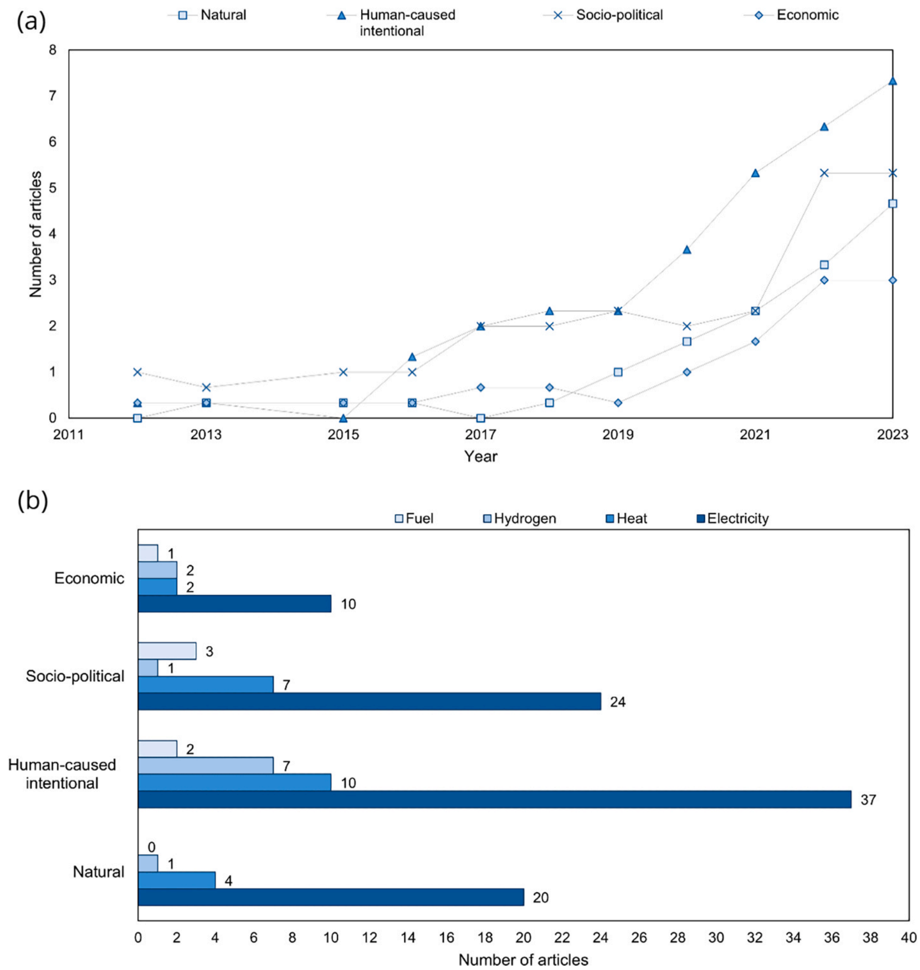

Fig. 3. a. Three-year moving average number of articles in each category that have been published in each year. Articles published from 2003 to 2011 do not show a clear trend hence omitted in this figure. **b.** number of disruptive events that focused on the four demand sectors of electricity, fuel, hydrogen, and heat demand in each category of disruptive event.

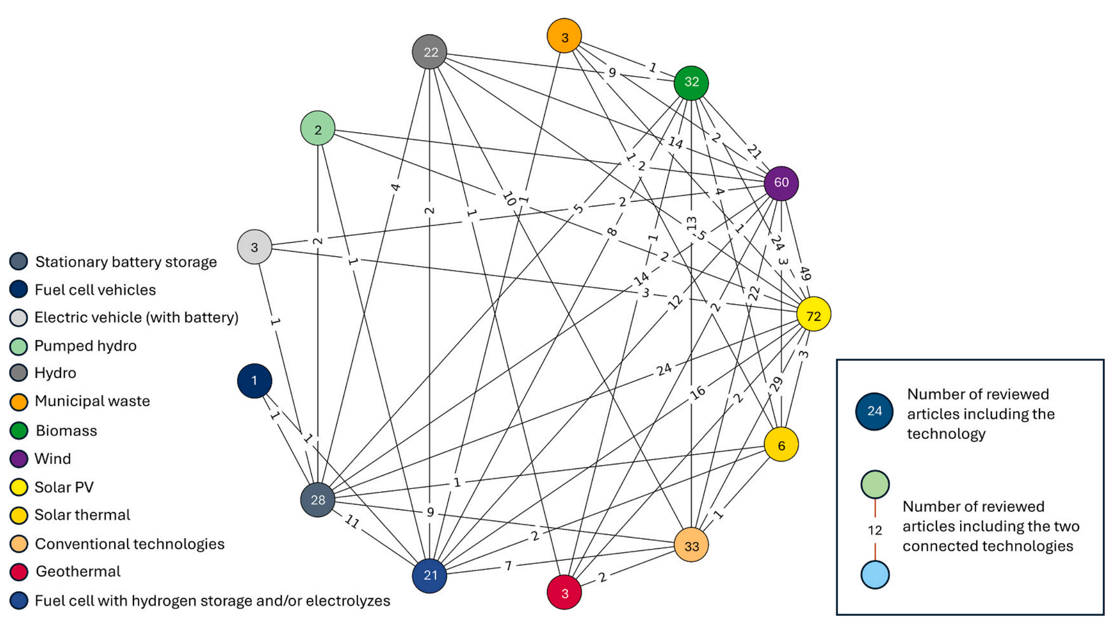

Fig. 4. Overview of the number of articles including specific technologies. If two nodes are connected by an edge, the number of articles that include both two connected technologies is displayed on the edge.

Instead, the latter studies treated all renewable energy technologies as a single energy source. The remaining studies focused on multiple technologies, including conventional ones such as coal, natural gas, nuclear energy, and diesel generators, in addition to their renewable energy-based counterparts. However, in this review, only renewable energy-related technologies have been considered. The frequency of consideration of each energy technology in the reviewed articles is shown in Fig. 4.

Solar photovoltaic (PV) systems were the most modeled technology, appearing in 72 of the 102 studies (see Fig. 4). Notably, 68 of these studies combined solar PV with other technologies, such as stationary batteries or fuel cells with hydrogen storage, reflecting the need for complementary systems to address PV's intermittency. Several studies examined the resilience of hybrid systems under disruptive conditions such as pandemics or natural disasters, highlighting growing interest in integrating mobility and stationary storage into energy planning (e.g., Refs.[46,111]). Studies on battery–electric vehicles and stationary battery storage were also included if the usage of these technologies directly relates to renewable energy supply. Although fuel cell vehicles have emerged as a promising technology, particularly for the transportation sector [143], very few studies have addressed their vulnerability or performance under disruptive conditions. This points to a significant research gap in this regard. The notable insights for the main energy technologies identified in the reviewed articles are summarized in Table 2, which was developed by combining the findings in Sections "category of disruptive events and impacts" and "considered technologies".

Spatial resolution and location

Table 3 presents the studies that focused on the different types of geographic scopes. 14 did not disclose this information. Of these 14 studies, more than 85 % discuss new technological inventions and thus consider human-caused intentional disruptive events. The reason for this may be that modeling a new technological invention is typically not limited to a specific geographic area, as the benefits of the inventions are likely to be experienced in other regions as well.

