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Building Technologies & Urban Systems Division
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Vulnerability and resilience of urban energy ecosystems to extreme climate events: A systematic review and perspectives

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Abstract

We reviewed the present studies on the vulnerability and resilience of the energy ecosystem (most parts of the energy ecosystem), considering extreme climate events. This study revealed that the increased interactions formed during the transformation of the energy landscape into an ecosystem could notably increase the vulnerability of the energy infrastructure. Such complex ecosystem cannot be assessed using the present state of the art models used by the energy system modelers. Therefore, this study introduces a novel analogy known as the COVID analogy to understand the propagation of disruption within and beyond the energy ecosystem and organized the present state of the art based on the COVID analogy. The analogy helps to categorize the vulnerability of the energy infrastructure into three stages. The study revealed that although there are many publications covering the vulnerability and resilience of the energy infrastructure, considering extreme climate events, the majority are focused on the direct impact of extreme climate on the energy ecosystem. In addition, most of the studies do not consider the impact of future climate variations during this assessment. The propagation of disruptions was assessed mainly for wildfires and hurricanes. Further, there is a clear research gap in considering vulnerability assessment for interconnected energy infrastructure. The transformation of energy systems into a complex ecosystem notably increases the complexity, making it difficult to assess vulnerability and resilience. A shift from a centralized to decentralized modeling architecture could be beneficial when considering the complexities brought by that transformation. Hybrid models consisting of both physical and data-driven machine learning techniques could also be beneficial in this context.

Highlights

- An exponential increase in publications covering the vulnerability and resilience of the energy infrastructure, especially for extreme climate events
- A novel analogy known as the *COVID analogy is introduced* to classify the state of the art while understanding the propagation of disruption within and beyond the energy ecosystem
- Transformation of the energy landscape into an ecosystem could notably increase the vulnerability during extreme events
- There is a clear research gap in considering vulnerability assessment for interconnected energy infrastructure

Keywords: Urban system, energy ecosystem, climate change, extreme climate event, resilience, modeling

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1. Introduction

Cities are growing at a rapid speed, and are centers of energy consumption and carbon dioxide (CO₂) emissions [1]. More and more people tend to move into urban areas, increasing urban densities (vertical and horizontal growth). It is expected that global urban coverage will increase by 40% in 2050, adding several billions of people [2]. A significant change in activities linked to commercial and industrial processes takes place within the cities, which are hubs to social and economic growth. As a result of such activities, CO₂ impacts will notably increase; it is predicted that cities will contribute to 70% of the global CO₂ emissions in 2050 [3]. Therefore, improving the sustainability of cities plays a major role in reducing CO₂ emissions.

The energy sector is the main contributor to CO₂ emissions in urban areas, therefore, that sector requires a major transition [1]. Large-scale integration of renewable energy technologies occurs at the building level and direct grid integration of renewables improves sustainability [4,5]. Solar and wind energy plays a significant role in substituting fossil fuel-based energy technologies in the electricity sector. These technologies are non-dispatchable, as their energy generation is strongly influenced by the weather conditions, in contrast to fossil fuel-based systems where controllers can control the power generation much more effectively [6]. As a result, auxiliary support through energy storage and demand response strategies are needed to improve the penetration level of these technologies [6]. In addition to transforming the electricity sector, renewable energy technologies must play a major role in transforming the building and transportation sectors [7]. Transforming the fossil fuel-based heating sector to an electricity-based sector while accommodating increasing cooling demand, especially due to climate change and urban heat islands, makes the challenge even greater [8,9]. Similarly, an increasing number of electric vehicles depend on the grid. It is expected that major part of the transportation sector will consist of electric vehicles in the future [10].

Inclusion of the building and transportation sectors in overall energy infrastructure planning, design, and operation has certain advantages [9,11]. These sectors can substantially enhance the flexibility of the energy infrastructure, which can help to increase the penetration level of non-dispatchable renewable energy technologies. Furthermore, coupling building and transportation sectors with the energy infrastructure significantly enhances the electricity market, creating more opportunities (job creation and technology development) in the energy sector and speeding the energy transition [12]. However, catering to the energy demand for building and transportation sectors while going through the energy transition is difficult. Coupling energy infrastructure with the building and transportation sectors will create a complex ecosystem, especially when using the flexibility of building and transportation sectors to implement demand response strategies. Disruption in one sector could quickly propagate and lead to a blackout in the entire ecosystem [13,14]. Therefore, the reliability and resilience of the urban energy ecosystem need to be enhanced while going through the transition.

Extreme climate events driven by climate change have a notable impact on the transformation of the energy ecosystem [15]. The frequency and intensity of extreme climate events has notably increased during the last decade and will continue to increase further [1]. These events are having a multidimensional impact on the energy ecosystem [13]. For example, the recent extreme cold event in Texas directly affected the building stock, increasing heating energy demand significantly [16]. At the same time, the extremely low temperatures interrupted the operation of gas turbines and wind turbines. Mismatch in demand and generation at the different parts of the state collapsed the transmission and distribution, leading to a rolling blackout, causing a loss of 130 billion dollars [16] and resulting in more than 200 deaths [17]. The compound impact of extreme climate events on the entire energy ecosystem makes it quite challenging to improve resilience [14,15]. Therefore, it is important to take special measures to improve resilience while improving interconnectivity.

Therefore, climate change mitigation and adaptation make it essential to improve sustainability, interconnectivity, and resilience, which is a major challenge human civilization has to face.

There has been an ongoing interest in the present state of the art to improve the sustainability, resilience, and interconnectivity in the urban energy ecosystem. A clear trend can be seen since 2015 (Fig. 1). Therefore, it is crucial to review the present state of the art and summarize the work performed and identify the research gaps that can be addressed in the future. Several review articles have also been presented that cover broad topics related to the resilience of cities. A holistic overview of these reviews is presented in Section 6. They are either focused on a top-down approach that addresses the resilience at the urban context or focused on specific areas of the energy ecosystem (further discussed in detail under Section 6). Such holistic assessments do not provide a clear understanding of the cascading impact on an interconnected energy infrastructure. On the other hand, reviews focused on specific areas of the energy ecosystem do not provide an overall impact. Balancing both depth and breadth while organizing the study is a challenging task. Within this context, the authors aim to:

- Introduce a COVID analogy to understand the propagation of disruption in energy ecosystems to help grasp both a holistic and detailed (bottom-up) overview regarding the propagation of disruption due to extreme events.
- Review existing workflows developed to quantify the vulnerability for disruption propagation created by extreme climate events within the energy ecosystem being based on the COVID analogy.
- Review possible descriptions for the resilience, in order to arrive at a more holistic interpretation of resilience considering the energy ecosystem and the propagation of disruption in multiple sectors.
- Highlight promising modeling frameworks in the present state of the art and research gaps to visualize (generate a more holistic viewpoint) resilience and sustainability of the urban energy ecosystem.

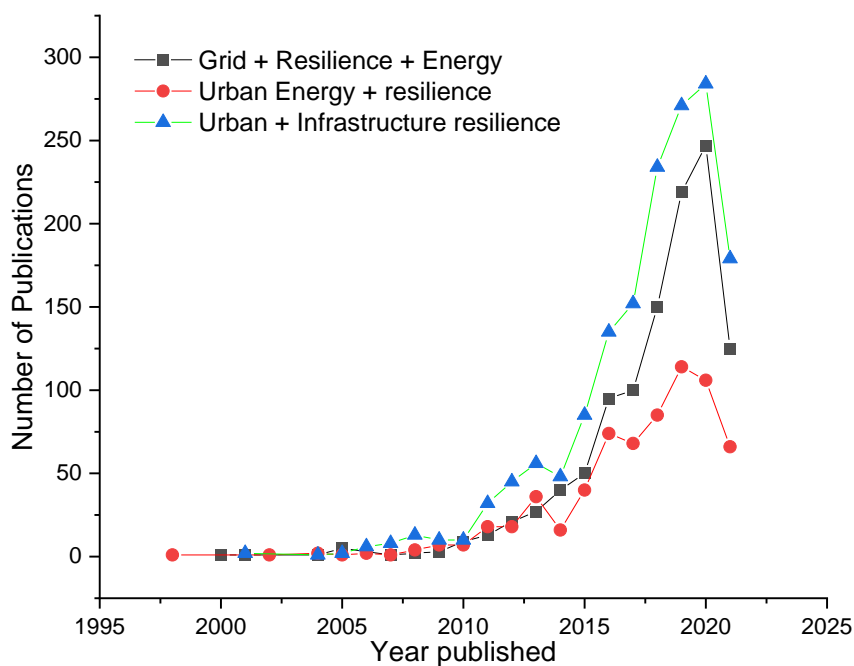


Fig. 1: Recent trend in publications considering resilience, sustainability, and interconnectivity in the urban energy infrastructure indexed in the Scopus database.

The review is performed considering the extreme events and urban energy resilience in a more holistic manner. The intersection of extreme events and resilient communities (urban scale) leads to a broad research outlook (Fig. 2) which cannot be reviewed in a single paper. In general, urban resilience is a result of resilient networks and flows, resilient urban infrastructure and form, resilient governance and network, and resilient socioeconomics and dynamics (Fig. 2). Within this paper we limit our scope to networked materials and energy flows (energy flow is given a major priority) and urban infrastructure and form. The broad approach we used within the urban context enables us to move beyond the boundaries of energy systems and consider the urban energy ecosystem. Within this context, we used several combinations of the following keywords and performed a literature review in Scopus. The keywords include climate change, extreme events, urban resilience, network cascade failures, infrastructure, energy systems, vulnerability, wildfires, hurricanes, urban resilience, energy resilience, building energy, extreme heat events, and interconnectivity.

