BERKELEY LAB

Lawrence Berkeley National Laboratory

Developing and Evaluating a Metric for Office Building Energy Resilience During a Power Outage

Lino Sanchez, Paul Mathew, Sang Hoon Lee, Travis Walter

Lawrence Berkeley National Laboratory, Berkeley

Energy Technologies Area
August, 2020

Disclaimer:

Acknowledgments:

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

Developing and Evaluating a Metric for Office Building Energy Resilience During a Power Outage

Lino Sanchez, Lawrence Berkeley National Laboratory
Paul Mathew, Lawrence Berkeley National Laboratory
Sang Hoon Lee, Lawrence Berkeley National Laboratory
Travis Walter, Lawrence Berkeley National Laboratory

ABSTRACT

There is growing interest in resilience among building owners, service providers, and policymakers. However, there is a lack of consensus on how resilience is measured, particularly energy resilience. This paper describes an effort to develop and test a metric for energy resilience. First, it presents a review of current trends and practices in resilience planning, focusing on which standards and metrics are currently being used across various sectors to assess energy resilience for buildings, and where inconsistencies and gaps exist. This study builds upon the literature by narrowing the scope and boundaries of resilience to focus specifically on thermal comfort resilience within an office building, and uses parametric building energy modeling to evaluate the feasibility of "occupancy hours lost" (OHL) as a resilience metric to measure human productivity lost during a power disruption. Using this data, a multiple regression model was developed to show which building improvements would have the most significant effect on decreasing OHL during a disruption, and thus allow resilience to be calculated for a building based on the specifications of these parameters. This study determined that OHL may be used as a key resilience metric for assessing how prepared an office building will be when faced with the possibility of a power outage, and further addresses the key assumptions that must be considered for a resilience metric to be calculated.

Introduction

As architects, engineers, designers, and scientists seek to address a changing climate and its impact on our environment, the topic of resilience has gained traction as a key priority to guide the planning, development, and maintenance of today's building stock, so that buildings will continue to support occupants during a disaster or energy disruption. What makes resilience unique is the breadth and range of goals, missions, and livelihoods it applies to, across a wide array of sectors and stakeholders, concerning the wellbeing of both people and the environment. However, resilience is a very broad and loosely defined concept, covering many different themes and topics.

Resilience, which translates to the ability for a system to swiftly resume functionality during a disruption, can apply to a wide range of issues concerning the built environment, ranging from energy resilience, ecological resilience, economic resilience, and psychological resilience, to social and community resilience. While these themes are certainly not mutually exclusive, a holistic pursuit of resilience for the built environment that addresses each of these needs simultaneously tends to be a complex endeavor that leads to ambiguity over what features and characteristics should define a resilient building and how the same resilience goals would apply to multitudes of building types and purposes. An issue with this holistic pursuit of resilience for the built environment, however, is that it tends to ignore the priorities of individual buildings, making investment in resilience measures less appealing for stakeholders, who may be more immediately interested in keeping their buildings functional than larger-picture resilience goals of climate change mitigation and social welfare, as are often the aims of many city-wide and regional resilience plans. Thus there is not only a need for resilience metrics for buildings, but metrics that are specifically catered to the needs of stakeholders in charge of operating buildings, whether their main priority be keeping people safe and comfortable during a disaster or maintaining the business operations of an office building during a power disruption. Acknowledging the significant emphasis on natural disaster resilience throughout the literature, this study seeks to focus on the needs of stakeholders who would benefit from resilience as a means of maintaining business operations for an office building. It is important to state at the outset that resilience has many dimensions, including the impacts of pandemics such as COVID-19. No one metric can capture all these dimensions. Rather, a suite of metrics are needed to measure resilience.

This paper presents an approach and initial results from an effort to develop and test a metric for the *energy resilience* of office buildings i.e. the ability of a building to continue to provide energy-related services during extreme events, such as a full or partial power outage, and extreme hot and cold weather, also known as "passive survivability" (Ozkan et al. 2018). Energy related services in an office building include thermal comfort, visual comfort, indoor air quality, and plug power. The paper is organized as follows: First we review the literature on resilience metrics, focusing on studies that directly address energy resilience in buildings or are closely related to it. Based on the literature review, we characterize gaps in the current state of the art and practice. We then propose a metric for energy resilience, with definitions and a methodology to compute it. Following that, we describe a pilot analysis wherein we test the application of the metric in a set of parametric simulations of office buildings. Finally we conclude with further research needs.