Among the studies that mentioned the geographic scope, the majority focused on modeling disruptive effects at the individual country level. For the socio-political event category, most studies focus on government policy decisions that impact the entire country [35,94,103,116,121,144]. In the category of natural disruptive events, there has been a greater emphasis on regional geographic scopes. These studies include flood events in river basins [42,51] and typhoon events in coastal areas [52]. The "selected region" geographic scope refers to specific areas within a country, such as counties or provinces (e.g., Refs. [75,129]) and specific areas within a region, such as western Europe [54]. Disruptive events in remote rural areas and villages have received little attention so far. However, rural communities are more vulnerable to long-term disruptive events, such as the effects of climate change, due to poor economic conditions, emergency facilities, or inadequate health systems [145]. Therefore, it is important to pay more attention to potentially disruptive events associated with renewable power supply in rural areas in the future.

Table 2
Summary of technology focuses on the reviewed studies.

Energy technology	No. of studies	Notable insights
Solar PV	72	Key technology for most studies however, fewer studies on standalone PV systems.
Stationary battery storage	28	An essential element of enhancing system reliability.
Fuel cell with hydrogen storage	21	Growing attention for long-term storage, but less focus in natural disaster contexts.
Electric vehicle (with battery)	3	Linked to demand-side flexibility and resilience, however, few resilience-focused case studies.
Fuel cell vehicles	1	High future potential in transport applications, but significant gap in disruption-focused modeling.

Table 3
Number of articles based on the disruptive events category that have focused on different types of geographic scopes.

Geographic scope	Natural	Human-caused intentional	Socio-political	Economic
Remote rural area	–	3	–	–
Continent	–	–	1	2
Country	4	5	12	5
Village	–	1	1	1
Municipal city	4	2	4	4
Industrial park	1	1	–	–
Building	1	6	1	2
Island	2	2	1	–
Selected region	5	6	10	3

Considered criteria

Approximately 22 % of the reviewed articles use multiple criteria or objectives to assess the impact of the disruptive events on renewable energy supply. Among the multi criteria that have been used in the reviewed articles, cost was an important criterion, with 58 (57 %) of the total studies utilizing it. In some of the studies that do not take costs into account, the additional consideration of costs would have allowed for better results in order to compare the results with other studies. For example, in Hai et al. [84], the objectives were to achieve a balance between energy output and environmental sustainability regarding the addition of hydrogen to both the anode and afterburner of a solid oxide fuel cell. Considering cost as a criterion would have been important in this study, as the future deployment of this technology may be influenced by the decision to prioritize cost considerations.

The results of the reviewed articles demonstrate that the application of more relevant criteria leads to a greater degree of realism in the findings. Table 4 lists the target criteria other than cost that were considered in the multi-criteria studies. Here, similar types of criteria that feature a common focus are clustered together. For example, Ding et al. [36] used the criterion of wasted renewable energy to improve the utilization of renewable resources. Sasse and Trutnevyte [93] used the criterion of renewable electricity generation to increase the generation of renewable electricity. Both these are listed under renewable energy usage in Table 4 due to their similarity in the outcome. In the reviewed articles, greenhouse gas emissions were a key criterion in six studies (see

Table 4
Target criteria other than cost in multi-criteria studies.

Criteria	Study	No. of studies
Greenhouse gas emission	[36,64,89,120,133,135]	6
Criteria related to environmental damage	[68,80,83,84,107]	5
Energy efficiency	[58,66,80,90]	4
Stakeholder satisfaction	[68,77,107]	3
Renewable energy usage	[43,93]	2
Net power output	[83,84]	2
Impacts on distribution grids	[77,107]	2
Primary energy consumption	[89]	1
Jobs generated	[120]	1
Power tracking	[47]	1
Heat control	[47]	1
Loss of power supply probability	[44]	1
Hydraulic damping	[75]	1
Fuel consumption	[66]	1
Energy saving ratio	[64]	1
Availability of spare parts	[68]	1
Optimal policy mix	[103]	1

Table 4), all of which have a smaller geographical scope, such as a city or smaller settlement. Surprisingly, there was not a single multi criteria study with a larger geographic scope such as regional or country level, that applied this criterion. Four of the five studies considering the environmental damage criterion [68,83,84,107] were in the human-caused intentional category. This shows that human-caused intentional disruptive events tend to have an impact on the environment.

The use of multi-objective optimization has helped many authors address the needs of different stakeholders in the context of disruptive events in renewable energy supply. Liu et al. [77], for instance, discussed the planning and optimization of a sea water desalination plant-based hybrid renewable energy system as a solution to energy crisis and freshwater shortage. The authors used three optimization criteria, namely cost, demand-side management loss, and distribution grid impact. The cost criterion is derived from a planning and investment perspective, whereas the demand side management loss criterion measures the end user dissatisfaction from a customer perspective and the distribution grid impact criterion attempts to minimize the impact on the system grid from a utility perspective. Using these criteria when modeling disruptive events can help design systems that are robust, resilient, and capable of meeting future demands and challenges. Similarly, Martínez-Martínez et al. [110] performed a Multi Attribute Decision-Making (MADM) site suitability analysis combined with an ecosystem services approach as a solution to land use conflicts in renewable energy development in south-central Chile. Here, 29 different attributes were used, taking into account the provisioning (e.g., wild food and mineral resources availability), regulatory (e.g., water and soil quality regulations), and cultural requirements (e.g., aesthetic value and cultural heritage) of each ecosystem. The manner in which these different criteria can be effectively combined to reduce uncertainity in the model outcomes are reviewed in Section "using socio-economic factors in the modeling of renewable energy systems".

Models and methodologies

This section presents the models and methodologies used in the studies. Most reviewed studies employed simulation (39 studies, e.g., [62,101]) or optimization (59 studies, e.g., [108,131]) methods in the modeling process. Some others made use of econometric models [127], statistical models [53] or simplified energy balance equations [78,88]. In this section, an overview is provided of the two main modeling methods employed in the reviewed articles (simulation and optimization) to model renewable supply disruptions. The tools used for simulation and optimization are summarized in Table 5. The tools include software (e.g., HOMER, EnergyPLAN), models (e.g., MARKAL), and toolboxes (e.g., PyPSA) used for modeling.

Renewable energy systems are complex and involve interactions between weather patterns, energy demand, grid infrastructure, and market dynamics. Simulation models can effectively capture these interactions and provide valuable decision support through the integration of technical, economic, environmental, and social factors [146]. Simulation models can be used to explore multiple scenarios [147], such as the impact of extreme weather events (like hurricanes or droughts) on wind, solar, or hydroelectric generation. This helps to understand the range of possible outcomes and the system's sensitivity to different types of disturbances. Simulation models play a particularly important role in risk assessment and management [148]. This is done by predicting potential disruptions and assess their impact on energy supply, demand, and prices [149]. For example, they can simulate the effect of prolonged cloud cover on solar power output or the impact of a wind turbine failure on overall power generation. This predictive power is critical for risk management and contingency planning. However, the quality and availability of data is critical to the accuracy of simulation models [150]. In regions where data on renewable energy performance, weather patterns, or grid operations is scarce or unreliable, model predictions may be less accurate. The simulation models used in the reviewed articles are discussed in more detail in section "using simulation tools in disruptive events modeling" in order to address how the impact of different disruptive events on renewable energy supply can be quantified and mitigated through these models.

