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RESI: A Power Outage Event and Typical Weather File Generator For Future RESIlient Building Design and Operation

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Abstract

Buildings are expected to be resilient in the face of future climate change and increasingly frequent disruptive events. Therefore, understanding building performance under various future weather conditions and disrupt events is crucial. However, accessing available data sources is always time-consuming. From this perspective, we developed a data generator tool for power outage events and future typical weather files, which provides both raw and synthetic data for researchers. They can download ready-to-use data with a single click by simply inputting the city name, time span, and CO2 emission scenarios, without the need for extensive data preprocessing effort. The future typical weather and power outage data could be used for future building energy simulation, energy system design and operation, etc. To demonstrate its application potential, we conducted an EnergyPlus case study to compare energy consumption differences and building performance under power outages and future weather files. The results indicate that in an extreme warm weather condition under RCP (Representative Concentration Pathway) 8.5, ambient air temperature could increase by up to 7°C, which doubles the cooling demand. While the 50th and 90th percentile of historical power outage is 5.5 hours and 72 hours respectively and can be used as reference for resilience-based design. The study also identified extreme weather as the dominant factor in power outage events, potentially causing up to 60% uncertainty in energy system management.

Keywords: Resilience, Power Outage, Future Climate

Introduction

Over the past decades, climate change has led to an increasing occurrence of disruptive events, such as extreme weather (e.g., heatwaves, snowstorms), power system failures, and natural disasters. For example, as reported by the National Centers for Environmental Information, 90 disruptive events occurred in the U.S. over the past five years, resulting in \$624 billion in losses and 1,751 deaths (NCEI, 2023). These increasingly frequent and intense disruptive events have caused enormous damage to society, human health, and infrastructure systems (Change, I. C., 2014). In this context, buildings are expected to be resilient to meet occupants' needs by providing safe, stable, and comfortable conditions in the face of varying external conditions (United Nations Environment Programme, 2021). To facilitate resilient building design, it is essential to understand building behavior under future climate scenarios and disruptive events, where building performance simulation (BPS) plays a vital role.

The most commonly used weather file for BPS is the Typical Meteorological Year (TMY), which represents average climate conditions based on 15–30 years of historical observations (Chan, et al., 2006). To generate a future TMY for BPS, the first step is to select a future greenhouse gas emission scenario from the Intergovernmental Panel on Climate Change (IPCC). There are three emission and concentration scenarios, namely RCP2.6, RCP4.5, and RCP8.5, where 'RCP' stands for 'Representative Concentration Pathways,' a framework adopted by the Intergovernmental Panel on Climate Change (IPCC) (Pachauri, et al., 2014). These emission scenarios provide the initial conditions for Global Climate Models (GCMs) to forecast future climate changes with a spatial resolution of 100–300 km² and a monthly temporal resolution (Moazami, et al., 2019). Then, the future weather file needs to be downscaled to an appropriate spatial and temporal resolution for BPS, a detailed discussion on this can be found in the review done by (Herrera, et al., 2017). However, as the TMY file represents an average of climate conditions, it cannot capture the effects of extreme weather uncertainties. These uncertainties can cause up to a 28.5% increase in energy demand compared to typical conditions (Moazami, et al., 2019). Furthermore, they can lead to a significant performance gap (up to 34% for grid integration) and a decrease in power supply reliability (up to 16%) due to extreme weather events (Perera et al., 2020). To address this limitation, (Nik, 2016) suggested assessing the effects of climate change on building energy performance by using not only a typical downscaled year (TDY) but also an extreme cold year (ECY) and an extreme warm year (EWY). However, generating such weather files for BPS is time-consuming. Researchers often face a long learning curve dealing with GCMs and huge datasets. More detailed methods for future weather data generation can be found in (Herrera, et al., 2017), (Li, et al., 2023) and (Nik, 2017). Currently, there is a lack of a standardized, 'click-and-run' tool for researchers to easily obtain future TDY, ECY and EWY files for a specified city, time span, and carbon emission scenarios.

Another important input for resilience-relevant studies involves power outage events. According to the Energy Information Administration (EIA), occupants in the U.S. experienced an average of eight hours of power disruptions in 2020, which has doubled compared to five years earlier (Sheng, et al., 2023). Furthermore, lots of power outage events coincide with extreme weather events, highlighting the importance of considering their combined effects. However, finding an open-access dataset and performing the necessary data cleaning is always time-consuming. Additionally, due to the absence of a benchmark dataset, many studies (Tian, et al., 2021) (Gong, et al., 2021) (Rosales et al., 2023) are using predefined fixed schedules for blackout analysis. These schedules assume that power outages occur periodically with a specific starting point, which has limited alignment with real-world cases.