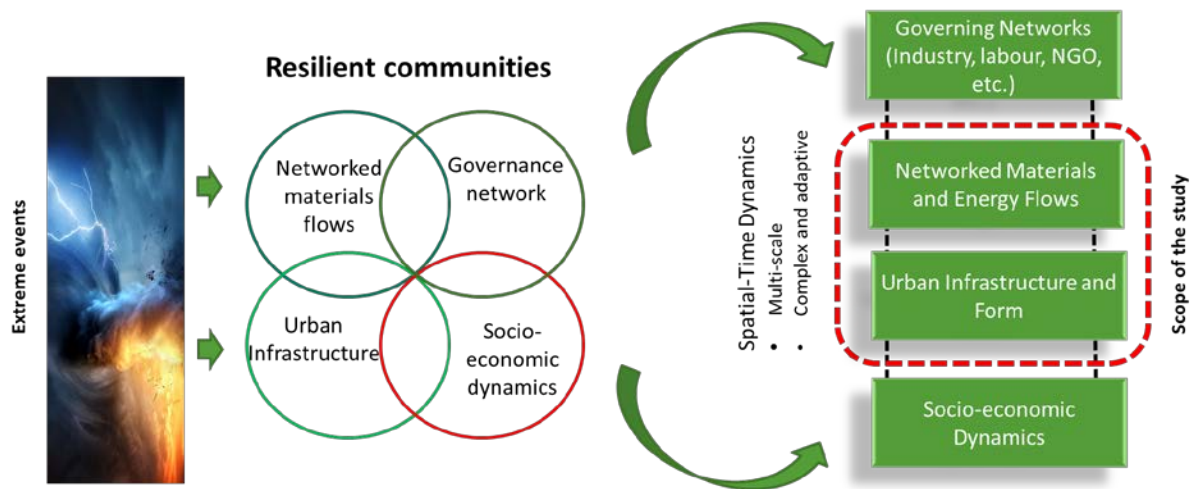


Fig. 2: scope of the study within the broad umbrella of urban resilience and extreme events focusing on urban energy ecosystem

The paper is organized as follows: Section 2 presents a compressive overview of the changes taking place in the energy sector. Section 3 presents a novel analogy to understand the vulnerability of energy infrastructure for extreme events. Section 4 presents the direct impact of extreme events on the energy infrastructure. Section 5 presents the propagation of such extreme events within and beyond the energy infrastructure. Section 6 presents the limitations within the present state of the art for understanding the impacts brought by these extreme events. Section 7 presents areas of interest for future research activities to improve the resilience of energy ecosystems. Finally, conclusions are presented in Section 8.

2. Transition in the urban energy sector

The energy sector is going through a major transition, where renewable energy technologies replace traditional power generation technologies based on fossil fuels. Power generation using fossil fuels based on the Rankine cycle, the Bryton Cycle, or internal combustion generators are mature technologies that have been amply discussed in the literature [18]. Similarly, the literature has amply discussed the concurrent generation of heat and electricity using fossil fuel resources with a vapor power cycle and a gas power cycle. However, this should not undermine recent efforts to develop thermodynamic cycles such as the Organic Rankine Cycle, the Kalina cycle, and others. These are live examples of improvements in energy conversion methods [19,20].

Recent trends to reduce the carbon impact has led to the introduction of geothermal, biomass, and bioenergy to replace fossil fuel resources. However, a notable change in energy system architecture cannot be observed in these instances, although improvements in energy conversion technologies are reported (except for hybrid power cycles). Similar to renewable-based thermal energy, grid integrated solar photovoltaic (PV) systems and wind farms have been amply discussed, especially due to the pressure brought by climate change and the uncertainty in fossil fuel availability [21]. Integration of PV and wind turbines has increased the complexity of the energy infrastructure due to their intermittent nature [22]. Hybrid energy systems consisting of battery banks and dispatchable energy technologies are often used to withstand these fluctuations locally [22,23]. This leads to the emergence of distributed energy systems, and popularized by concepts such as energy hubs [24]. Requirements to decarbonize the building, industry, and transportation sectors add burden and further increase complexity. Several system configurations have been proposed to provide multi-energy services [12], depending on the sectors coupled with the energy infrastructure. Energy markets facilitate the interaction between multiple sectors while maintaining a reliable supply. Participation in many sectors makes a complex landscape that leads to an ecosystem, as shown in Fig. 3.

These connections between different participants through multiplex networks creates a complex ecosystem which can be extremely vulnerable to extreme events. Therefore, maintaining a robust and resilient service in such an ecosystem is a challenging task. As a result, we may need to move beyond typical energy system models to capture these interactions. The ecosystem concept becomes quite ideal in such a context which has already been formulated in the context of industrial ecosystem, business ecosystem, digital ecosystem, and innovation ecosystem [25]. The interactions between different actors, taking into account energy and material flows within the urban context, makes industrial ecosystems a much closer terminology when we consider the energy ecosystem, although usual industrial ecosystem models do not consider detailed bottom-up models used in the energy system domain. Within this context, energy ecosystems rely on co-existence of different actors within the urban context including building, industrial, commercial and transportation sectors. Each sector may try to utilize the materials, energy (heat, electricity, gas) in a manner that the waste, dependence beyond the boundaries, and environmental impact will be minimal.

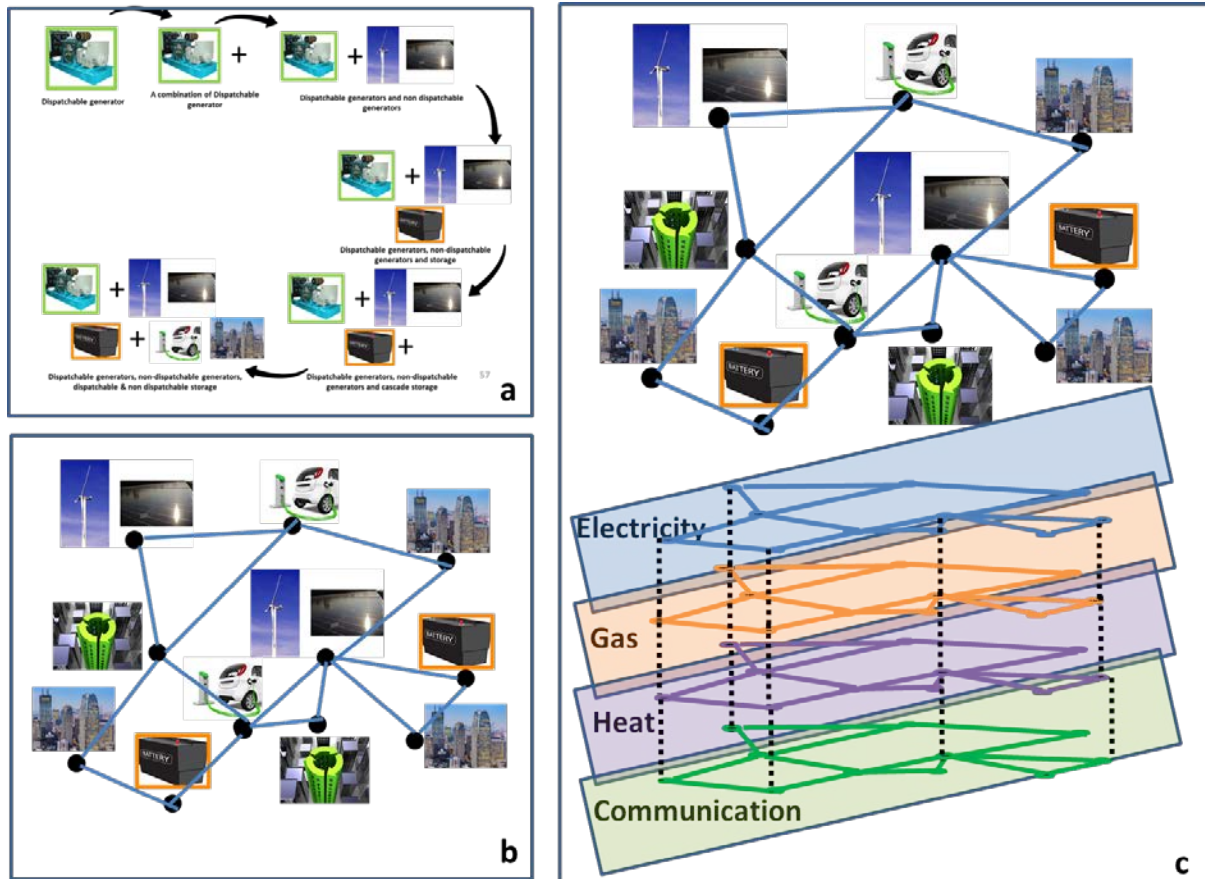


Fig. 3: Formulation of a complex energy ecosystem: (a) the transformation in the energy infrastructure starting from dispatchable energy sources, dispatchable energy sources with non-dispatchable energy technologies, dispatchable energy sources with non-dispatchable energy technologies with energy storage, and finally becoming an ecosystem being connected to buildings (commercial, residential, and industrial) and electric vehicles with demand response strategies. (b) the interconnections within an energy ecosystem. (c) further elaboration of the interconnections between the energy ecosystem through multiplex networks including energy and cyber interactions. The interconnection between different layers highlights the interdependency between different layers. For example, the functioning of electricity depends on the support by the communication layer in order to maintain a stable electricity grid. On the other hand, communication layer depends on the electricity grid to obtain energy to function.

3. Moving beyond the domino effect: A COVID analogy to understand the vulnerability of energy ecosystems

The domino effect/theory has been widely used to demonstrate the catastrophic chain of events triggered by a simple event. The domino effect brought by climate change has been amply discussed in the present state of the art. Understanding the propagation of a chain of events becomes more challenging when it comes to the energy domain, due to complex interactions between different energy carriers, as well as the interactions with the other service sectors at the urban scale. Therefore, defining the resilience, as well as understanding the vulnerabilities, become challenging. Discussions in Section 3.1 and Section 3.2 are devoted to a broader understanding of the concept of resilience and propagation of disruption within the energy ecosystem.

3.1 The concept of resilience

The importance of resilience has been widely discussed recently, mainly due to the disruption in the energy sector, which has been driven by extreme climate events. Nonetheless, the concept of resilience has a much broader scope beyond energy. According to Hamilton [26], resilience is defined as the “ability to recover and continue to provide their main functions of living, commerce, industry, government and social gathering in the face of calamities and other hazards.” According to Coaffee [27], resilience has been defined as the “capacity to withstand and rebound from disruptive challenges.” Desouza and Flanery [28] introduce resilience as the “ability to absorb, adapt and respond to changes” while Asprone and Latora [29] define resilience as “the capacity to adapt or respond to unusual often radically destructive events.” These definitions provide a much more holistic understanding of resilience.

A reasonable change in the definition can be seen when moving from the general expression of resilience into the resilience of energy infrastructure. More importantly, the concept of resilience has been associated quite closely with reliability, flexibility, stability, and robustness [14]. According to Perera et al. [30] *flexibility* has been defined as the capability of a system to withstand the disturbances brought by the external forces with a minimum impact, while *reliability* [31] is defined as the capability to cater the services with a minimum disruption due to the changes in both internal/external conditions. Nik et al. introduced *resilience* as the capability of energy infrastructure to be flexible and reliable during high-probable low-impact events [14]. Besides being flexible and reliable, being able to restore a system to stable operation following a disruption is also an important characteristic of a resilient system [32]. And last, but not least, resilience of energy infrastructure demonstrates the capability to be predictable when responding to extreme events (partly known as *robustness*).