Optimization models facilitate decision making by providing insight into the best strategies for investment and operation of renewable energy [149]. This includes activities such as identifying where renewable energy resources such as wind farms or solar arrays should be located, and how energy storage should be distributed to mitigate the effects of disruptive events. However, their effectiveness depends on how well they can represent the complexity and uncertainty of such events [151]. Similar to simulation models, optimization models require detailed and accurate data to work effectively. Incomplete or inaccurate data can lead to sub-optimal or unrealistic solutions [152]. Optimization models use different optimization methods such as stochastic optimization and robust optimization for the optimization process (see Table 6). In energy system optimization models, these different optimization methods have their own advantages. The optimization methods used in the reviewed

Table 5
Tools used for simulation and optimization in the reviewed articles.

Tool	Type of tool	Study	No. of studies
HOMER/HOMER PRO	Simulation	[49,55,59,60,62,65,67,73,81,82,86,111,113]	13
LEAP	Simulation	[95,112,116,119]	4
EnergyPLAN	Simulation	[35,97,109]	3
MESSAGE	Optimization	[56,114,126]	3
TIMES	Optimization	[56,94,121]	3
Calliope	Optimization	[42,123]	2
MARKAL	Optimization	[96,124]	2
PyPSA	Optimization	[93,115]	2
BeWhere	Optimization	[98]	1
CleanGrid	Simulation	[79]	1
CCAM	Simulation	[39]	1
DECAPLAN	Optimization	[135]	1
EMPIRE	Optimization	[117]	1
EXPANSE	Optimization	[93]	1
GAMS	Optimization	[48]	1
GUSTO	Optimization	[117]	1
GCAM4.0	Simulation	[57]	1
GENeSYS-MOD	Optimization	[130]	1
NESSI4D	Simulation	[132]	1
PCR-GLOBWB	Simulation	[51]	1
PRIMES	Simulation	[105]	1
RIES	Optimization	[43]	1
Risk matrix	Simulation	[45]	1

Table 6
Optimization-based methods used in the reviewed articles. It should be noted that some of the optimization methods such as robust optimization and Myopic optimization utilize mixed integer linear programming (MILP) or linear programming (LP) in their basic optimization algorithms but are not counted. Only the studies that have used MILP and LP without specifying a further specification are counted as MILP and LP, respectively. Furthermore, genetic algorithms, particle swarm optimization, and differential evolution methods are usually considered as variants of stochastic modeling [153] but are listed separately from stochastic optimization.

Method	Study	No. of studies
Stochastic optimization	[37,38,40,100,104,108,117]	7
Mixed integer linear programming (MILP)	[41,44,48,52,98,117,135]	7
Linear programming (LP)	[54,70,96,121,124,125]	6
Particle swarm optimization (PSO)	[66,69,75,118,133]	5
Robust optimization	[37,38,89,104]	4
Modeling to generate alternatives (MGA)	[93,94,122,123]	4
Genetic algorithms	[61,77,90]	3
Multi criteria decision making (MCDM)	[68,107]	2
Monte Carlo	[85,94]	2
Agent based	[134]	1
Multi objective optimization	[43]	1
Myopic optimization	[115]	1
AHP-CRITIC mixed weighting	[80]	1
Branch-and-cut	[58]	1
Differential evolution	[103]	1
Slime mould algorithm	[87]	1
Zone model predictive control	[47]	1

articles are discussed in section "using optimization methods in disruptive events modeling" in order to address how these methods can be used to quantified and mitigate the impact of different disruptive events on renewable energy supply.

Discussion

In this section, the findings from Section "Results" are reviewed and assessed. In Section "using socio-economic factors in the modeling of renewable energy systems", the research hypothesis that incorporating socio-economic factors into energy system modeling reduces uncertainties in planning for disruptive events and leads to more robust and context-sensitive outcomes is tested. The main research question of this review, which is how the impact of different disruptive events on renewable energy supply can be quantified and mitigated through different types of modeling techniques are assessed in Section "using simulation tools in disruptive events modeling" and "using optimization methods in disruptive events modeling". The research hypothesis that integrating appropriate modeling techniques significantly enhances the resilience and sustainability of renewable energy systems under disruptive events is tested in Section "using modeling tools to enhance resilience and sustainability of renewable energy systems".

Using socio-economic factors in the modeling of renewable energy systems

Section "considered criteria" showed that most of the simulation-based studies are based on cost evaluations. The studies that utilize cost as a modeling criterion illustrate the significance of incorporating cost as a criterion in the modeling of disruptive events. According to the simulated results of Pedersen et al. [115], if Europe aims to keep the temperature increase below 2 °C, the average electricity cost could increase up to 65 €/MWh by 2025 due to the gas supply limitation caused by the Russia–Ukraine war. This offers a clear indication of how geopolitical conflicts can disrupt energy markets, leading to higher energy prices. It converts the abstract concept of energy supply limitations into a tangible, economic burden on consumers and industries. As per the findings of Bennett et al. [40], projected electricity costs based on the historical hurricane frequencies in Puerto Rico in 2040 could increase by as much as 32 %. It shows how natural disasters can lead to significant financial challenges. This further highlights the need to invest in resilient infrastructure that can withstand extreme weather, potentially reducing future costs.

Although cost is a very important parameter in the modeling of disruptive events, taking only the direct costs associated with a disruptive event into account is not an ideal way to evaluate the results thereof [154]. This is due to the fact that not only disruptive events but also the activities associated with the methods used to mitigate the effects of such disruptive events are uncertain in today's context. For example, the ideal renewable energy supply for an electrolysis-based green hydrogen system to reduce carbon emissions in the transport sector can be considered. Here, apart from the renewable energy supply with the lowest direct cost, policy regulations and the consent of the people living near power plants etc. should also be considered to evaluate the project's feasibility. The impacts of these other factors on the above problem are not visible in relation to the direct cost of the project unless they have been properly identified and converted into monetary values. Therefore, the lack of consideration of these factors increases the uncertainty of the outcome of the disruptive event. This section will explore how the factors such as renewable energy usage, greenhouse gas emissions, environmental damage, and stakeholder satisfaction as listed in Table 4 can be used to reduce the uncertainty in the model outcomes.

The use of renewable energy diversifies the energy mix and reduces dependence on imported fossil fuels, which can be prone to geopolitical risks (e.g. the Russia-Ukraine conflict). Therefore, utilizing renewable energy usage as a modeling criterion helps to assess energy security by identifying the vulnerability of energy supply to external disruptions. The transition to energy systems with lower greenhouse gas emissions could reduce operating costs over the long term. This is especially important for small communities with limited budgets, where cost-effective energy solutions are critical. Environmental damage often represents an externality, a cost that is not borne by the producer or consumer, but by society as a whole (e.g., health effects of air pollution, degradation of ecosystems). Including environmental damage as a criterion in energy system modeling helps account for these externalities. This leads to more accurate cost-benefit analyses and more economically efficient outcomes. Stakeholders in energy system planning are guided by a set of defined objectives, including cost effectiveness, reliability, environmental impact, or profit margins. Using stakeholder satisfaction as a modeling criterion ensures that energy system design aligns with these diverse objectives, leading to broader support and smoother implementation of the energy transition.