In summary, this study develops a data tool for generating power outage event data and future weather files, aimed at providing a benchmark dataset for future resilient building design and operation. A detailed description of the raw dataset will be introduced in the next section. To use this tool for data query, users are required to input the city name, the desired time span and potential carbon emission scenarios. Two types of data are then available for further analysis and download. The first type includes raw weather data for the periods 2045 to 2054 and 2085 to 2094, as well as power outage event data from 2002 to 2023. The second type comprises synthetic data, including TDY, ECY, EWY weather, along with power outage start times and durations sampled from history dataset.

Methods

1. Data Source

Argonne National Laboratory (Zeng et al., 2023) has recently released an hourly future weather dataset derived from the output of a Regional Climate Model (RCM). An RCM is a numerical climate prediction model capable of simulating atmospheric and land surface processes and it can be used for weather prediction, understanding the climate, and forecasting climate change. This dataset is directly compatible with building energy modeling tools such as EnergyPlus and ESP-r. A summary of the dataset is shown in Table 1.

Table 1 Summary of future weather dataset

Features	Information
Coverage	North America
Spatial Resolution	12 km by 12 km
Time Resolution	One Hour
Time Span	2045 – 2054; 2085 - 2094
Format	EPW
Emissions Scenarios	RCP8.5; RCP4.5(Ongoing)
Centroid Area	2368 PUMAs (Public Use Microdata Area)
Data Size	7.25GB
Download Link	https://data.openei.org/ submissions/5974
Weather variables	Dry-Bulb Temperature, Dew Point Temperature, Relative Humidity, Atmospheric Pressure, Horizontal Infrared Radiation Intensity from Sky, Global Horizontal Irradiation, Direct Normal Irradiation, Diffuse Horizontal Irradiation, Wind Speed, Wind Direction, Sky Cover, Albedo, and Liquid Precipitation Depth

Table 2 Summary of power outage dataset

Features	Information
Coverage	NERC Regions
Time Span	2002 – 2023(Still Updating)
Format	xls
Download Link	https://oe.netl.doe.gov/oe417 .aspx
Event Begin Datetime	Start time
Event Restoration Datetime	End time
Affected Area	\
Alert Criteria	Loss and duration
Event Type	Weather, Cyber Attack, Vandalism, etc.
Demand Loss	Megawatt
Number of affected customers	\

The power outage dataset originates from the Department of Energy's Electric Emergency Incident and Disturbance Report (Form DOE-417). The form requires mandatory filing for any electrical incident or disturbance that is significant large to surpass the reporting thresholds. A detailed summary of the dataset can be found below in Table 2.

2. Typical and Extreme Weather Generator

In this study, the TDY is synthesized based on the hourly values of outdoor air temperature (Nik, 2016). Taking January as an example, we first compile ten years of January weather data and calculate the overall temperature distribution. The distribution is represented by its percentile (dividing the cumulative probability interval into 100 evenly spaced probabilities), and these 100 percentiles are recorded as a reference vector **r**. Then we calculate January temperature distribution for each individual year, donated as a comparison vector **c**. After that, we calculate the difference between **r** and **c** to identify the Typical Meteorological Month (TMM). For TDY, TMM is defined as the month with the distribution most similar to the reference (the minimal least absolute difference between **r** and **c**). Conversely, for EWY and ECY, TMM is defined as the month with the largest positive and negative distribution difference relative to the reference (the maximum positive and negative difference between **r** and **c**, respectively). This process is repeated for the remaining 11 months, and the 12 TMMs are to form the TDY, EWY, and ECY.

3. Power Outage Event Generator

The raw data, spanning the last 20 years, was presented in various formats, necessitating thorough data cleaning to ensure consistency. The terms "Noon", "Midnight" are replaced by 12:00 PM and 12:00 AM respectively. Rows with unknow/NaN (Not a Number) values for power outage start time/end time are removed. Finally, 3496 data points are available from 2002 to 2023, with features including "Start time", "End time", "NERC Region", "Reason", "Area", "Loss", "People Affect", "Year", "Month", "Duration". We also provide a synthetic power outage event generator for resilient building energy system design. Generally, disruptive events can be categorized into (1) low-probability, high-impact (LPHI) events (These events have a relatively low chance of occurring but can cause significant impacts once they do occur) and (2) high-probability, low-impact (HPLI) events (In contrast to LPHI events, 'HPLI' events occur more frequently but have relatively minimal impacts) (Perera, et al., 2020). In terms of power outages, if the system is designed according to HPLI events only (long term outage), the sizing could be overestimated and requiring a high capital cost. On the contrary, if the sizing is calculated based on LPHI events only (short term outage), the building energy system will fail once an LPHI event happened. Thus, it is important to consider the resilience design problem according to different scenarios. From this perspective, our generator can generate power outage events duration with different probability percentiles. And the event start time can be sampled directly from the historical data. For example, if the user wants to improve building resilience that can cover 60% of power outage scenarios, the generator will return the 60th percentiles of the power outage duration with a start time sampled from the database.