Given the breadth of these definitions, it is clear that the resilience of energy infrastructure is a broad concept closely linked to a group of other concepts. More importantly, the definition is highly specific to the application considered, as well as to the nature of extreme events. Extreme events could disrupt multiple sectors within the energy ecosystem simultaneously and ultimately collapse the operation of the entire ecosystem. As a result, the entire ecosystem could collapse. Such disruptions can easily penetrate the other interconnected sectors such as buildings, transportation, and industry, leading to a complete blackout, resulting in substantial economic loss. Therefore, vulnerability of the energy ecosystem is closely discussed, along with resilience.

3.2 The analogy of the domino effect to COVID

Although vulnerability and the resilience of the energy infrastructure have been widely discussed, the complexity of energy ecosystems and the diversity of extreme events have made it difficult to arrive at a more holistic model regarding the vulnerability of energy ecosystems for extreme events. The COVID analogy is presented to provide a more holistic understanding of the vulnerability of the energy ecosystem for extreme events (Fig. 4). The overall process is divided into three stages. In Stage 1, the COVID virus infects the respiratory tract, which is the entry point. Similarly, an extreme event could disrupt a particular component or a part of the energy ecosystem (Fig. 5). For example, extreme drought can disturb hydropower generation, and a wildfire season can disturb the distribution/transmission system.

Stage 2 describes the propagation. In the case of the Covid virus, it propagates in the respiratory system and damages the lungs. Similarly, the disruption initiated at a specific sector can easily propagate to the entire ecosystem and disrupt its operation. As a result, the entire electricity sector

can collapse in a particular area. The disruption during Stage 2 is more critical than Stage 1 and may require more time to recover.

Stage 3, where the virus further penetrates and damages the heart, kidneys, and digestive system leading to multiple organ damage beyond the respiratory system, is more destructive. Similarly, the disruption in the energy ecosystem can penetrate beyond the energy infrastructure and start to disrupt other interconnected infrastructure such as transportation, communication, and water supply. Such propagation beyond the boundary of the energy ecosystem is more disruptive and leads to a huge economic loss. Further, it takes a much longer time to recover during such a multi-sector disruption. Therefore, improving resilience to avoid such penetration is vital when designing urban systems. The present state-of-the-art studies on improving the resilience of energy ecosystems for Stage 1 to 3 type of events are reviewed in sections 4 and 5, respectively.

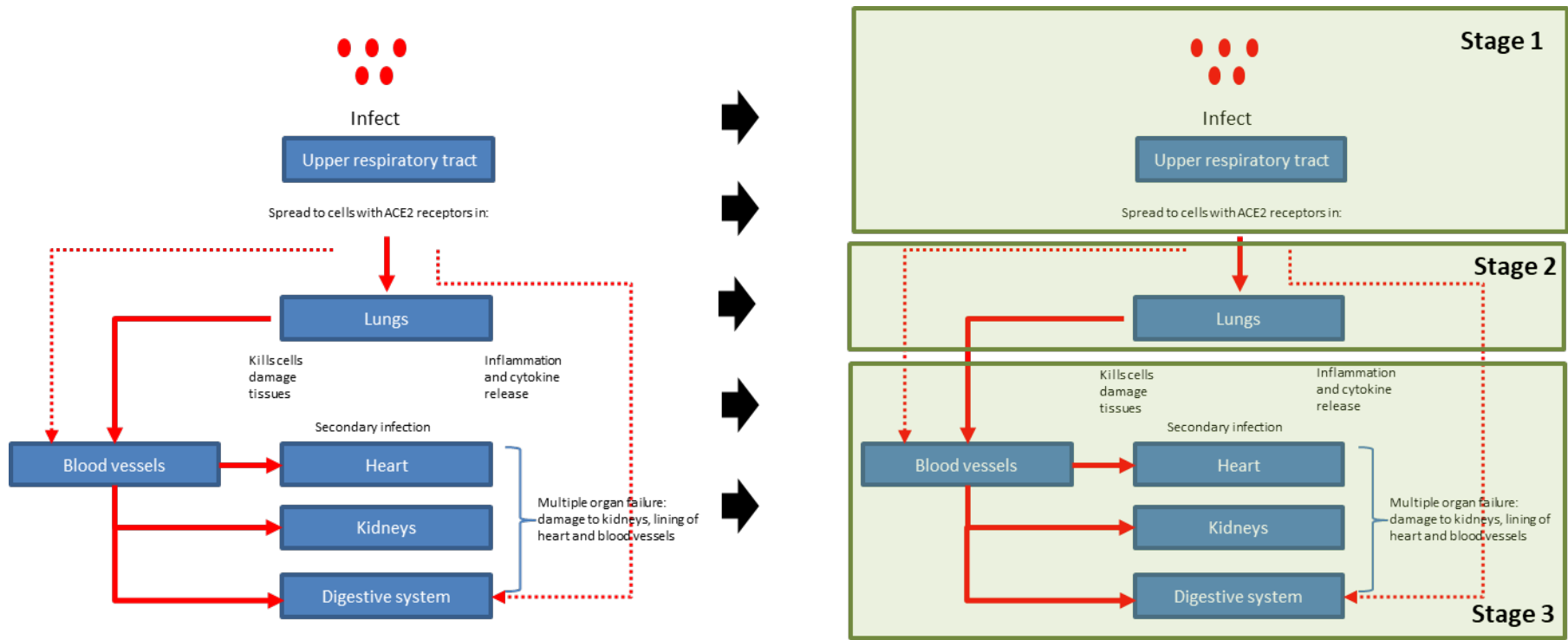


Fig. 4: Analogy of Covid to the human system to extreme events on the urban energy ecosystem.

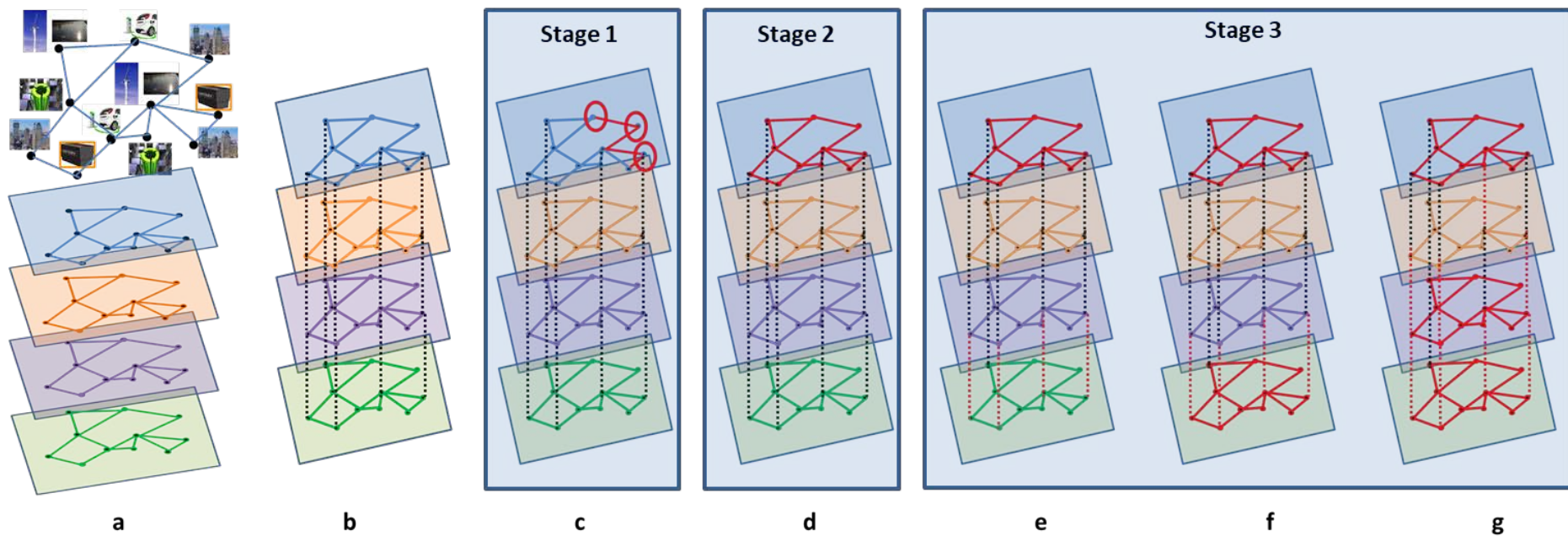


Fig. 5: Understanding the three stages of the disruptions propagation in an energy ecosystem (inline with the COVID analogy). (a) The complex interactions maintained within the energy ecosystem using a multiplex network (inline with Fig. 3) (blue: energy, orange: gas, purple: heat, green: communication). (b) The layers of the multiplex network maintain interactions with each other when operating. (c) Disruptions taken place at a few locations within the energy layer (Stage 1). (d) Propagation of the disruptions within the energy layer, leading towards a blackout (Stage 2). (e) The blackout penetrating the disruptions into the communication layer due to the dependencies of communication networks on the electricity sector. (f) Subsequently, the disruption propagates in the communication layer. (g) Similarly, it propagates into the other layers, collapsing the operation of the entire energy ecosystem.

4. Direct impact of extreme events on the energy ecosystem (Stage 1)

Extreme events can have a direct impact on generation, demand, and distribution/transmission. The direct impact on the energy ecosystem may change depending on the characteristics of the extreme event. This section covers three such extreme events—wildfires, hurricanes, and extreme cold/heat events—and reviews the present state-of-the-art studies that quantify their direct impacts on the energy ecosystem (Fig. 6).