Therefore, energy system modeling can be enriched by incorporating socio-economic modeling criteria, which can help mitigate uncertainty surrounding disruptive events. This is achieved by capturing the broader context in which energy systems operate, including human behavior, policy responses, market dynamics, and institutional factors. The modeling of disruptive events in renewable energy supply should not focus on a single objective. Instead, the inclusion of criteria related to a broader context associated with the disruptive event in the modeling process will result in a significant reduction in the risk associated with the modeling output.

Based on the reviewed studies, Fig. 5 represents the criteria that are likely to be of interest to various stakeholder groups. Therefore, in the event that the stakeholders are also involved in the modeling process, it would be most prudent for them to prioritize the criteria that are relevant to their role. For example, if a novel hybrid power renewable energy plant is modeled by the utility electricity supplier, more focus should be placed on the loss of power probability and its impact on the distribution grid, in addition to cost. This will help attain more precise and resilient results from the utility supplier's perspective. This tailored focus on relevant criteria ultimately leads to more precise and resilient modeling outcomes.

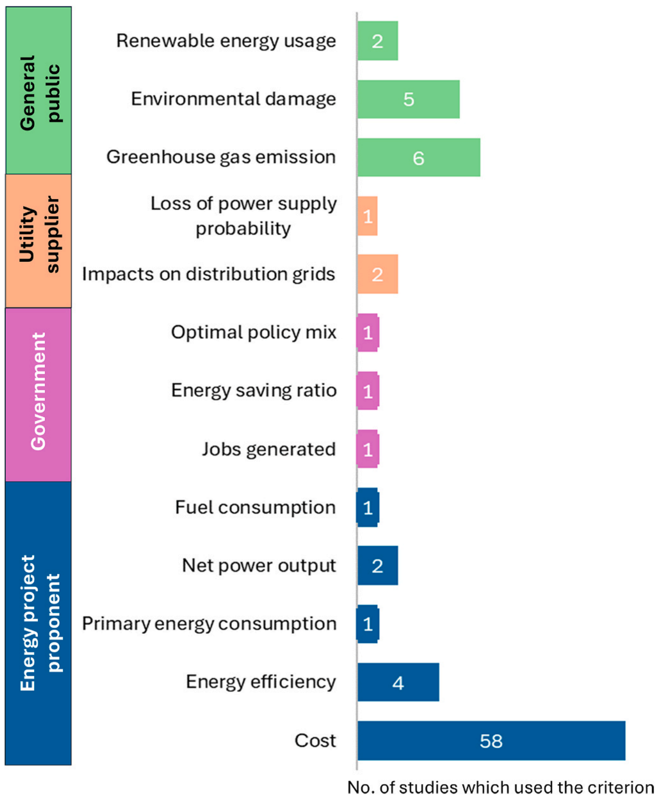

Fig. 5. Main modeling criteria used and the parties likely to be interested in the criteria in the reviewed articles and the number of studies which used each criterion.

These findings support the hypothesis presented in Section "Introduction" which is, incorporating socio-economic factors into energy system modeling reduces uncertainty in planning for disruptive events and yields more robust and context-sensitive outcomes. Furthermore, the ways in which different modeling techniques aid the stakeholders in attaining improved resilience and risk reduction outcomes are explored in Sections "using simulation tools in disruptive events modeling" and "using optimization methods in disruptive events modeling".

Using simulation tools in disruptive events modeling

This section reviews the major simulation-based models and software that have been used to model disruptive events, and how well each modeled the uncertainty of the events in the reviewed studies. HOMER (Hybrid Optimization of Multiple Energy Resources), EnergyPLAN, and LEAP (Long-range Energy Alternative Planning) represent the most used simulation-based models and software. The strengths and weaknesses of these models are summarized in Table 7, along with the cases of their use in the reviewed articles and the practical relevance of these models for various stakeholders.

HOMER first simulates multiple configurations based on user requirements and ranks these configurations against their associated lifecycle costs which are calculated using total net present cost (NPC) [155]. As mentioned in section "considered criteria", using cost as a criterion is important when modeling for disruptive events. However, in HOMER simulations, the lowest NPC configuration may not always be sufficient to reflect the uncertainty associated with the operational part of the problem, whereas configurations with higher NPCs may have this capability (see the case study example of HOMER in Table 7). Furthermore, HOMER can perform sensitivity analysis on the modeled outcomes by measuring how sensitive the output could be to changes in the input data. This helps with robust decision making in long-term energy planning. When using sensitivity analysis, the reviewed studies assumed that changing one parameter did not affect the other parameters hence the varied parameter was always independent during the sensitivity analysis. In reality though, in modeling disruptive events in renewable energy supply, one parameter change can affect the performance of other parameters significantly. For instance, when simulating the impact of heat waves on solar PV generation, various factors, including solar panel efficiency, electricity demand, and transmission line capacity, can be impacted concurrently. Therefore, when the sensitivity of solar panel efficiency to temperature is analyzed, overconfident or misleading conclusions could be reached if the other factors are assumed to be constant. In such instances, global sensitivity analysis, which has the capacity to quantify the extent to which the variance in model output is attributable to each input, including interaction effects, is a useful tool [156].

Using EnergyPLAN, Mathiesen et al. [96] provide a good example of taking multi-criteria in addition to cost into account for modeling to reduce uncertainty (see Table 7). Sections "considered criteria" and "using socio-economic factors in the modeling of renewable energy systems" discussed the importance of using multiple criteria, including cost, to reduce the uncertainty of model outcomes. Although EnergyPLAN is ideal for modeling of short-term rapidly changing events, the usually used one-year modeling horizon limits the inclusion of long-term dynamics such as technological advances, aging infrastructure, changes in energy consumption, and gradual climate change. This makes EnergyPLAN less feasible for long-term forecasting or multi-year transitions. Therefore, based on the reviewed articles that used EnergyPLAN, it may not be the ideal simulation tool when modeling for policy-related events because the effects of such events cannot usually be measured in a single year [157]. In situations where planning across multiple years is essential, particularly for assessing policy transitions, investment strategies, or the progression of emissions over time, it is advisable to utilize approaches as in Ghanadan et al. [95] with the LEAP simulation.

The LEAP model can be used for scenario-based studies [147] to explore a wide range of possible outcomes and thereby reduce the uncertainty in the outcomes. As all simulation models, the LEAP model has the risk that the choice of scenarios and assumptions may result in biased results that reflect the perspective of the modeler rather than objective outcomes (see the case study example of LEAP in Table 7). LEAP can also develop future forecasts based on certain assumptions using a simulation approach [158]. Forecasting is useful when future energy demands are needed to be anticipated for long-term strategic planning [159]. Compared to scenario-based modeling, forecasting identifies the most likely pathways and is only effective when ample information about the disruptive event is available [95]. While LEAP can be used for long-term forecasting of CO_2 emissions as shown in Table 7, the accuracy of such forecasts is limited by uncertainties in technological innovation, policy dynamics, and socio-economic behavior. Once forecasts are established, they may diverge significantly from reality if disruptive events such as breakthroughs in clean energy or sudden regulatory shifts occur. This highlights the importance of scenario modeling and sensitivity analysis in modeling of disruptive events.