4. Framework of RESI

Figure 1 presents the framework of the RESI tool. Users are prompted to input the city name, time span, and desired power outage percentile. Then, we query data based on the specified location by Google Geo APIs. Preprocessed data is then available for download. Additionally, we provide synthetic data, which includes TDY, EWY, and ECY weather files, as well as power outage events for further analysis. The necessary statistical distribution of the dataset is also available.

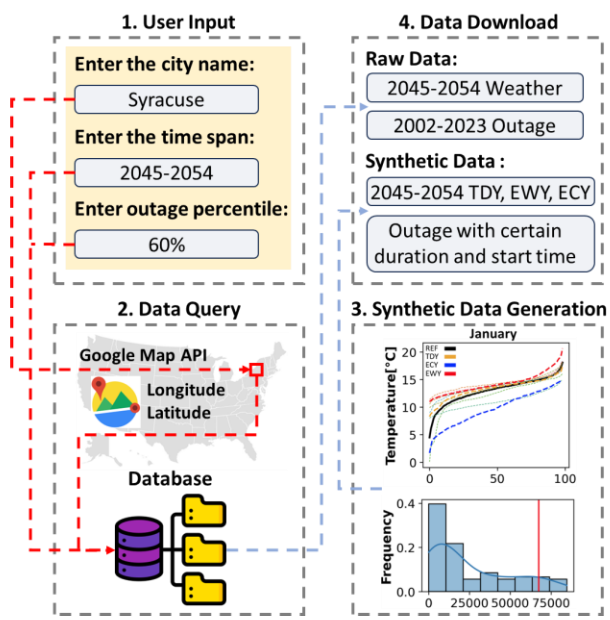

Figure 1 A diagram of RESI instruction

5. Case Study

An EnergyPlus case study is employed to demonstrate how researchers can benefit from this tool. The model used here is a DOE prototype residential building model, specifically a single-family house equipped with a heat pump. Taking San Francisco under RCP 8.5 as an example, we compare the building's performance and energy consumption under different scenarios, as shown in Table 3. Where the current year is 2023, the mid-term represents the years from 2045 to 2055, and the long-term refers to the years from 2085 to 2095.

Table 3 Summary of different simulation scenarios

Scenarios	Weather File	Power Outage Percentiles
Scenario 1	Current TMY	
Scenario 2	Mid Term TDY	
Scenario 3	Mid Term EWY	
Scenario 4	Mid Term ECY	0th, 50th, 90th
Scenario 5	Long Term TDY	
Scenario 6	Long Term EWY	
Scenario 7	Long Term ECY	

Different weather files are used to assess monthly building energy consumption under both normal and extreme climate conditions. Then the combined effects of power outage are analyzed on design days for each weather file. The start time of power outage is sample from the raw dataset, and the duration is calculated based on the 0th, 50th, 90th percentiles of the historical data.

6. Thermal Resilience Evaluation

To evaluate the thermal resilience of our case study, we use the heat index (HI) (Rothfusz et al., 1990), humidity index (humidex) (Steadman et al., 1979) and setpoint unmet hours as performance indexes. The HI can be calculated by equation 1:

$$HI = -8.78 + 1.61T + 2.33R - 0.14TR - 0.012T^2 - 0.016R^2 + 0.002T^2R + 0.0007T^2R - 0.000003T^2R^2 \quad (1)$$

Where T represents the ambient dry-bulb temperature and R is the relative humidity, a percentage value between 0 and 100. HI reflects five different thermal risk levels: Safe (below 27°C), Caution (27-32°C), Extreme Caution (32-41°C), Danger (41-54°C), and Extreme Danger (higher than 54°C) (Sheng, et al., 2023).