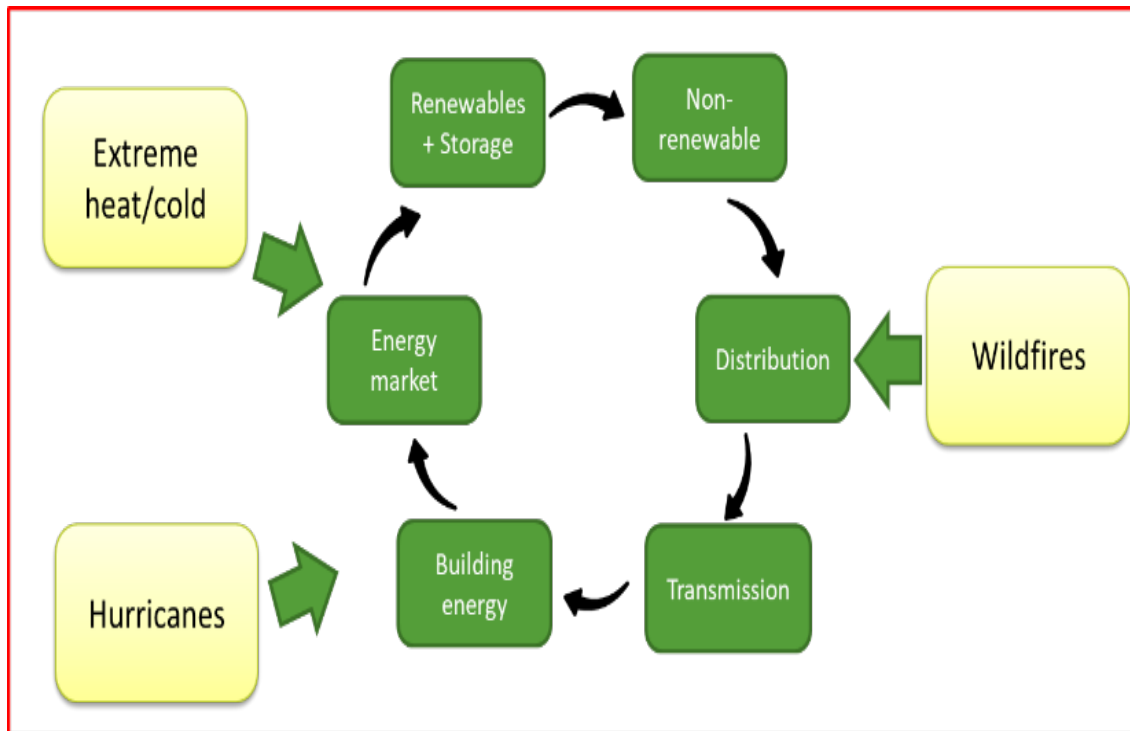


Fig. 6: Extreme events considered in the present study.

4.1 Impact of wildfires on energy and built infrastructure

Understanding the impact of wildfires on energy (Table 1) and built infrastructure is a challenging task [33]. There exists a complex coupling between the wildfires, energy, and building infrastructure [34]. First, the emission from construction and energy sectors directly help to speed climate change, leading to increased frequency of extreme hot weather conditions that lead to wildfires. In addition, the electricity grid has been a main root cause in triggering wildfires [35]. Although energy infrastructure is responsible for about 3% of all wildfire ignitions, power lines have ignited four of the twenty largest fires in California and 90% of the fatal bushfires in Australia [35]. Therefore, public safety power shutdowns (PSPS) are often performed during wildfire periods, curtailing the power supply in many areas vulnerable to wildfires [36]. Wildfires usually take place during extremely hot climate conditions when cooling energy demand is notably high. A drop in power supply can easily lead to an increase in the health impacts of heatwaves and may increase the mortality rate [34,37]. During wildfire season, such PSPS events lead to poor air quality in buildings and make it difficult to maintain communication between communities, as the telecommunication towers cannot provide the service without electricity. Therefore, wildfires are having a direct impact on both urban and energy ecosystems.

Quantifying the impact threat imposed by wildfire on the energy infrastructure presents many challenges to the energy community [38,39]. Integrated assessment models that couple climate and ecological models help to capture the wildfire threats in the long run, taking into account future

climate variations. Sathaye et al. [33] present a perspective of linking grid models to climate and ecological models to plan the expansion of the energy grid in a wildfire resilient manner. Nonetheless, bottom-up models linking energy planning with climate and ecological models were not found in the present state of art, mainly due to the complexity that arises when linking climate-wildfire and energy system models (Table 1).

The present state-of-the-art models on energy infrastructure resilience during wildfires mainly focus on modeling and assessing the threat of the electricity grid triggering wildfires and understanding the cost-optimal and reliable strategies for PSPS. In many studies, detailed thermal models are often used to understand the threat of triggering wildfires [36,40,41]. At the same time, Wischkaemper et al. [42] discuss the instrumental methods to detect the risk of wildfires. Based on the risk assessment, optimal power flow and dispatch problems are formulated to determine the optimal power shut down strategy, as explained in many papers (Table 1). Optimal power flow and dispatch problems are combined to consider the shutdowns in power lines due to the threat of wildfires, known as the optimal power shutdown problem (OPSP) [36,43–45]. OPSP has been formulated as a deterministic operation problem in most instances. Trakas and Hatziaargyriou [44] used stochastic models to consider the uncertainties in the OPSP. Renewable energy generation and energy storage are often not considered in the OPSP problem, making it relatively easy for optimization algorithms. For example, only Trakas and Hatziaargyriou [44] considered energy storage in the OPSP. Hay and Mohit [46] discuss the impact of wildfires, taking into account the future scenarios for building and transportation energy demand. Furthermore, most of the studies are limited to the operational aspect of the problem. Design improvements that could help to withstand public safety power shutdowns have not been incorporated into the discussion. Pacific Gas and Electricity (PG&E), a utility in California, USA, recently introduced microgrids to support the areas surrounded by wildfires [47,48]. These areas do not need to depend on the transmission network during wildfire periods. Incorporating such microgrids into the existing energy infrastructure would be an interesting area of research. Improving climate resilience in energy infrastructure to cope wildfires is an emerging area of research. However, the frequent occurrence of wildfires will demand much attention on this area of research. It will be essential to move beyond the operational level to discuss the design aspects to improve the resilience of energy infrastructure for wildfires.

4.2 Impact of hurricanes on energy and built infrastructure

Hurricanes are a major climate threat to the U.S. energy sector, and are responsible for 47% of weather-related events. A significant economic loss up to \$95 million with an average of \$12 million per extreme event may occur as a result [49]. These events result in adverse structural damage to the grid, which takes 117.5 hours on average to recover from following an extreme event [49]. More importantly, the frequency of extreme climate events has increased due to climate change. As a result, power disruptions increase by 2% every year [50]. Therefore, it is vital to improve the resilience of energy infrastructure in relation to hurricanes.

A number of recent studies have focused on improving the climate resilience of energy infrastructure to withstand hurricanes. Parker et al. [51] reviewed the present state-of-the-art publications, and Chen et al. [52] presented future perspectives that could shape the research to improve resilience. A comparative assessment of the present state-of-the-art publications that focused on improving climate resilience during hurricanes is presented in Table 2. A majority of the papers on hurricane resilience focused on improving the network resilience of the electricity grid during extreme climate events, which is considered a major challenge, as shown in Table 2. Studies [49,53,54] evaluated the tendency for cascade failures during extreme climate events. Besides being limited to the resilience of the network, the compound impact on both generation and distribution/transmission was

investigated in several studies. For example, the need for optimal power flow and dispatch strategy to be adapted during hurricane events was studied by [53,55].

Most of the present state-of-the-art studies are focused on operating energy infrastructure during hurricanes, limiting the focus to the operational aspects. However, it is essential to design energy infrastructure that can withstand hurricanes with a minimal impact. Bennett et al. [55] considered the energy infrastructure design, taking into account hurricanes where sequential optimization technique is used to derive transition pathways to improve the climate resilience for hurricanes in Puerto Rico. Stochastic models have been used in Dehghani [56]. Addressing the challenge of improving climate resilience at the design stage would be an interesting future direction. Considering n-1 security, incorporating uncertainties introduced by climate, human system, and other factors would be necessary in this regard, where multi-level optimization algorithms proposed by Wang and Perera [57] can be pretty valuable. Machine learning algorithms can be quite beneficial in this regard, as reported by Dehghani [56] and Mojtaba et al. [58]. Such algorithms will help address complex design and operation problems.

4.3 Impact of heat and cold waves on energy demand, generation, and transmission/distribution

As a consequence of climate change, the frequency of extreme hot and cold events has increased notably [1]. Therefore, a number of research studies are now focused on extreme hot and cold climate events. A significant increase in temperature is observed when considering the temperature variation at a finer temporal resolution, which increases the heating/cooling demand up to 70% [59]. Such a significant increase in the energy demand can easily influence thermal comfort within the building and the energy systems used to cater to the demand [60]. Accordingly, two different classes of papers were reviewed: (1) impact assessments considering energy demand and thermal comfort, and (2) impact assessments considering energy generation.

Quantifying the impacts of future climate variability and extreme climate events plays a vital role in improving climate resilience [61]. Therefore, a number of studies focused on evaluating the influence of climate change on energy demand, which can be further divided into two classes: studies based on historical data and future climate data. Publications on past climate data use past climate conditions to predict future energy demand while analyzing the trend. However, predicting the energy demand using past climate data does not fully capture the dynamics brought about by climate change [14]. Therefore, instead of depending on past climate data, most researchers use climate models to obtain the data [59,62,63] (Table 3). Regional and global climate models have been used in this context, taking a spectrum of representative concentration pathways (RCPs). Often, bottom-up models based on detailed hourly building simulations have been used to evaluate the impact of future climate variations on energy demand, such as in [59,62,63]. However, temperature-driven top-down approaches have also been used to quantify the impact of future climate variations on energy demand [50,64,65]. The majority of studies focused on assessing the impact of future climate variations on energy demand study the impact of extreme climate events on building energy demand (Table 3). Impacts on both heating and cooling have been considered in this context. In addition to assessing energy demand, Mutschler et al. [66], Tian et al. [67], and Lee & Levermore [68] assessed thermal comfort during extreme events. In addition to consider the energy demand Qin et al. [64] and Dasaraden et al. [69] considered the impact on renewable energy generation. Regional climate models used in the present state of the art provide mesoscale data. The majority of the present state-of-the-art publications assessed the impact of future climate variations on the energy demand based on regional climate models (Table 3). Urban climate or urban microclimate models provide high-resolution climate data, which are important when quantifying the impact of extreme events at the urban scale, since those models can represent the impact of the urban heat island, which can have a significant impact on energy infrastructure [70]. However, the majority of publications did not

consider the influence of urban climate when assessing the impact of future climate variations on energy demand (Table 3), and this can lead to a significant performance gap. Javanroodi and Nik [63] considered the influence of urban climate along with future climate conditions.

Quantifying the impact of extreme hot and cold events on distributed energy systems has been discussed quite comprehensively in the present state of the art (see Table 4). About six publications present either reviews or perspectives on this topic, summarizing the recent progress and promising research directions (see Table 4). The pool of papers can be classified into three classes: (1) design optimization, (2) optimal dispatch, and (3) resilience and reliability during extreme heat and cold events. Most of the publications, such as [71–74], focus on the optimal dispatch problem (directly or as a part of the design optimization). These studies focus on deriving the optimal operation strategy for the energy system to cater to the multi-energy demand (heating, cooling, and electricity). At the same time, several studies focused on optimizing the system design to cater to extreme energy demands while minimizing lifecycle cost. Different optimization techniques such as deterministic [72,75,76], stochastic [15,30,77], and robust [77] have been used in these studies. Uncertainty brought by future climate variations is considered in the stochastic models. In certain instances, hybrid approaches such as the stochastic-robust optimization technique have been used. Both low-probable high-impact (extremes) and high-probable low-impact events have been considered in these studies. The majority of the publications discuss the integration of renewable energy technologies while maintaining resilience during extreme events (Table 4). Although the majority of studies use detailed bottom-up approaches, several studies use the top-down approaches [76,78]. Several studies focus on the energy market and grid constraints along with the extreme conditions [76,78]. However, reasonable simplification has been made when considering the interactions between the different parties within the energy ecosystem and the uncertainties. Furthermore, climate flexibility has not been considered comprehensively in many studies.