Using optimization methods in disruptive events modeling

In this section, the main optimization-based methods that have been used to model disruptive events in renewable energy supply are reviewed. The optimization methods that were used in this study are shown in Table 6 and Table 8 provides a summary of the strengths and weaknesses of each reviewed optimization method. The latter also includes the used cases for each method in the reviewed articles and the practical relevance of the methods for stakeholders.

Stochastic optimization

The most commonly used optimization method among the reviewed

Table 7
Major simulation-based models and software that have been used in the reviewed articles. This table provides information about the advantages and drawbacks of these models and software in the studies considered. For each model, the cases used by the reviewed articles are provided, as well as the model's suitability for reducing the uncertainty of the given case. The practical relevance of these modeling tools for various stakeholders is demonstrated based on these used cases.

Model/Software	Approach	Strengths	Weaknesses	Applied by	Practical relevance of the model/ software for;
EnergyPLAN	Uncertain and radically changing events modeling	Can take multi-criteria into account for modeling to reduce uncertainty.	Has a modeling horizon of only one year [160].	Mathiesen et al. [96] used EnergyPLAN to simulate Denmark's policy for achieving a 100 % renewable energy system by 2050. The EnergyPLAN software helped to identify effective strategies for maximizing the use of renewable energy while maintaining the stability of the system and meeting the energy demand in the year 2050. It considers other criteria such as technical feasibility, economic benefits of the transition to a renewable energy-based system, and social impacts which have a fast changing behavior.	Policymakers: Gain insight into long-term energy transition strategies by simulating key milestone years and evaluating how well future scenarios align with short-term policy goals and technical constraints. Industry stakeholders: Able to test the yearly impact of renewable integration, demand fluctuations, and flexibility measures due to long-term transition plans.
HOMER (Hybrid Optimization of Multiple Energy Resources)	Lifecycle costs calculated using total net present cost (NPC) to select the ideal configuration	NPC can be used to identify the benefits and trade-offs between multiple configurations in an effective and straightforward manner.	Use of NPC as the sole modeling criterion could make the results less useful for multi-objective requirements.	Ali et al. [49] used HOMER to simulate and analyze the resilience of different energy systems during grid disruptions for a hospital on Lombok Island in Indonesia. The model analyzed NPC and cost of energy (COE) for two scenarios to decide the more cost-effective setup in case of a utility power outage. Conversely, a slightly more expensive option may offer improved reliability and sustained power which are essential for critical purposes like hospitals or emergency services.	Policymakers: Support the planning of energy resilience strategies for critical infrastructure, particularly in remote or disaster-prone areas. Utility supplier: Use the analysis to prioritize backup systems emergency services such as hospitals, thereby reducing vulnerability during blackouts.
	Sensitivity analysis	Solutions which remain viable under a range of conditions can be identified.	Change of only one parameter at a time is considered.	Huseyin [86] used sensitivity analysis on various factors such as interest rate, fuel costs, wind speed, solar radiation, and maintenance expenses to assess a hybrid renewable energy system's feasibility for city power supply. Sensitivity analysis revealed a higher sensitivity of the energy system's NPC to diesel fuel prices and maintenance costs, with minimal impact from changes in solar radiation and wind speed. This reduces financial uncertainty caused by solar and wind power intermittency, allowing modelers to prioritize diesel price variations and maintenance costs for the project.	Disaster Management Agencies: Identify financial risk in system disruptions due to price volatility (e.g., diesel shortages) to enable better planning for contingency fuel needs. Project proponent: Make informed decisions by focusing on the most impactful cost factors and thereby reducing financial risk.
LEAP (Long-range Energy Alternative Planning)	Scenario based modeling	Helps consider different future scenarios, such as best, worst, and most likely outcomes, managing uncertainty from disruptive events.	Results can be biased by the modeler's choice of scenarios and assumptions.	Asim et al. [116] used scenario-based modeling in LEAP to determine the best choice for Pakistan's future energy system. The LEAP model assessed scenarios for energy use and CO_2 emissions to find the most sustainable and cost-effective solution. It identified a green energy option with the lowest costs as the best system. However, the use of CO_2 emissions may appear to be biased in favor of getting a green energy scenario as the ideal solution.	Policymakers: Support the decision-making process by comparing multiple future energy paths and identifying the ones that minimize costs and emissions.

(continued on next page)

Table 7 (*continued*)

Model/Software	Approach	Strengths	Weaknesses	Applied by	Practical relevance of the model/ software for;
	Forecasting	Useful when the actual data for an event is not readily identifiable.	Once forecasts are established, they cannot easily adapt to unexpected changes.	Raza et al. [112] used energy demand, production and CO_2 emissions forecasts to model the energy sector of Pakistan from the year 2020 until the year 2070. However, the results may not always be accurate when predicting parameters such as CO_2 emissions. This is because once forecasts are established, CO_2 emissions can change with technological breakthroughs or policy changes that could arise later.	Industry stakeholders: Can anticipate future energy needs and emission targets, aiding infrastructure and research and development planning.

Table 8
Summary of the optimization methods used in the reviewed articles including strengths and weaknesses of each method. For each method, the cases used by the reviewed articles are provided. The practical relevance of these optimization methods for various stakeholders is demonstrated based on these used cases.

Method	Strengths	Weaknesses	Applied by	Practical relevance of the method for;
Stochastic optimization	Accounts for uncertainty using probabilistic scenarios Enables more accurate cost and risk projections Commonly used in energy system planning	Requires a lot of data or expertise knowledge to assign probability values High computational complexity and time	In Bennet et al. [40], stochastic optimization was used to identify hurricane risk in energy system planning for Puerto Rico. Their scenarios were based on different levels of hurricane severity and the probability of hurricane severity was calculated using historical data.	Policymakers: Helps in formulating disaster response strategies and infrastructure investment strategies that take risk into account and are tailored to high-risk regions. Disaster management agencies: Assists with contingency planning by identifying system vulnerabilities and anticipated performance under various scenarios related to natural disasters.
Particle swarm optimization (PSO)	Efficient in exploring complex solution spaces	May converge to local optima	Zhao et al. [75] introduced a novel small signal model for pumped storage units. In this study, PSO was used to enhance the performance of the pumped storage plant by considering primary frequency control, hydraulic damping caused by the pumped storage plant, and hydraulic damping caused by surge tanks.	Plant operator: Help to optimize complex operations and reduce downtime in critical infrastructure. Policymakers: Supports grid stability regulations by demonstrating the role of flexible power plant operation (pumped storage in this instance) in improving grid performance.
	Suitable for multi-objective and parallel problems Fast convergence in practice		Yang et al. [66] introduced a hybrid power system for ships, emphasizing the integration of solar power with a diesel generator. This study used PSO to reduce fuel consumption and maximize the diesel generator efficiency of the ship to improve the efficiency and stability of its power systems.	Heavy machinery industry: Provides cost beneficial plans to improve fuel efficiency in complicated machines with numerous systems.
Modeling to generate alternatives (MGA)	Provides multiple near-optimal solutions Past data or probability values are not required	Increased computational time with the number of alternative solutions Requires interpretation of many alternatives	Patankar et al. [122] used MGA to generate 160 carbon–neutral electricity generation portfolios in order to evaluate the land use impacts associated with solar and wind power generation. These portfolios were generated with respect to some qualitative rather than quantitative facts such as technology options, key trade-offs, and policy considerations associated with a carbon-free electricity supply plan.	Policymakers: Enables the exploration of multiple viable options that incorporate non-quantifiable sociopolitical concerns, such as land use and public acceptance. Investors: Supports flexible investment strategies and adaptation to a range of feasible regulatory and market scenarios.
Robust optimization	Provides worst-case resilient solutions Lower computational burden than stochastic optimization and MGA	Can be overly conservative May lead to higher costs or rigid plans	Henao et al. [37] used robust optimization to address uncertainty in the Colombian power sector's expansion planning. In this case, the optimization model suggested that in order to meet Colombia's electricity demand over the next 15 years, even under adverse conditions, 37.8 GW of solar PV and 2.1 GW of wind power should be installed	Disaster management agencies: Ensures that critical power systems remain operational in high-impact, low-probability scenarios, thereby enhancing emergency resilience. Policymakers: Provides long-term, conservative infrastructure investment strategies which maintain energy security even under extreme conditions.