The humidex measures the combined effects of heat and humidity on personal comfort and can be calculated by equation 2:

$$Humidex = T_{air} + \frac{5}{9}\left(6.11 \times e^{5417.7\left(\frac{1}{273.15} - \frac{1}{273.15+T_{dew}}\right)} - 10\right) \quad (2)$$

Where T_{air} and T_{dew} is the air temperature and dew-point temperature respectively. Setpoint unmet hour is used to quantify overheating hours during power outage events, summarizing the time when space temperature cannot maintain within the cooling setpoint.

Discussion and Result Analysis

1. Future Weather Distribution

Figure 2 illustrates the differences in dry bulb temperature distribution between the current data (downloaded from the EnergyPlus weather file webpage) and future scenarios, including the TDY (Typical Day Year), EWY (Extreme Warm Year), and ECY (Extreme Cold Year). Additionally, we have summarized the average monthly temperature differences under the RCP 8.5 scenario (the highest carbon emission condition) in Table 4. We compare current temperature conditions with both the mid-term (2045 to 2055) and the long-term (2085 to 2095) scenarios. This comparison is made for both typical years and years with extreme warm or cold conditions. Through this analysis, a significant global warming phenomenon is observed.

Table 4 Summary of averaged temperature difference

Month	Mid Term[°C]			Long Term[°C]		
	TDY	EWY	ECY	TDY	EWY	ECY
Jan.	4.3	5.2	0.6	5.8	7.1	3.6
Feb.	2.8	4.4	1.5	3.9	5.1	2.4
Mar.	4.0	6.8	2.7	4.9	6.3	3.1
Apr.	3.4	4.6	2.9	3.9	4.8	3.0
May.	3.4	4.4	2.4	4.9	5.8	3.6
Jun.	2.6	3.9	1.7	3.7	4.9	3.2
Jul.	2.6	3.5	1.2	3.6	4.7	3.0
Aug.	1.6	3.0	0.4	2.9	3.8	1.9
Sep.	1.1	3.0	0.1	1.8	4.0	0.6
Oct.	2.3	5.1	0.5	3.5	5.3	2.2
Nov.	3.0	4.1	2.3	5.2	6.5	2.7
Dec.	3.8	5.6	2.6	5.4	7.0	3.6

2. Power Outage Events Distribution

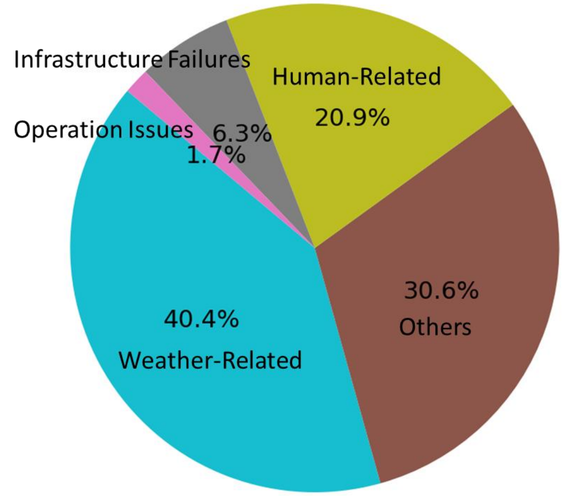

Figure 3 Categories of reasons for power outage

Due to the initial disorganization of the raw data, we have regrouped power outage events into five categories, as shown in Figure 3: (1) Human-related, such as vandalism, theft, physical attacks, human errors for example cable cuts and similar causes; (2) Infrastructure failures, related to equipment failure, transmission equipment failure, cable failure, generator failure, breaker failures, and similar infrastructure-related issues; (3) Operation issues, such as load shedding, voltage reduction, unplanned generator outage, unit shutdowns; (4) Weather-related (accounts for around 40% of the overall power outage events), such as high wind, winter storm, heat wave, extreme weather, snow/ice storms, wildfires, tropical storms, and other weather-related events; (5) Others, including cyber-attacks, earthquakes, and other external events not covered by the previous categories.

Figure 4 depicts the duration, economic loss and number of affected individuals during power outages categorized by factors for last 20 years. The Y-axis represents the duration, magnitude of loss and number of affected people, respectively, while the X-axis displays the years. The weather-relate factor has consistently been the dominant cause for power outages, leading to significant losses, especially in the recent 5 years. A clear trend is observed, with the frequency of occurrences nearly doubling compared to 2017.