Table 1: Present state-of-the-art publications assessing the impact of wildfires on energy infrastructure

| | Modeling wildfire impact on line rating (thermal) | Renewables | Distributed generation | Storage | Optimization-operation | Optimal power flow | Optimal power shutoff problem | Future scenarios | Climate models | Grid Impact/cascade failures | Transportation | Building | Stochastic modeling | Review | Instrumentation to detect wildfires |
|-----------------------------------|---|------------|------------------------|---------|------------------------|--------------------|-------------------------------|------------------|----------------|------------------------------|----------------|----------|---------------------|--------|-------------------------------------|
| Sathaye et al. [33] | | | | | | | ✓ | ✓ | ✓ | | | | | | |
| Koufakis et al. [40] | ✓ | | | | | | | | | | | | | | |
| Rhodes et al. [36] | ✓ | | ✓ | | ✓ | ✓ | | | | | | | | | |
| Mohagheghi & Rebennack [43] | ✓ | | ✓ | | ✓ | ✓ | | | | | | | | | |
| Trakas and Hatziargyriou [44] | ✓ | | ✓ | ✓ | ✓ | ✓ | | | | | | ✓ | | | |
| Soulinaris et al. [79] | ✓ | | | | | | | | | | | | | | |
| Hay & Mohit [46] | | | 1 | | | | | ✓ | | ✓ | ✓ | | | | |
| Hojjatinejad & Mona Ghassemi [80] | ✓ | | | | | | | | | | | | ✓ | | |
| Erickson et al. [81] | ✓ | | | | | | | | | | | | | | |
| Wischkaemper et al. [42] | | | | | | | | | | | | | | | ✓ |
| Muhs et al. [41] | ✓ | | | | | | | | ✓ | | | | | | |
| Tandon et al. [45] | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | | | | | | |
| Nazaripouya [39] | | | | | | | | | | | | | ✓ | | ✓ |
| Jazebi et al. [38] | | ✓ | | | | | | | | | | | | | ✓ |
| Jazebi et al. [35] | | ✓ | | | | | | | | | | | | | ✓ |

Table 2: Present state-of-the-art publications assessing the impact of hurricanes on energy infrastructure

| | Network | Energy system | Demand | Dispatch | Optimal power flow | Design optimization | Stochastic model | Renewables | Storage | Dispatchable sources | Component level | Outage/cascade failure | Machine learning | Review/perspective |
|--------------------------|---------|---------------|--------|----------|--------------------|---------------------|------------------|------------|---------|----------------------|-----------------|------------------------|------------------|--------------------|
| Shield et al. [49] | ✓ | | | | | | | | | | | ✓ | | |
| Bennett et al. [55] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | |
| Cole et al. [82] | | ✓ | | | | | | ✓ | | | | | | |
| Tavakoli et al. [83] | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | | | | |
| Baghbanzadeh et al. [53] | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | ✓ | | ✓ | | |
| Parker et al. [51] | | | | | | | | | | | | | | ✓ |
| Cicilio et al. [54] | ✓ | | | ✓ | | | | ✓ | | | | ✓ | | |
| Dehghani [56] | ✓ | ✓ | ✓ | | | | ✓ | | | | | | ✓ | |
| Khomami & Sepasian [84] | ✓ | | | | | | | | | | | | | |
| Pantua et al. [85] | | | | | | | | ✓ | | | ✓ | | | |
| Hashemi et al. [86] | | | | | | | | ✓ | | | ✓ | | | |
| Mojtaba et al. [58] | ✓ | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | | | ✓ | |
| Qian et al. [87] | ✓ | ✓ | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | | | |
| Chen et al. [52] | | | | | | | | | | | | | | ✓ |
| Amirioun [88] | ✓ | ✓ | | ✓ | | | | | ✓ | ✓ | | | | |
| Rose et al. [89] | | | | | | | | ✓ | | | ✓ | | | |
| Hosseini & Parvania [90] | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | | | ✓ | |

Table 3: Present state-of-the-art publications assessing the impact of heat waves on energy demand

| | Climate scenarios | Extreme events | GCM/RCM | Urban micro climate | Bottom-up models | Top-down | Electricity | Heating | Cooling | Thermal comfort | Renewable energy |
|-----------------------|-------------------|----------------|---------|---------------------|------------------|----------|-------------|---------|---------|-----------------|------------------|
| Qin et al. [64] | √ | | √ | | | √ | √ | | | | √ |
| Mutschler et al. [66] | √ | | √ | | √ | √ | | √ | √ | | |
| Kalvelage [91] | √ | | √ | | √ | | | √ | √ | √ | |
| Yuchen et al. [62] | √ | √ | √ | | √ | | | √ | √ | | |
| Larsen et al. [92] | √ | √ | | | | √ | | | | | |
| Li et al. [93] | | √ | | | √ | | | √ | √ | | |
| Hosseini et al. [94] | √ | | √ | | √ | | | √ | √ | | |
| Morakinyo et al. [65] | | √ | | | | √ | √ | √ | √ | | |
| Crawley [95] | √ | √ | √ | | √ | | √ | √ | √ | | |
| Tian et al. [67] | √ | | √ | | √ | | √ | √ | √ | √ | |
| Baniassadi [96] | √ | √ | √ | | √ | | √ | √ | √ | | |
| Farah et al. [97] | | √ | | | √ | | | √ | √ | | |
| Dasaraden et al. [69] | √ | | | | √ | | √ | √ | √ | √ | √ |
| Lee & Levermore [68] | √ | | √ | | √ | | | | √ | | |
| Javanroodi & Nik [63] | √ | √ | √ | √ | √ | | | √ | √ | | |
| Moazami et al. [59] | √ | √ | √ | | √ | | | √ | √ | | |

Table 4: Present state-of-the-art publications assessing the impact of heat waves on generation and distribution/transmission

| | Climate scenarios | Extreme events | High probable low impact | GCM/RCM | Bottom-up models | Top-down | Electricity | Heating | Cooling | Wind | PV | Grid | Uncertainty | Resilience | Flexibility | Deterministic | Stochastic | Robust | Market | Design | Operation | Perspective/ review |
|----------------------------|-------------------|----------------|--------------------------|---------|------------------|----------|-------------|---------|---------|------|----|------|-------------|------------|-------------|---------------|------------|--------|--------|--------|-----------|---------------------|
| Perera et al. [30] | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ | | ✓ | | | ✓ | ✓ | |
| Perera et al. [15] | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | | ✓ | 1 | | ✓ | ✓ | |
| Perera et al. [98] | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | ✓ | | | | ✓ | ✓ | |
| Abdin et al. [75] | ✓ | ✓ | | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | | | | ✓ | | | | ✓ | ✓ | |
| Wadsack et al. [72] | | ✓ | | ✓ | ✓ | | ✓ | | | | | | | | | ✓ | | | | | ✓ | |
| Pes et al. [99] | | ✓ | | | | | ✓ | | | ✓ | | | | | | | | | | | | ✓ |
| Su et al. [71] | | ✓ | | | | | ✓ | | | ✓ | ✓ | | ✓ | | | ✓ | | | | | | ✓ |
| Zhang et al. [100] | | ✓ | | | | | ✓ | | | ✓ | | | | | | | | | | | | |
| Ratnam et al. [101] | | | | | | | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | | | | | | | ✓ |
| Nik et al. [14] | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Chandramowli & Felder [78] | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | ✓ | ✓ | ✓ | ✓ |
| Ciscar & Dowling [76] | ✓ | | | | | | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | ✓ | | | ✓ | ✓ | | ✓ |
| Thomas et al. [102] | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | | | | | | | | | | | | |
| Wiel et al. [103] | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | ✓ | | | | | | | | | | | |
| Martin & Rice [104] | | ✓ | | | | | ✓ | | | | | | | | | | | | | | | |
| Demissie & Solomon [73] | | ✓ | | | | | ✓ | | | | | | | | | | | | | | ✓ | |
| Jordaan [105] | ✓ | ✓ | | | ✓ | | ✓ | | | ✓ | ✓ | | | ✓ | | | | | | | | ✓ |
| Donk [106] | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | | | | | | | | | | | | |
| Huang et al. [107] | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | ✓ | | | | | | | | | | | |
| Ward [108] | ✓ | ✓ | | | | | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | | | | | | ✓ |
| Höltinger et al. [74] | | ✓ | | | ✓ | | ✓ | | | ✓ | ✓ | | ✓ | | | | | | | | ✓ | |
| Cross et al. [109] | | ✓ | | | | | ✓ | | | ✓ | | | | | | | | | | | | |
| Patt et al. [110] | | ✓ | | | | | ✓ | | | | ✓ | | | | | | | | | | | ✓ |
| Mavromatidis et al. [77] | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | | | | | | | ✓ | | ✓ | ✓ | |
| Mavromatidis et al. [111] | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | ✓ | | | ✓ | ✓ | |

Table 5: Recent studies accessing the impact of wildfires on buildings

| | Occupant-behavior | CFD | Building simulation | Experiment data | Indoor Air Quality | Perspective/review |
|-----------------|-------------------|-----|---------------------|-----------------|--------------------|--------------------|
| Luo et al. [34] | √ | √ | √ | | √ | |
| Balmes [112] | | | | | √ | √ |
| Messier [113] | | | | √ | √ | |
| Fisk [114] | | | | | √ | √ |

4.4 Limitations in the present state of the models

Significant growth in the research studies that focused on climate resilience considering various aspects of the energy ecosystem was observed in the present literature. The majority of these studies were based on bottom-up approaches that consider the detailed physics of the problem. Dispatch problems, optimal power flow problems, and energy system sizing problems, which have been already well defined in the present state of the art, have been extended to consider extreme climate events. Furthermore, uncertainties brought by future climate variation have also been captured, especially for models that consider extreme heat and cold events. Therefore, it can be concluded that present state-of-the-art models can be adopted to help understand and quantify the impacts caused by the four types of extreme events discussed.