optimization-based articles is stochastic optimization (see Table 6). This approach is primarily used for problems that involve uncertainty because it introduces randomness into the optimization process [161]. Rather than relying on deterministic assumptions that may not hold in the real world, the inclusion of randomness allows the model to account for a wide range of possible scenarios. Therefore, similar to HOMER and LEAP, stochastic optimization also considers multiple scenarios [162]. Each scenario represents a possible outcome for an uncertainty factor related to the optimization problem, which is assigned with a probabilistic value [162]. There are several advantages to the use of probability values in the optimization process. In the study of Bennet et al. [40] (see Table 8), inclusion of probability values helps authors make more informed decisions by taking into account the likelihood of hurricane events and their impact on the power grid. It also allows for more accurate cost projections by factoring in potential damage and required rebuilding following hurricanes. This makes stochastic optimization an ideal method for uncertain probabilistic disruptive events modeling (e.g., natural disruptive events such as floods). Calculating or identifying the feasible probability value is very important in stochastic optimization in order to obtain accurate results. However, reliance on accurate probability distributions can be difficult to define for rare or unprecedented disruptive events. In such cases, robust optimization offers a practical alternative by focusing on worst-case scenarios without needing probability values.

Linear programming (LP) is a powerful mathematical technique that is used to find the best possible outcome in a given mathematical model represented by linear relationships [163]. However, LP lacks the ability to incorporate uncertainty and without this, LP cannot effectively manage or mitigate risk [164]. For example, in the supply of renewable energy, factors such as weather patterns, equipment failures, or market prices are inherently uncertain. LP in its basic form would have difficulty providing robust solutions that account for these uncertainties, resulting in solutions that may not perform well under real-world conditions. Therefore, stochastic optimization can be considered a technique that combines the advantages of both LP and simulation [165]. In addition, the fact that stochastic optimization is the most commonly used optimization method as identified in this review shows that it could deal with the uncertainty of disruptive events to a greater extent. However, solving exact stochastic optimizations is also associated with significantly higher model complexities and longer computing times compared to simulations [166]. On such occasions, metaheuristic approaches such as particle swarm optimization (PSO) can provide faster, approximate solutions in large and complex problem spaces.

Particle swarm optimization

The metaheuristic particle swarm optimization (PSO) is also used in several of the reviewed studies. PSO was developed based on the social behavior of flocks of birds and uses an iterative process to identify and update the best solution following each iteration [167]. Therefore, it can be used in computationally-intensive applications, because it can explore the solution space in parallel, which speeds up the optimization. Table 8 includes two used cases of PSO from the reviewed articles. These cases demonstrate the effectiveness of the PSO model in coordinating conflicting objectives and thus providing decision support to operators for complex tasks. PSO's ability to explore a wide range of solutions effectively avoids oversimplified or unstable solutions that might not be ideal for modeling disruptive events in renewable energy supply, thereby reducing uncertainty. Although PSO is suitable for complex, computationally-expensive problems, it carries the risk of not being able to escape local optima [168]. This can be problematic when global optima are required, especially when modeling critical disruptive events. For example, a local optimum could lead to a sub-optimal system design that reduces only costs but does not provide adequate backup during a critical grid failure. Furthermore, due to the possibility of converging to a local optimum, PSO is less reliable for modeling worst-case disruptive events.

Modeling to generate alternatives

Some of the problems related to disruptive events in renewable energy supply are qualitative rather than quantitative in nature (e.g., user acceptance of a policy decision). Therefore, it is sometimes difficult for the modelers to translate these into a mathematical formula. Modeling to generate alternatives (MGA) has been developed as a solution to this [169]. In this review, MGA has been used in studies in the socio-political [93,94,122] and economic [123] categories of disruptive events. MGA provides multiple feasible near-optimal solutions that differ significantly from each other and may be evaluated significantly better than the optimal solution [170]. Fig. 6 shows how the optimal solution and the results of the MGA are illustrated in the near-optimal region for a problem with two decision variables. In the MGA formulation, an additional constraint is introduced in order to identify the region of the near optimal solutions as shown in the figure.

When it comes to energy system modeling, due to the uncertain nature of the real world disruptive events, a single optimal solution may not be able to satisfy all the requirements set by decision makers [171]. However, if there are alternative near-optimal solutions that fall within the appropriate bounds of these requirements, there is a greater chance

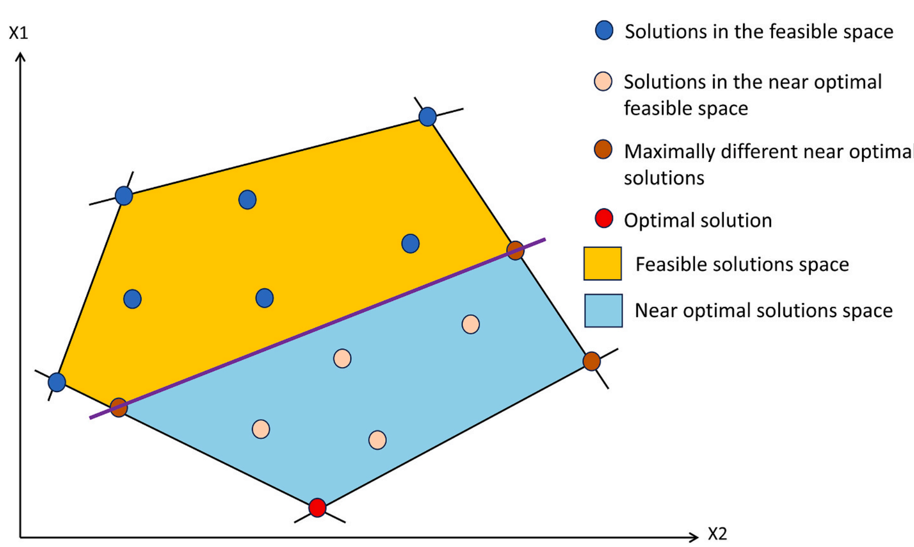

Fig. 6. Illustration of near-optimal solutions of the MGA problem with two decision variables. An additional constraint is introduced for the identification of the near-optimal solution space within the feasible solution space. Maximally different near-optimal solutions are identified compared to the optimal solution.