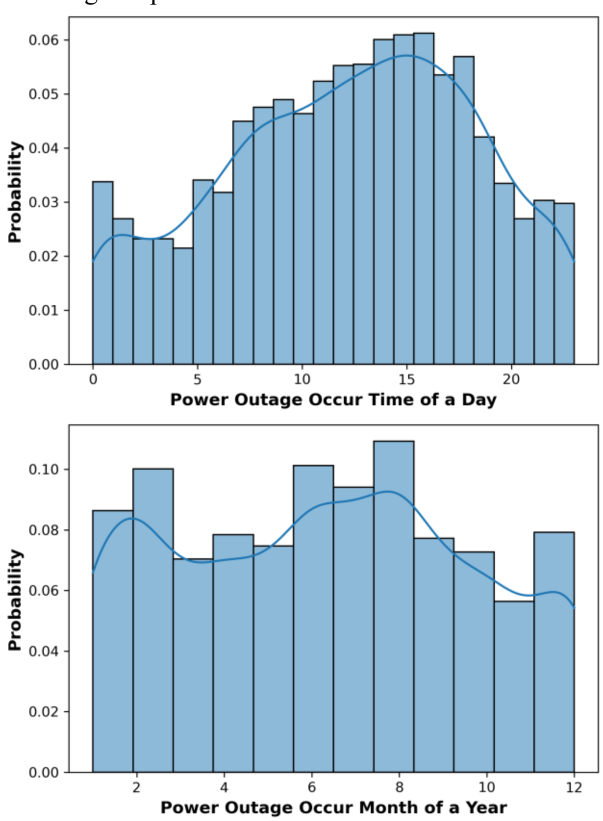

Figure 5 Distribution of power outage happening time

Figure 5 shows the distribution of the timing of power outages. Most outages occur in the afternoon, around 14:00 to 16:00, coinciding with the peak hour for most cities. And most power outages happen in the summer (June to August) and winter (December to February) months. This pattern is largely because extreme weather events, such as heatwaves and winter storms, are more prevalent during these periods.

3. EnergyPlus Simulation

Figure 6 compares the monthly cooling and heating energy consumption. Due to increasing outdoor temperatures, the projected cooling demand will increase by 95% by mid-century and by 159% by the end-century under normal weather conditions. In contrast, heating demand is expected to decrease by 64% and 76%, respectively. Additionally, annual HVAC energy consumption is going to decrease by 41.5% by mid-century and 42.5% by the end-century. We also compared the energy consumption differences between the mid-term and long-term projections. The long-term cooling demand could increase by 32.7% compared to the mid-term, alongside a 32.6% reduction in heating demand. In terms of extreme weather uncertainty, an extreme hot year could double the cooling energy consumption and decrease heating energy consumption by up to 85%. Additionally, both an extreme cold year and an extreme warm year could result in a cooling energy difference ranging from -31.3% to 61% and a heating energy difference from -42.9% to 64.8%. These findings indicate that climate change is likely to have a significant impact on building energy performance. Extreme weather conditions, in particular, introduce considerable uncertainty into building performance simulations, highlighting the need for further studies in this area.

According to Table 3, we randomly sampled a power outage event start time on the cooling design day (July 21st), with the outage beginning at 6:00 AM. It is worth to note that this process can be enhanced statistically for example, through Monte Carlo sampling to get a more robust result. Then the power duration time was determined based on the percentile from 0th, 50th and 90th, which is (1) no power outage, (2) 335 minutes (5 hours and 35 minutes) of power outage and (3) 4491 (around 3 days) of power outage. Future studies might select durations according to specific areas. Additionally, it is crucial to consider that the future patterns of power outages may differ significantly due to upgrades in power grid infrastructure, the implementation of onsite energy generation units and the impacts of future climate changes. Therefore, a more detailed power outage event model should be developed in the future studies.

Figure 7 illustrates the distributions of space air temperature with and without power outages. In case one without a power outage, the space effectively maintains the cooling setpoint, and no overheating issues are observed. But it is important to consider the actual system performances and capacities in future studies. For case two with a 5.5-hour power outage, the space temperature gradually increases until 11:35AM, at which point the cooling system begins its recovery process. And it took approximately 1 hour and 35 minutes for the space to cool down to the desired temperature. Additionally, due to climate change, the open-loop space temperature in an extreme warm year is 2.17°C higher than the current TMY.