- **Considering the future climate data**

Improving resilience of the energy infrastructure demands that we move beyond quantifying the impacts of extreme events. It is important to predict future events that may arise, derive strategies to operate existing infrastructure during such events, and improve the design of the energy ecosystem to improve resilience. Except for the extreme cold/heat events, the connectivity between energy and climate models was weak. Most of the assessments were conducted using data obtained for past events. Only two studies used future climate data in improving the resilience for wildfires, and one study considered future intensification of hurricanes due to climate change in the assessment. The work on the impact of wildfires on building energy is also limited (Table 5). As we come across more and more intensive and frequent extreme events, the resilience and reliability of infrastructure designed using historical data may be inadequate. Therefore, it is vital to link the energy models with future climate models.

- **Considering uncertainties and use of stochastic models**

Capturing uncertainties play a vital role during the decision-making process. Uncertainties brought about by climate, energy markets, the evolution and adoption of technologies, grid operation, and other factors play a key role. A number of studies have focused on capturing the uncertainties during energy system operation (dispatch), optimal power flow, energy system optimization, and grid expansion problems. Nonetheless, most of the studies on extreme events focused on deterministic models. Stochastic, robust, and hybrid (stochastic-robust) models have been used to model extreme hot/cold events on the energy infrastructure. Only a few studies used stochastic models to examine the impact of wildfires and hurricanes. Consideration of uncertainties brought by climate models and the impact of the human activities (consideration of uncertainties for the RCP or SSP [Shared Socioeconomic Pathway] taken) has been trivial. However, considering these uncertainties increases the complexity of the existing models, which makes it difficult to consider them within the modeling

framework. Statistical and machine learning methods are promising ways to address these limitations, and these are gradually becoming popular.

- **Planning for a resilient energy ecosystem**

Most of the present state-of-the-art studies have focused on impact assessment. The impact of past events and forecasted future extreme events have been considered in these studies. A number of studies moved beyond the impact assessment and developed methodologies for optimal and resilient operation during extreme events (optimal power flow and optimal dispatch). Developing such methodologies help to retard the propagation of disruption and improve resource efficiency. However, the operation of energy infrastructure solely and heavily depends on the infrastructure, i.e., the superstructure of the grid, capacity, location, and type of energy sources and storage. Therefore, improving the design plays a vital role for improving climate resilience. However, the focus on design optimization has been quite limited when considering the present state of the art. For example, the authors did not find any publication about long-term energy planning to improve climate resilience for wildfires. Moreover, it is important to consider the resilience for multiple extreme events, not just a single event, especially during extreme events. In certain instances, the compound impact of multiple extreme events must be considered during the design phase. For example, in California, the energy infrastructure needs to be resilient to both extreme heat events and wildfires at the same time. Therefore, improving the resilience of the energy ecosystem for multiple extreme events and considering the compound impact is quite important. However, the authors did not come across such holistic design procedures to enhance the climate resilience of energy ecosystems. Many important research gaps must be addressed within the design improvement in energy infrastructure to improve energy ecosystem resilience.

5. Propagation of disruptions

The main challenge of a virus following infection is its spread. The virus uses the human cell to multiply the virus population and continue the spread. In the case of COVID 19, the virus initially infects the respiratory tract and subsequently spreads through the respiratory system. Similarly, extreme events can obstruct a part of the energy ecosystem and spread through the entire ecosystem. Energy infrastructure is critical infrastructure that further increases the risk for such cascade failures. Such failures could cause much more damage than the local disruptions discussed in Section 4. However, the disruption can move forward beyond the limits of a single sector, as we observe for COVID-19. The virus can start its infection in the respiratory tract and propagate through the respiratory system to reach a level that it moves beyond the limits of the respiratory system. Thereafter, it starts to attack other systems, damaging the functionality of the heart, kidney, and digestive systems, further increasing the damage, as shown in Fig. 4.

Similarly, the disruption propagated within a single sector such as electricity could reach a critical limit where it moves beyond the boundary of electricity and starts to disrupt other interconnected infrastructure such as communications, gas, water, transportation, and others. Such propagation damaging multiple sectors could lead to a significant economic loss, disrupting social activities. Such propagation of disruption due to extreme events within the energy ecosystem considering single and multiple sectors are discussed in this section, respectively in Section 5.1 and Section 5.2. Possible ways to improve the resilience in the urban energy ecosystem holistically is addressed in Section 5.3.

5.1 Propagation of disruptions in a single sector

Conducting vulnerability assessment for critical infrastructure has been a rich area of study, specifically for the electricity sector. Disruption in the energy infrastructure can occur due to several

reasons, including the extreme events discussed previously in Section 4. Following such an extreme event, the disruption can easily propagate and disrupt a large area, multiplying the impact of the extreme event by orders of magnitude. In general, vulnerability assessment of critical networked infrastructure has been a rich area of study. We do not intend to review the existing pool of studies on vulnerability assessment since it is not the focus of the study. However, this section briefly reviews a vulnerability assessment of the energy ecosystem solely related to extreme climate events. It is summarized in Table 6.

The present state-of-the-art literature on vulnerability assessment of energy infrastructure (mainly electricity) can be divided into two classes: (1) methods based on statistical approaches and (2) methods based on graph theory. Although both approaches have been used within the energy domain, the majority of the publications linked to climate events have used graph theory. The methods based on graph theory can be further classified into three groups: (1) simple graph, (2) weighted graph, and (3) detailed physics-based models considering the alternating current (AC) power flow. Vulnerability assessments have been linked to wildfires in many studies, as discussed in Section 4.1 (see Table 1 for the summary). However, the impact of other extreme events has been fewer studies, as shown in Table 6. Vulnerability assessment considering multiple events is more challenging. Xu et al. [115] and Noebels et al. [116] conducted vulnerability assessments considering multiple extreme climate events. Furthermore, a majority of the publications are focused on electricity grids with dispatchable sources. The integration of renewables and storage has been less discussed in the present state of the art. Uncertainties of renewable energy generation and direct impacts on renewable energy generation during extreme events (especially for wind power generation during hurricanes) complicate consideration of renewable energy integration. The research performed by Athari & Wang [117], Noebels et al. [116], and Nesti et al. [118] are examples of vulnerability assessments that consider renewable energy technologies while also taking into account extreme events. Operational optimization (optimal dispatch and power flow) to minimize the tendency for cascade failures has been assessed in several studies. However, we did not come across any study that presents design improvements (optimal system sizing or optimal grid reinforcement) to avoid cascade failures, which will be an interesting future research direction.

5.2 Propagation of disruptions in multiple sectors

Extreme events can lead to obstruct the operation of a certain part of the energy ecosystem. Being a critical infrastructure vulnerable to cascade failures, the disruption could propagate and disrupt the sector in a large area, as discussed in Section 5.1. Interdependency between different infrastructures could easily lead to obstruction of the connected infrastructure during extreme weather events. As a result, the propagation of the disruption will be accelerated and continue in more than one sector.

Let's take an example based on the communication and electricity networks. The communication network depends on the electricity network in order to obtain power for the operation. At the same time, the electricity network depends on the communication network to maintain communication between different parts of the electricity grid. Cascade failure in the electricity grid can collapse the operation of the communication network and lead to a cascade failure in communication networks. Failure in the communication network disrupts the control in the electricity grid, further extending the disruption. As a result, the obstruction taking place at a location can easily penetrate into a region and multiple sectors due to the interdependence in the infrastructure. Therefore, it is vital to improve the resilience of the interconnected infrastructure.

Understanding the propagation of disruption in interconnected infrastructure is much more complex than assessing the vulnerability of one sector [101]. As a result, literature that assesses the

vulnerability of interconnected networks is quite limited [13]. The majority of the publications on vulnerability assessment of interconnected networks related to climate are based on bottom-up approaches, since it is difficult to consider the interactions between different sectors when using statistical approaches (Table 7). Most of these studies are focused on coupled infrastructure where interdependencies between all the sectors are considered. For example when considering the electricity and communication networks (the same example taken before), rather than limiting the focus to the dependency of the communication network on the electricity network, they also consider the impact of the dependency of the electricity network on the communication network [119–121]. Some of these interactions are solely based on physical activities such as gas and electricity [122] networks, while some are cyber-physical interactions (for example communication and electricity grid) [122–124]. Several concepts have been introduced to handle the complexity that arises through the interactions between the infrastructures. The concept of multiplex networks was used initially to consider the interactions between different sectors [119,125,126]. However, conducting vulnerability assessment by using the concept of multiple networks is quite challenging. Therefore, Thacker et al. [120] proposed a system of system architecture to consider the complexity. Agent based modeling also has been used in the vulnerability assessment [127]. Later, it was further extended, and Shekhtman et al. [128] proposed a networks of network architecture to consider the interactions between different sectors. Although different approaches have been proposed to assess the vulnerability of interconnected infrastructure, research studies that use these different approaches for extreme climate events are quite limited. Intercomparison between different approaches cannot be observed when reviewing the literature. Therefore, it is difficult to propose the most promising approach when considering extreme climate events. This challenge led to many open research problems concerning the vulnerability assessment of interconnected infrastructure. It is essential to address these research gaps to improve the climate resilience of urban energy ecosystems.