Literature Review of Resilience Metrics and Frameworks for Energy Resilience

Through reviewing the literature on resilience for the built environment, this study has found that while metrics for assessing the resilience of buildings have been proposed, there are currently no universally agreed upon metrics for assessing the resilience of buildings, with existing metrics belonging to various resilience measurement systems and frameworks with distinct scopes and criteria (Marjaba and Chidiac 2016). A significant theme of the literature surrounding resilience assessment for buildings is focused around the need for metrics and what methods may be used to develop and test them. A key challenge that has made it difficult to pinpoint specific concrete metrics for building resilience is the matter of how to address the broad and ambiguous nature of resilience as a concept, amidst the challenge of distinguishing it from seemingly related concepts, such as sustainability (Phillips et al. 2017). Others note the wide range of disciplines that resilience encompasses, including engineering, psychology, ecology, materials science, and beyond (Florin and Linkov 2016), with suggestions to focus only on certain aspects of a specific site (Carlson et al. 2012). These efforts however, particularly the pursuit of a single comprehensive resilience metric for buildings, are complicated by the need to balance resilience goals across multiple technical, environmental, economic, and social priorities, warranting a need for multiple metrics to be considered when evaluating the overall resilience of a site (Willis and Loa 2015).

Efforts to narrow the scope of resilience down to the individual building level to gain specificity, while a necessary preliminary step for measuring resilience, are met with a diverse array of quantitative and qualitative contextual factors that may further complicate the implementation of simple and clear metrics. Building resilience may simultaneously be subject to considerations of power grid stability (Bie et al. 2017), security, ecological integrity (Molyneux et al. 2016), natural disaster preparedness (Cutter, Burton, and Emrich 2010), comfort (Lomas and Giridharan 2012), business continuity (Petit et al. 2013), and beyond. Others present conceptual frameworks (Cerè, Rezgui, and Zhao 2017) as a method for assessing the resilience of buildings, by providing users with a logical and streamlined approach for categorically mapping out and organizing the relevant resilience priorities and data requirements that are needed for making informed decisions on measurement applications (Sharifi and Yamagata 2015), often taking the form of matrices (Roege et al. 2014), workflow charts (Petit et al. 2013), and decision trees (Bie et al. 2017).

Conceptual frameworks, offered throughout the resilience literature, are generally proposed as agnostic to any one resilience focus, but are widely adopted as the most appropriate means for assessing the resilience of buildings, despite being loosely grouped together with considerations for infrastructural resilience and energy resilience. For example, the Resilience Measurement Index (RMI) framework breaks down the pursuit of infrastructural and community/regional resilience into the categories of preparedness, mitigation measures, response capabilities, and recovery mechanisms, with associated action items assigned to each category, with specificity achieved by breaking these categories down into subcategories based on the resolution of data required (Petit et al. 2013). A similar framework proposed by Vugrin, Castillo, and Silva-Monroy (2017) builds upon the previously established Resilience Assessment Process (RAP) by providing guidelines to define context-specific electrical grid resilience metrics through organization into "consequence categories" that allow for disruptions to be evaluated by their unique impacts on critical functions, with evaluation of improvement determined by appropriate units of measurement, calculation processes, and relevant statistical properties (Vugrin, Castillo, and Silva-Monroy 2017). It is important to recognize that these frameworks ultimately provide a means to strategically approach and think through the process of resilience metric development and application for buildings, and do not necessarily themselves propose explicit metrics.

Additional epistemological considerations in the literature include: how to define baseline functionality (Cutter, Burton, and Emrich 2010), weighting of resilience criteria (Alshehri, Rezgui, and Li 2015), and defining the achievement of resilience as either binary or on a spectrum (Vugrin, Castillo, Silva-Monroy 2017).

A common concept used throughout the resilience literature to represent the quantification of resilience is the resilience curve, which demonstrates the performance of a desired function over time relative to a baseline, where resilience is defined as the area above this curve and underneath the baseline after a disruption event, with resilience increased by simultaneously diminishing damage severity and decreasing recovery time (Cimellaro, Reinhorn, and Bruneau 2010; Afrin and Yodo 2019; Florin and Linkov 2016; Kammouh et al. 2019; Ladipo et al. 2019). A vital component of the ubiquitous "resilience curve", performance baselines provide the necessary means to define acceptable levels of functionality for a system inflicted by a disruption and serve as a means to compare resilience measures, with different authors having developed unique methods for defining this baseline. Notably, Watson et al. (2015), use the RAP method to establish performance baselines based on resilience goals and associated evaluation metrics; Sharifi and Yamagata (2015) detail the basic approach of measuring resilience against an established performance baseline, additionally arguing that multiple baselines may be necessary for a comprehensive assessment of resilience (Sharifi and Yamagata 2015), where for the case of building resilience, baselines may even represent other buildings. Resilience may be measured as continuous (Vugrin, Castillo, Silva-Monroy 2017), or binary i.e. a system is either resilient or not resilient, which is an especially vital consideration when planning for energy availability (Department of Defense 2017).