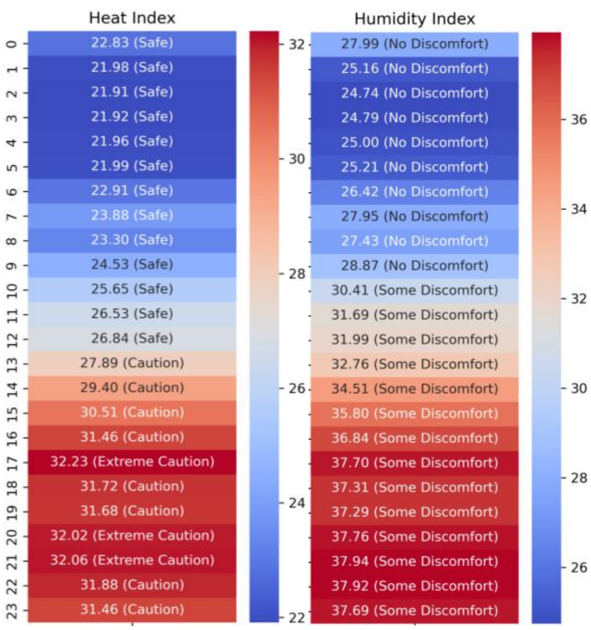

Figure 8 Distribution of heat index and humidity index of an example day

For case three, the space temperature continuously rises until sunset, reaching a peak indoor temperature of 32.6°C, with an unmet cooling setpoint duration of 18.3 hours. In this scenario, the open-loop space temperature in an extreme warm year is 5.27°C higher than the current TMY, indicating the urgent need for resilience-based building design.

Figure 8 presents an example of thermal resilience assessment for a building under end-century conditions, during an EWY, with a power outage at the 90th percentile. We use heat index and humidity index calculated by equation (1) and (2) to evaluate the overheating level in this case building. At the onset of power outage, the space temperature begins to rise slowly. By around 1:00 PM, the building starts to encounter overheating issues, reaching "Extreme Caution" levels at 17:00 and again at 20:00. From humidex point of view, occupants are likely to experience discomfort throughout the afternoon without cooling.

Conclusion

In this study, we developed a 'click-and-run' tool to generate power outage event data and typical weather files, facilitating future research related to building resilience. We provided a detailed introduction to the processed dataset and demonstrated its application through an EnergyPlus case study. We found that the weather-related factors are the predominant cause for power outages, with an increasing number of events occurring in recent years, particularly during afternoon peak hours. Seasonally, power outages are more common in winter and summer. Furthermore, as outdoor air temperatures rise, there is a significant increase in cooling demand, accompanied by a noticeable decrease in heating energy consumption in the future. Extreme weather conditions could result in up to a 60% variance in energy operations, underscoring the critical importance of incorporating resilience considerations in building design and energy system planning.

Acknowledgment

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Code and Data Availability

The data mentioned in this study (Raw data, TDY, EWY, ECY and power outage data) are available for download at the following URL: **https://resitool.streamlit.app/**.

References

Chan, A. L., Chow, T. T., Fong, S. K., & Lin, J. Z. (2006). Generation of a typical meteorological year for Hong Kong. Energy Conversion and management, 47(1), 87-96.

Change, I. C. (2014). Mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change, 1454, 147.

Gong, H., & Ionel, D. M. (2021). Improving the power outage resilience of buildings with solar pv through the use of battery systems and ev energy storage. Energies, 14(18), 5749.

Hall, I J, Prairie, R R, Anderson, H E, & Boes, E C. Generation of a typical meteorological year. United States.

Herrera, M., Natarajan, S., Coley, D. A., Kershaw, T., Ramallo-González, A. P., Eames, M., ... & Wood, M. (2017). A review of current and future weather data for building simulation. Building Services Engineering Research and Technology, 38(5), 602-627.

https://www.oe.netl.doe.gov/oe417.aspx#:~:text=The%20Electric%20Emergency%20Incident%20and,well%20as%20for%20analytical%20purposes.

Li, H., Zhang, T., Wang, A., Wang, M., Huang, J., & Hu, Y. (2023). A new method of generating extreme building energy year and its application. Energy, 128020.

Moazami, A., Nik, V. M., Carlucci, S., & Geving, S. (2019). Impacts of future weather data typology on building energy performance–Investigating long-term patterns of climate change and extreme weather conditions. Applied Energy, 238, 696-720.

Nik, V. M. (2016). Making energy simulation easier for future climate–Synthesizing typical and extreme weather data sets out of regional climate models (RCMs). Applied Energy, 177, 204-226.

Nik, V. M. (2017). Application of typical and extreme weather data sets in the hygrothermal simulation of building components for future climate–A case study for a wooden frame wall. Energy and Buildings, 154, 30-45.

NOAA National Centers for Environmental Information U.S. Billion-Dollar Weather and Climate Disasters (2023). https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., ... & van Ypserle, J. P. (2014). Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change (p. 151). Ipcc.