Table 6: Research studies focused on vulnerability assessment of critical infrastructure for cascade failures taking into account a single sector

| Paper | Statistical | Bottom-up | Stochastic | Optimization | Graph | Weighted graph | AC power flow | Vulnerability for cascade | Renewables | Storage | Dispatchable generators | Hurricanes | Extreme heat | Case study |
|-------------------------|-------------|-----------|------------|--------------|-------|----------------|---------------|---------------------------|------------|---------|-------------------------|------------|--------------|------------|
| Panigrahi & Maity [129] | | ✓ | | | | | ✓ | ✓ | | | ✓ | | | ✓ |
| Rios et al. [130] | | ✓ | ✓ | | | | | ✓ | | | ✓ | | | |
| Qi [131] | | | | | | | | ✓ | | | ✓ | | | |
| Fang et al. [132] | | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | | | ✓ |
| Nakarmi [133] | | ✓ | | ✓ | | | | ✓ | | | ✓ | | | |
| Athari & Wang [117] | | | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| Xu et al. [115] | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | | ✓ | ✓ | |
| Noebels et al. [134] | | ✓ | | ✓ | ✓ | | ✓ | ✓ | | | ✓ | | | |
| Wu et al. [135] | | | | | ✓ | | ✓ | ✓ | | | ✓ | | | |
| Noebels et al. [116] | | | | | | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Gupta et al. [136] | | ✓ | ✓ | | ✓ | | | ✓ | | | | | | |
| Hu & Fan [137] | | ✓ | ✓ | | ✓ | | | ✓ | | | | | | |
| Eisenberg et al. [138] | | ✓ | ✓ | | ✓ | | | ✓ | | | | | | |
| Nesti et al. [118] | ✓ | | | | ✓ | | | ✓ | ✓ | | | | | |
| Fang et al. [139] | | ✓ | | ✓ | ✓ | | | ✓ | | | ✓ | | | |

Table 7: Research studies focused on vulnerability assessment of critical infrastructure for cascade failures taking interconnected energy infrastructure

| | Statistical | Bottom-up | Optimization | Graph | Weighted betweenness | Vulnerability for cascade | Flood | Climate | Extreme hot/cold | Coupled systems | Comm | Elec | Water | Cyber Physical system | Gas | Transport | Multiplex | System of systems | Network of networks | ABM | Other | Perspective |
|----------------------------|-------------|-----------|--------------|-------|----------------------|---------------------------|-------|---------|------------------|-----------------|------|------|-------|-----------------------|-----|-----------|-----------|-------------------|---------------------|-----|-------|-------------|
| Jin et al. [119] | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | | | | |
| Ouyang [122] | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | | | ✓ | | ✓ | | | | | |
| Thacker et al. [120] | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | | | | |
| Heracleous et al. [127] | | ✓ | | | ✓ | ✓ | | | | ✓ | | | | | | | | | | ✓ | | |
| Kong [121] | | ✓ | ✓ | | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | | | | |
| Kamissoko et al. [140] | | ✓ | | | | ✓ | | | | ✓ | | ✓ | | | | ✓ | | | | | | ✓ |
| Guan and Chen [125] | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | | | | ✓ | | | | | | |
| Yang et al. [141] | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | | | | ✓ | | | | | ✓ |
| Bloomfield et al. [123] | | ✓ | | ✓ | | ✓ | | | | ✓ | ✓ | ✓ | | | | | | | | | | ✓ |
| Tsavidaroglou et al. [124] | | ✓ | | | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | | | | | | ✓ |
| Arrighi et al. [142] | | ✓ | | | | ✓ | ✓ | ✓ | | | | | ✓ | | | ✓ | | | | | | |
| Shekhtman et al. [128] | | | | | | | | | | | | | | | | | | | ✓ | | | ✓ |
| Korkali et al. [126] | | ✓ | ✓ | ✓ | | ✓ | | | | ✓ | ✓ | ✓ | | | | | ✓ | | | | | |

Table 8: Review publications on holistic assessment of urban energy resilience

| | Quantitative | Qualitative | Statistical | Energy | Economic | Social | Water | Transportation | Climate | Networks | System models | Design optimization | Uncertainty | Renewables | Storage | Dispatchable | Grid | Cyber resilience | Perspectives /reviews | Urban resilience | |
|-----------------------------|--------------|-------------|-------------|--------|----------|--------|-------|----------------|---------|----------|---------------|---------------------|-------------|------------|---------|--------------|------|------------------|-----------------------|------------------|---|
| Mazur et al. [143] | | ✓ | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | | |
| Arghandeh et al. [144] | | ✓ | | ✓ | | | | | | | | | | | | | ✓ | ✓ | ✓ | | |
| Sukhwani et al. [145] | ✓ | | | ✓ | | | ✓ | | | | | | | | | | | | | ✓ | |
| Sharifi & Yamagata [146] | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | | | | | | | ✓ | | ✓ | |
| Mendizabal et al. [147] | | ✓ | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | ✓ | |
| Cantelmi [148] | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | | | | | | | | | | | | ✓ | |
| Meerow et al. [149] | | ✓ | | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | ✓ |
| Shi et al. [32] | | ✓ | | | ✓ | ✓ | | | | | | | | | | | | | | | ✓ |
| Ribeiro and Gonçalves [150] | | ✓ | | | ✓ | ✓ | | | | | | | | | | | | | | | ✓ |
| Nelson et al. [151] | ✓ | | | | ✓ | ✓ | | | | | | | | | | | | | | | ✓ |
| Cariolet [152] | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | | | | | | | | | | | ✓ |
| Rus et al. [153] | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | | | | | | | | | | | ✓ |
| Salimi & Ghamdi [154] | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | | | | | | | ✓ |

6. Broader understanding of the resilience

Section 5 clearly presents the complexity brought by the propagation of disruptions due to extreme climate events. Therefore, it is important to consider the concept of resilience broadly, rather than being limited to the boundaries of energy systems. Most of the studies on resilience were focused on the urban scale, using more holistic representation of resilience and taking into account the aspects of social, economic, technological, and environmental (natural systems) resilience [143,144,152]. Energy resilience is often considered under technological resilience. A more holistic (top-down approach) is used in this context. In contrast, resilience of energy systems has been broadly discussed with the energy community, where a top-down approach is used [144]. This section provides a discussion of both approaches, which can help to improve the understanding of the resilience concept being linked to the energy ecosystem.

The concepts of urban resilience or resilient cities have been broadly discussed in the present state of the art [152]. It has been studied from different perspectives, including sociological, economical, technological, and health. Later, a multidisciplinary approach combining all these different aspects was introduced to address resilience in a more descriptive manner [146–148]. Significant progress has been made since, covering a large number of publications, which are difficult to review one by one (Fig. 7). Similarly, a large pool of review papers cover urban resilience. We selected a group of review papers among them and analyzed the content discussed in these publications. The results are presented in Table 8.

The number of publications in Table 8 clearly shows that urban resilience has been discussed quite comprehensively, as well as broadly, although that discussion has been limited to one stream. Social, economic, and technological streams have been covered in many studies reviewed in these papers. However, considering social or economic aspects broadly requires consideration of a large number of parameters which increases the complexity of the analysis. Therefore, most of the publications select one specific parameter to present an entire stream (e.g., one parameter to represent economic resilience, another parameter to represent social resilience). More importantly, often finer temporal and spatial resolution is not used. Therefore, detailed system dynamic models have been implemented. However, it is challenging to directly extend the approach to the energy domain. Most of the studies have discussed energy resilience at the urban context more holistically. Therefore, energy resilience obtained by using a detailed bottom-up energy model can be used as an input to the urban resilience models. By doing so, a more comprehensive understanding of urban resilience can be obtained beyond a mere holistic understanding of urban resilience.

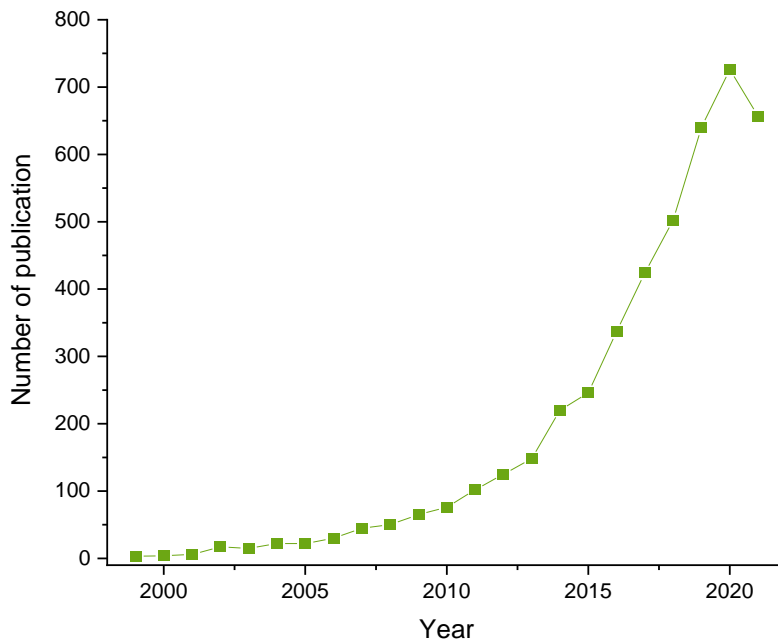


Fig. 7. Publications indexed in Scopus since 1999 with keywords “energy system” and “resilience”

7. Limitations and future perspectives

Improving the resilience and impact assessment for extreme events has gradually been getting more attention. When reviewing the progress in the present state of the art, it has been quite clear that there are many bottlenecks in quantifying the direct impact of extreme climate events, assessing the vulnerability of the energy ecosystem for extreme climate events, and improving resilience.

7.1 Paradigm shift in the modeling architecture

Considering the influence of extreme events requires extending the existing models, which makes them quite bulky and computationally exhaustive. As a result, most of them are very specific and often can only be used to consider a single extreme event, rather than the compound impact. At the same time, most of the studies were limited to impact assessment; possible ways to improve the system operation and design have not been addressed. Therefore, there is considerable room to improve the existing models. First, existing energy models are becoming extremely bulky when considering future climate variations, especially at the urban scale. The present models often use a centralized approach when operating or designing energy infrastructure. However, there is a recent trend to move from the centralized approach to a decentralized approach, especially when operating or performing design changes in the energy ecosystem. Such an approach to move into decentralized models was not witnessed in the literature review. There are several challenges when implementing completely decentralized modeling architecture, since energy infrastructure depends heavily on spatial interactions, which are somewhat challenging to represent using completely decentralized architecture. Therefore, agent-based models based on leader-follower methods and hierarchical-distributed models are becoming popular. This has led to a paradigm shift in the modeling architecture, moving from system models to the system of system models. Using concepts such as Urban Cell (Perera et al. 2021) based on the system of system architecture would be a beneficial approach.

7.2 Use of machine learning techniques

The energy systems domain has been quite successful, based on the bottom-up approaches with analytical models. Conversely, there were many limitations of using top-down or statistical approaches. Mainly, performance indicators of the energy system models were based on the detailed system dynamics. Statistical models fail to present such detail system dynamics. Furthermore, top-down models are based on poor spatial and temporal resolution, making them difficult to use for operational purposes. Therefore, statistical models cannot be directly used to address the modeling challenges presented by extreme climate events. Machine learning algorithms have become quite attractive in this context, and have proven to be efficient when handling complexity. Graph neural networks have already been used to investigate the vulnerability for cascade failures during extreme climate events and have shown the potential to be competitive with bottom-up graph models. More importantly, machine learning models are data-driven, and have already shown potential to be efficiently linked with climate models. Machine learning techniques such as reinforcement learning techniques have been deployed efficiently for dispatch and optimal power flow problems where energy system operation considering complex settings has been captured. Furthermore, reinforcement learning and transfer learning have been used with energy system design. Therefore, machine learning techniques have shown the potential for further investigating usability to improve the climate resilience of energy infrastructure. Therefore, introducing machine learning techniques to enhance the climate resilience of energy ecosystems will be an interesting research direction.