that one or more of them will satisfy the decision makers. These alternative solutions are similar to the different scenarios used in stochastic optimization. However, in MGA, these solutions are identified by the optimization model during the optimization rather than the modeler defining each scenario prior to optimization. These alternative solutions can also be used as a tool for reducing risk. For example, MGA can explore flexible solutions that can adapt to changing circumstances, such as the integration of different types of renewable energy sources or varying levels of storage and demand response in the event of disruptive events. Furthermore, MGA offers a variety of system configurations that can all achieve the same objective (e.g., net-zero emissions), but with different combinations of technologies or investments. This flexibility allows policymakers to test multiple approaches and reduce their reliance on one policy assumption. However, the computation time may increase when a larger number of alternative solutions are generated by MGA [172]. This is especially true for optimizations that involve detailed weather patterns, regional renewable energy networks, and market dynamics. To address this issue, metaheuristic methods, such as particle swarm optimization, can be integrated with MGA. This allows for the efficient exploration of a broad solution space while keeping computational demands manageable.

Robust optimization

Robust optimization is another relevant method for the modeling of disruptive events. Robust optimization also generates multiple solutions to the uncertain parameters and, at the same time, ensures that the optimal solution, which is based on a robustness criterion defined by the modeler, performs well in all scenarios [173]. Thus, robust optimization is ideal when planning for a worst-case scenario with respect to a disruptive event. Although the worst-case scenario may not be the most cost-effective solution, it is important to have a worst-case solution in place in case of uncertain critical disruptive events. When modeling high-probability disruptive events, this approach is very helpful because it greatly reduces the uncertainty of not having a robust energy system in the face of such events. Furthermore, robust optimization is beneficial for modeling socio-political and economic disruptive events because the worst-case result of such crucial events can be observed beforehand in the event of a critical error. Compared to stochastic optimization, robust optimization does not require probability values, and at the same time the computational complexity is lower [174]. When robust optimization is being used, modelers should pay special attention to ensure that the occurrence of the disruptive events is not overestimated. For example, if the energy system is designed to withstand the worst 1 % of hydroelectric power availability due to a drought, but in reality, if the probability of getting less than 10 % of hydroelectric power is very low, the model will oversize storage and backup capacity, increasing costs significantly.

Using modeling tools to enhance resilience and sustainability of renewable energy systems

In Sections "using simulation tools in disruptive events modeling" and "using optimization methods in disruptive events modeling", the use of various features to reduce uncertainty in the outcome of disruptive events related to renewable energy supply by simulation tools and optimization modeling methods has been analyzed. The impact of each feature's strengths and weaknesses on the uncertainty surrounding the modeling outcomes has also been examined. These features used are summarized in Fig. 7. Some of the models and methods have more than one uncertainty reduction feature (e.g., LEAP or stochastic optimization). The figure also shows that some features are applied by both simulation models and optimization methods (e.g., scenario modeling). Combining the strengths of individual features could lead to enhanced, resilient modeling outcomes. The effectiveness of the combined features in modeling disruptive events related to renewable supply was determined by examining which features have been used in combination in

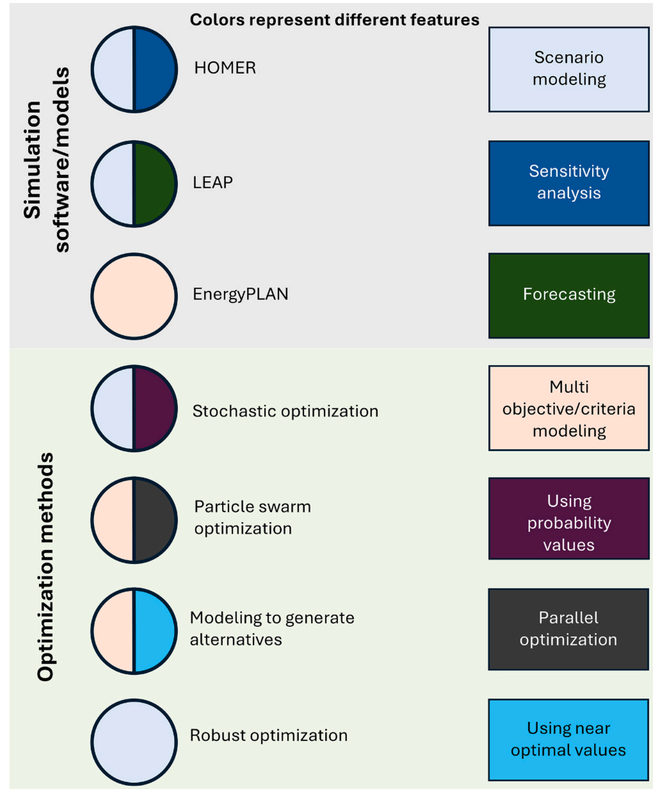

Fig. 7. Comparison of simulation software/models and optimization methods used in the reviewed articles. These software, models and methods are linked to various features which are used to reflect the uncertainty of the model outcome. Colors are used to represent different features associated with each software/model/method.

the reviewed articles.

Of the 59 reviewed articles that used optimization in this review, only three used combined optimizing models. The used combination of optimization methods are hybrid stochastic – robust optimization [37,38] and combined Monte Carlo – MGA [94]. All hybrid stochastic – robust optimization-based studies are related to the natural category of disruptive events. According to Piltan et al. [46], stochastic – robust hybrid optimizations can identify the optimal solutions in less computation time compared to non-hybrid optimization methods. Perera et al. [38], used stochastic optimization to consider high-probability, low-impact scenarios to reflect typical climate variations in Sweden. At the same time, robust optimization was used to ensure system reliability during low-probability, high-impact extreme weather events. The authors applied this method to 30 Swedish cities and found that the hybrid algorithm prevented significant performance gaps and power supply drops that could arise from either neglecting extreme events or failing to account for common variations in demand and supply. A balanced trade-off between economy and security is achieved when both methods are used, and the energy system is made cost-efficient during normal operations and resilient during extreme conditions. This shows that stochastic optimization is a reliable and affordable approach to planning, especially when dealing with common variations. However, it might not be prepared for rare and extreme situations if it is used as the only planning method. Although robust optimization ensures system resilience in worst-case scenarios, it could be overly conservative and expensive if used alone.