Perera, A. T. D., Nik, V. M., Chen, D., Scartezzini, J. L., & Hong, T. (2020). Quantifying the impacts of climate change and extreme climate events on energy systems. Nature Energy, 5(2), 150-159.

Rosales-Asensio, E., Icaza, D., González-Cobos, N., & Borge-Diez, D. (2023). Peak load reduction and resilience benefits through optimized dispatch, heating and cooling strategies in buildings with critical microgrids. Journal of Building Engineering, 68, 106096

Rothfusz, L. P., & Headquarters, N. S. R. (1990). The heat index equation (or, more than you ever wanted to know about heat index). Fort Worth, Texas: National Oceanic and Atmospheric Administration, National Weather Service, Office of Meteorology, 9023, 640.

Sheng, M., Reiner, M., Sun, K., & Hong, T. (2023). Assessing thermal resilience of an assisted living facility during heat waves and cold snaps with power outages. Building and Environment, 230, 110001.

Steadman, R. G. (1979). The assessment of sultriness. Part I: A temperature-humidity index based on human physiology and clothing science. Journal of Applied Meteorology and Climatology, 18(7), 861-873.

Tian, M. W., & Talebizadehsardari, P. (2021). Energy cost and efficiency analysis of building resilience against power outage by shared parking station for electric vehicles and demand response program. Energy, 215, 119058.

United Nations Environment Programme. (2021). A Practical Guide to Climate‐resilient Buildings & Communities.

Zeng, Zhaoyun, Kim, Ji-Hyun, Wang, Jiali, & Muehleisen, Ralph. Dynamically Downscaled Hourly Future Weather Data with 12-km Resolution Covering Most of North America. United States. https://dx.doi.org/10.25984/2202668