7.3 Enhancing the interlinks between energy, climate, and human systems models

Understanding the impact of future climate variations on the energy infrastructure requires a detailed understanding of the interactions between climate, energy, and human systems. Future climate variations notably influence the resilience of the urban energy ecosystem. Already, there are many research gaps in capturing the impact of future climate variations when developing energy models, as highlighted in Section 4.4. Therefore, further improving the interconnectivity between energy and climate system models plays a vital role (Fig. 8). Similarly, human systems play a vital role in considering both climate and energy. The climate system already considers the impact of the human system (socio-economic) in the long run through the integrated assessment models. Similarly, the human system influences the energy sector (both design and operation of energy infrastructure). For example, changes in socio-economic factors (taken within the human system) may significantly influence design solutions and the transition path taken by the energy infrastructure. At the same time, the impact of human systems would be quite significant in relation to the operation of energy infrastructure during extreme events. For example, heating and cooling demand will be significantly influenced during extreme cold and hot events. Similarly, equipment usage patterns could notably change, which will affect energy demand. Considering the impact of human systems is important when improving the resilience for extreme climate events. Therefore, improving the interconnection between energy, humans, and climate systems plays a major role. Handling the complexity of the models when considering these interactions presents a major challenge. Paradigm change in the existing modeling frameworks, as explained in 7.1 and 7.2, will be crucial.

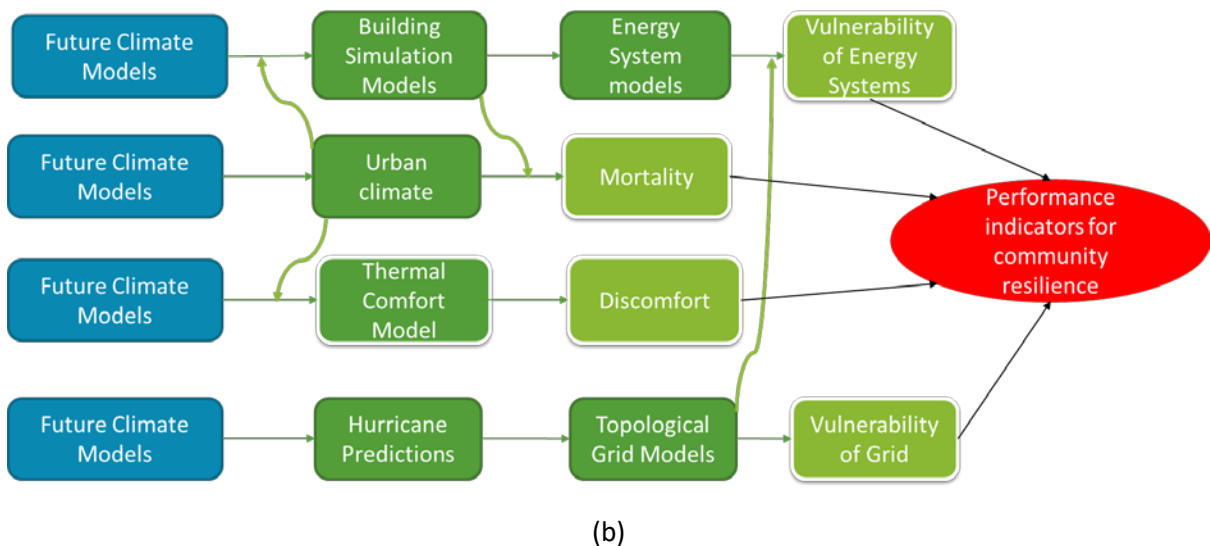
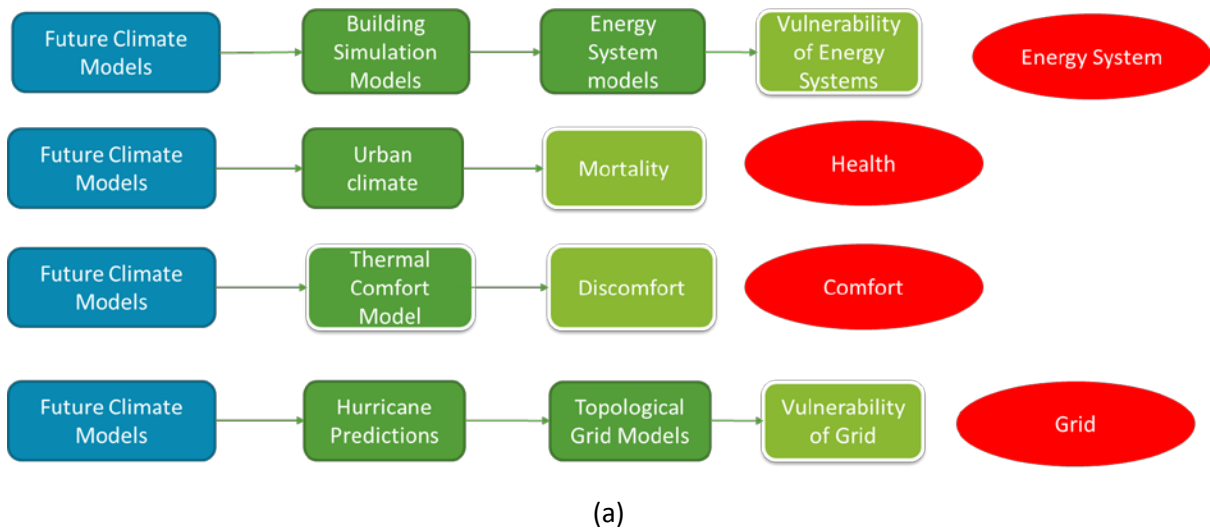


Fig. 8 moving from (a) a disintegrated to (b) an integrated modeling framework to improve the interconnectivity in models for enhancing resilience of urban energy ecosystem

8. Conclusions

Improving the resilience of the urban energy ecosystem is vital, although the definition of resilience has been quite vague, especially within the energy system domain. The focus of these definitions varies from improving the resilience of a single component to the entire social system in a city. Some of the models are extremely qualitative with a very broad scope, while the others are quantitative. The same problem has been observed when considering the climate resilience of the energy ecosystem.

A comprehensive literature review is performed considering the threat caused by wildfires, hurricanes, and extreme hot and cold events brought up by future climate variations on the energy ecosystem. Research studies have focused mainly on minimizing the direct impact of extreme events. During the review process, two clear strategies were observed in the present state of the art to improve the resilience of the energy ecosystem:

1. Short-term planning: Develop resilient operational strategies to cope with extreme events

2. Long-term planning: Improve the design to withstand extreme events

Most of the publications have focused on minimizing the direct impact of extreme events by improving short-term planning strategies such as optimal dispatch and optimal power flow. More than 90% of studies focused on a single extreme event, and improving resilience for multiple extreme events was not considered.

- **Main bottlenecks in the present state of the art**

There were several major bottlenecks observed in the present state of the art which hinder the process of improving the resilience of urban energy ecosystem.

A clear research gap was observed in developing tools for long-term planning.

Most of the modeling tools are used to operate existing energy infrastructure during an extreme event with a minimal impact on the day-to-day activities. However, besides operating the existing energy infrastructure, it is important to design energy infrastructure in a manner that they can withstand extreme events with a minimal impact on social activities. Towards this end, the present state of the art models need to be updated to evaluate long-term planning activities.

Future climate data

Energy community often relies on the past weather data. Except for extreme hot/cold events, most of the studies do not consider future climate data. However, relying on the past data does not guarantee the resilience of the energy ecosystem for future extreme events since the climate change is intensifying the severity of extreme climate events. Therefore, many interesting research problems arise when trying to improve the resilience for wildfires and hurricanes considering future climate data.

Uncertainties and stochastic models

Considering uncertainties plays a vital role in enhancing the resilience especially during the long-term planning process. One major challenge in this context is consideration of future climate data. Climate models, which have relatively poor temporal and spatial resolution, result in many uncertainties. At the same time there is a requirement to consider more than one climate model in order to enhance the accuracy. Furthermore, technology maturity and market conditions bring many uncertainties that need to be considered in planning process. Although there are a few models that consider these uncertainties, majority of the publications do not consider the uncertainties. Moving into stochastic models that consider the uncertainty may notably increase the complexity that these models cannot handle.

Facing multiple extreme events

Most of the recent studies focus on a single extreme event. As tabulated in Table 1-5 these studies either focus on wildfires, extreme hot/cold event, or hurricane. However, we need to understand that there can be a possibility that energy ecosystem needs to withstand multiple extreme events at the same time. For example, wildfires taking place during the extreme hot period require the energy ecosystem to withstand both these events at the same time. The present modeling tools are not capable of handling such simultaneous multiple extreme events.

Propagation cascade failures beyond the electricity sector

Vulnerability assessment for cascade failures, especially in the electricity sector, plays a major role in improving resilience. There has been reasonable progress in assessing the n-1 security and

vulnerability of wildfires addressing the optimal power shutdown problem. Although such vulnerability assessment in the electricity sector has been quite common, studies that focus on extreme climate events have been fewer. More importantly, vulnerability assessments considering interconnected energy infrastructure have been quite limited. The impact of extreme events on coupled cyber-physical systems such as electricity- communication have been performed. However, the resilience of such interconnected infrastructure within the energy ecosystem for extreme climate events has not been performed yet.

There are several promising approaches to address these bottlenecks. We show that obtaining a more holistic understanding of the vulnerability of the energy infrastructure to extreme climate events could play a crucial role in addressing some of aforementioned limitations.

- **Promising approaches**

Covid analogy

the Covid analogy was developed to better understand which critical aspects need to be focused on. The three main stages of the coronavirus spread in human bodies were used to explain the propagation of disruption in the energy ecosystem and ways to improve resilience in different parts of the energy ecosystem.

Shift in the modeling architecture

In general, extreme climate events extend the typical energy system models used in the present state of the art, making them bulky and more complex. Therefore, improving the modeling framework is essential in order to improve the climate resilience of energy infrastructure. Moving from the centralized modeling architecture towards a modular-based decentralized architecture could be quite promising in this context, and could help to handle the increasing complexity. Methods such as Urban Cell could be helpful in this regard. Modeling architectures such as system-of-systems and network-of-networks can be quite interesting in this context.

Machine learning techniques

Machine learning methods that can help to improve the resilience of the energy ecosystem are also becoming popular within the energy system community. These methods can help to improve the connectivity between energy system models and climate and human system models.

Integrated assessment

In order to quantify the impact of future climate variations on the energy infrastructure a detailed understanding of the interactions between climate, energy, and human systems is essential. There are many research gaps in capturing the impact of future climate variations when developing energy models. However, there are more research gaps when linking human systems with both energy and climate systems. Therefore, it is essential to develop integrated assessment models coupling human, climate and energy systems.

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