Monte Carlo optimization, like stochastic optimization, involves incorporating randomness into the optimization process. However, unlike in stochastic optimization, uncertainty is captured through random sampling from probability distributions assigned to input variables [175]. Li & Trutnevyte [94] show that by combining Monte Carlo modeling with MGA, energy economy models can be better linked to power system models, which provides an advanced approach to uncertainty analysis. The authors explored technologically diverse pathways and their associated total costs to assess the future transition pathways for the electricity sector of the United Kingdom. The combined model allowed for a comprehensive exploration of uncertainty across multiple parameters, including policy, technology, and cost. By applying MGA in combination with Monte Carlo analysis, the authors investigated not only the cost-optimal but also the near-optimal pathways. The near-optimal pathways help to identify a variety of technologically different pathways that have similar total costs, providing multiple solutions rather than a single deterministic outcome. When combined with Monte Carlo, this helps decision-makers understand which configurations are robust and which are fragile under uncertainty. Monte Carlo focuses on quantitative uncertainty, meaning it is designed to handle uncertainty that can be described with numerical values and statistical distributions [175]. In contrast, qualitative constraints such as stakeholder preferences and political acceptability can be incorporated into MGA's processes. Consequently, combined Monte Carlo–MGA models have the capacity to generate solutions that are not merely mathematically optimal but also socially and politically viable.

Jing et al. [41], who considered extreme weather events in urban energy system planning, used an iterative combination of optimization and simulation approaches due to the computational cost of mixed optimization approaches. The objective of the study was twofold: first, to determine the optimal configuration and operation strategy for urban energy systems using stochastic optimization; and second, to validate whether the optimized strategy can meet critical energy demands during extreme weather events using simulations. This study shows that a mixed optimization and simulation approach helps planners make balanced decisions regarding the resilience, adaptability, and efficiency of energy systems. Disruptions in the supply of renewable energy can sometimes lead to non-linear cascading effects, such as grid instability or sudden changes in market prices. Hybrid simulation–optimization methods allow to explore these interactions in simulations, while optimization finds the best response strategy (e.g., dispatching storage, managing demand). In addition, hybrid simulation–optimization methods can be used to combine short and long-term decision making. For example, when modeling an event such as a blackout or dark renewable lull (dunkelflaute), simulations can model short-term operational behavior such as how real-time grid balancing works during the event. Then optimization can focus on long-term investments and planning such as for storage installations or transmission line expansion. Similarly, for the integration of renewable energy sources into the power grid, a combined simulation and optimization technique can be used for scheduling and dispatching of energy. Through the simulation of grid disturbances such as power outages or demand fluctuations, these models can optimize the integration process to maintain grid stability. Therefore, hybrid simulation–optimization methods enable strategic planning that remains effective in real operational conditions.

Findings on Section "Discussion" prove the hypothesis presented in Section "Introduction", that is the integration of appropriate modeling techniques significantly enhances the resilience and sustainability of renewable energy systems when subjected to disruptive events.

Summary and conclusions

The number of disruptive events that could threaten the growing supply of renewable energy around the world is increasing. Adequate modeling of these events is critical for robust renewable energy supply planning against such events. In order to address this prompt requirement, the present study systematically assessed how the impact of various disruptive events on the supply of renewable energy can be quantified and mitigated through the use of modeling techniques. These disruptive events were categorized based on the cause of the respective events, namely natural, human-caused intentional, socio-political, and economic. The impact of each category of disruptive events on different demand sectors was also identified and the system boundaries such as technology focus, location, and spatial resolution modeled in the reviewed studies were further analyzed.

This review addressed the importance of economic and social factors in the modeling of renewable energy systems and how these factors can be effectively integrated to reduce uncertainty. The reviewed studies used many criteria to evaluate the impact of the disruptive events. Among these, cost was primarily used to indicate the impact of the disruptive events. Disruptive events such as natural disasters, geopolitical tensions, or technology failures can have a significant impact on the cost of energy production and distribution. Therefore, cost-based modeling is useful in the assessment of the financial risk associated with renewable energy projects. Some studies used modeling criteria other than cost. This enables multiple factors to be considered simultaneously, including economic, environmental, social, and technical aspects associated with disruptive events. Criteria such as stakeholder satisfaction ensure broader sustainability goals and the long-term success of projects such as large-scale onshore wind farms.

Furthermore, this study investigated how stakeholders can benefit from these modeling methods to enhance resilience and mitigate risk in renewable energy supply, leading to more accurate model outcomes. The reviewed modeling approaches offer valuable decision-support insights for various stakeholders such as investors and disaster management agencies by enabling risk-informed planning, robust infrastructure investment, and adaptive system design. Sometimes, policymakers in renewable energy planning have strong concerns that are not addressed by most models, such as geopolitical dynamics, social equity, and public opinion. Therefore, due to these factors that are difficult to quantify in techno-economic models, feasible suboptimal solutions that can be obtained from modeling methods such as MGA may be preferable.

This review shows that simulation and optimization modeling are both critical for assessing the impact of disruptive events on renewable energy systems, though they have different strengths and limitations. Simulation tools, particularly those using scenario-based and forecasting techniques, are effective for exploring uncertainty and system behavior under various disruption scenarios. However, in some of these tools, their usefulness is constrained by narrow time horizons or modeling scope. Conversely, optimization methods provide targeted strategies for allocating costs and resources with strategies including probabilistic modeling, generating alternative solutions, and worst-case planning. Each of these approaches offers a different degree of resilience and adaptability. The evidence indicates that a single modeling method is not sufficient on its own. Rather, integrating multiple modeling features can enhance the realism and robustness of planning outcomes.

Therefore, this study examined how the integrated modeling methods could enhance the resilience and sustainability of renewable systems in the face of disruptive events. It is identified that combined optimization methods could combine the advantages of individual methods and thereby increase the robustness and flexibility of long-term planning under uncertainty. Similar to combined optimization, hybrid simulation and optimization techniques can provide a more comprehensive risk assessment by evaluating how optimized plans perform under simulated disruptions. Despite their advantages, there is still little focus on using combined approaches in modeling renewable energy supply based disruptive events..

In light of these findings, the following recommendations and limitations of this study could be helpful for future researchers regarding the modeling methods that can be used to reduce uncertainty in disruptive events in renewable energy supply.

Limitation

This study primarily focused on simulation and optimization approaches, which accounted for over 96 % of the reviewed articles. As a result, less attention was given to other modeling techniques such as econometric and statistical models. While these were not the focus of this review, their potential in addressing uncertainty in disruptive event modeling for renewable energy systems should be explored in future research.

Recommendations.

I. Identifying suitable modeling criteria is very important. Rather than focusing on one criterion, using multiple criteria, such as stakeholder satisfaction alongside cost, can help reduce uncertainty in model outcomes by providing a more balanced approach from an economic and social perspective.
II. Due to their ability to explore the system-wide impacts of different types of disruptive events over multiple narratives, scenario-based simulation models should be preferred when quantitative precision is limited. Also, optimization methods such as modeling to generate alternatives (MGA) should be used to support decision-making under uncertainty when probability data is scarce, or qualitative policy concerns are more important.
III. Development and application of combined optimization and hybrid simulation–optimization approaches should be promoted to improve the robustness and adaptability of renewable energy system planning under disruptive events.

Thus, combined optimization methods and hybrid simulation–optimization methods could open new avenues for the future modeling of disruptive events in renewable energy supply.

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CRediT authorship contribution statement

Lovindu Wijesinghe: Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **Jann Michael Weinand:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization. **Maximilian Hoffmann:** Writing – review & editing, Methodology, Formal analysis. **Detlef Stolten:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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