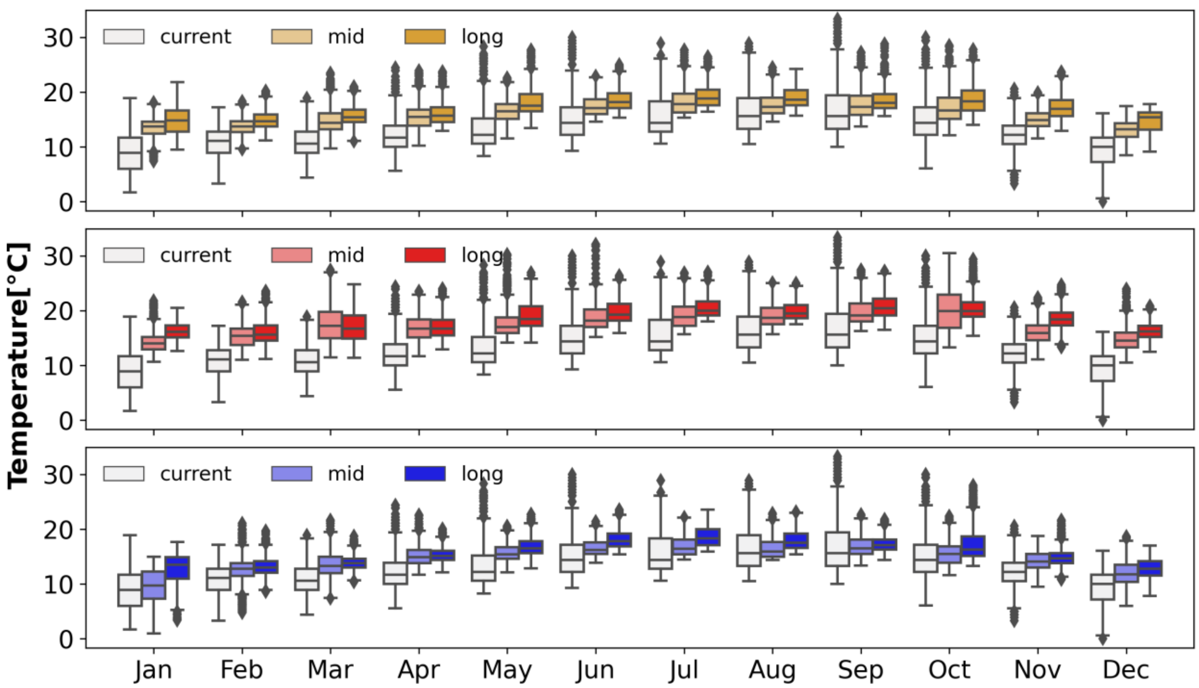

Figure 2 Future temperature distribution of TDY, EWY, ECY

Figure 4 Power outage duration, loss and affected people by year and factors

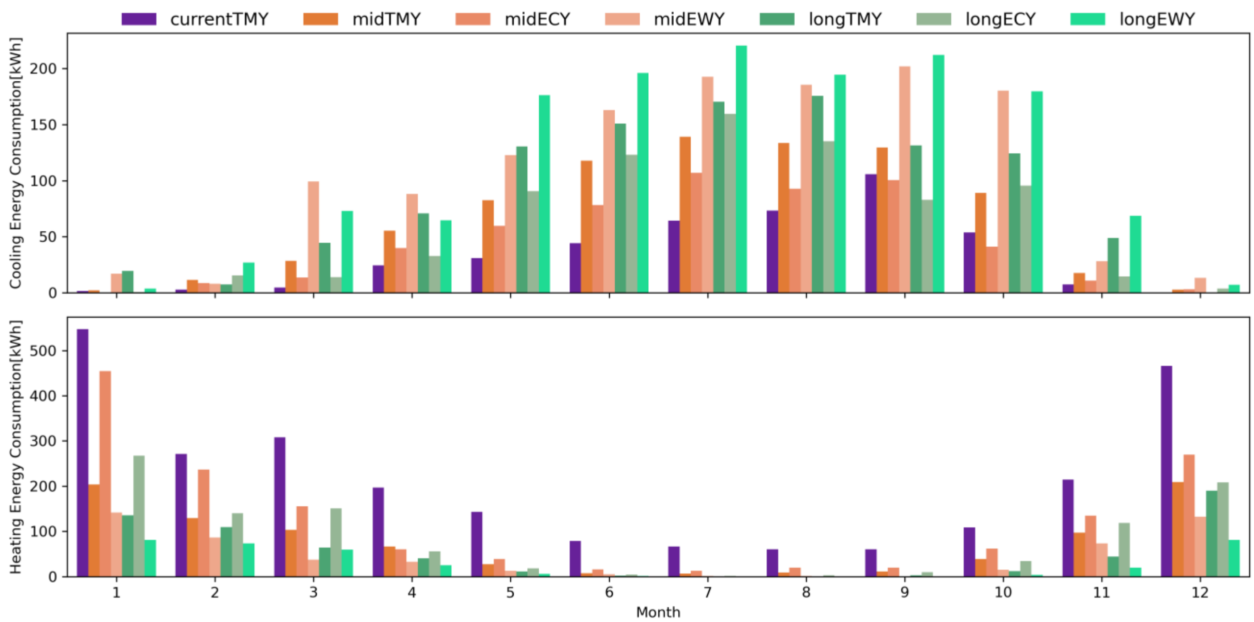

Figure 6 Building heating & cooling energy consumptions under different weather conditions

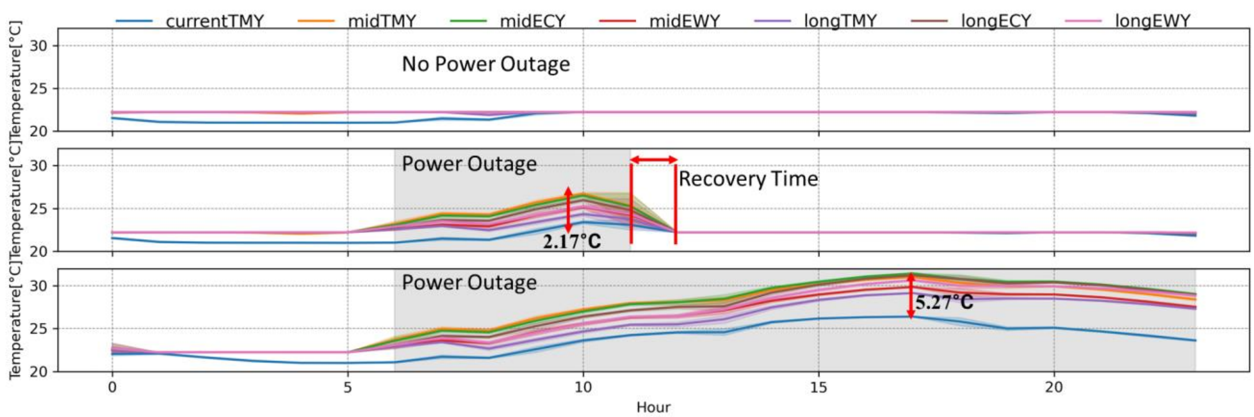

Figure 7 Space air temperature distribution under different weather conditions and power outage events