While certain resilience metrics, such as power availability and system redundancy (McAllister 2013; Florin and Linkov 2016) may seem relatively direct and transparent, some higher-level metrics, such as "cost of recovery" and "average number (or percentage) of critical loads that experience an outage" (Vugrin, Castillo, Silva-Monroy 2017), may provide stakeholders with a more comprehensive "big picture" assessment of resilience. However, other factors that are more interdisciplinary and integrative - such as human comfort and operational continuity- may not best be supported by single units of measurement, necessitating a system of weighting to detail the degree of influence certain factors will have towards overall resilience. Key approaches to weighting have been demonstrated through the analytical hierarchy process (AHP) and Delphi method for consensus assessment, where individual weights are calculated for the influence of multiple interdisciplinary resilience-related dimensions (Alshehri, Rezgui, and Li 2015), as well as through the use of multicriteria decision making (MCDM) and "expert-based indirect approaches", where resilience is calculated through the summation of "relevance coefficients" to gain clarity on the influence of various resilience "indicators" (Cerè, Rezgui, and Zhao 2017). Similarly, the RMI framework uses "subject matter expertise" (SME) to base the weightings of various resilience factors on, with ultimate weightings for resilience calculation established through various stages of consensus-building for solicited resilience experts (Petit et al. 2013). To contrast, Cutter, Burton, and Emrich (2010) use spatial assessment and empirical ranking through expert judgement and proxies to derive "disaster resilience scores" for multiple resilience criteria, rather than unique weightings for resilience criteria, basing their approach on the idea that resilience criteria should be weighted equally and that disaster preparedness should ultimately be measured by a score for each criterion, since it would be easier to understand than an abstract weighting process (Cutter, Burton, and Emrich 2010). In the "Benchmark Resilience Score" presented by Stephenson et al. (2010), an evaluation of 0% resilient to 100% resilient provides stakeholders with a straightforward indication of whether the resilience of a community or organization is either "very poor", "poor", "fair", good" or "excellent" (Alshehri, Rezgui, and Li 2015).

There are several criteria-based resilience rating systems and certifications, such as LEED (USGBC 2019), RELi 2.0 (USGBC 2018), U.S. Resiliency Council Building Rating System (Mayes and Reis 2017), and BREEAM (Building Research Establishment Environmental Assessment Method) (Marjaba and Chidiac 2016), where resilience assessment generally falls between approaches of "performance-based" verification or "feature-based" verification (Burroughs 2017). Similar to these resilience criteria and rating systems, are the multiple forms of resilience scoring systems used throughout the field of disaster resilience, such as the "Disaster Resilience Scorecard for Cities" (UNDRR 2017), which offers a high-level assessment of resilience that packages the factors of climate, energy, social, and economic into a single score, using similar weighting methods discussed by Cutter, Burton, and Emrich (2010).

Attempts to quantify resilience at the building-scale remain generally abstract and sporadic across a wide range of frameworks and methodologies, often diverging from core building science first principles. These research gaps indicate a need for clear and tangible resilience metrics that are based on the performance of key building energy technologies, with simple and straightforward applications for building-level stakeholders.

Proposed Metric for Energy Resilience

Our goal was to define a metric that could be used by building industry stakeholders - investors, owners, operators - to evaluate and support decision-making around the energy resilience of buildings. Toward that end, the metric should be appropriately responsive to changes in building features that affect resilience i.e. it should reflect the impact of these features based on underlying building science principles. At the same time, the metric should be meaningful, transparent, and reasonably easy to use for stakeholders to support decision-making.

There are already well-established metrics and criteria for thermal comfort, visual comfort, and indoor air quality in buildings. There are also well-established methods to evaluate these metrics at a given point in space and time. There have also been some studies on aggregate measures, such as daylight autonomy, thermal autonomy, and ventilation autonomy of buildings (Ko et al. 2018). Building on these criteria, we sought to define a metric based on the extent to which building occupants are able to occupy and work in the building during an extreme event.

Using hours of occupancy as the unit of office building functionality, we defined a metric of "**occupancy hours lost**" (**OHL**) to measure functionality lost during an energy disruption, on the premise that for an office building, lost hours of employee occupancy will translate to lost economic output[1]. This simple metric of OHL frames the benefits of resilience efforts for office buildings in a way that is meaningful for stakeholders and shows impacts on business continuity, while also being a measure of climate change adaptation and environmental stewardship.

The OHL for a given building is an absolute measure of resilience. In order to compare it and benchmark it with other buildings, we propose a second complementary metric: "**occupancy hours lost ratio" (OHLR)**, defined as the ratio of the OHL to the total occupancy hours under normal operating conditions. Both OHL and OHLR can be specified for a given condition and a given time period, e.g. one week of power outage during an extreme heat event.

Since it is difficult to realistically model what would determine if a person would choose to stay and work in their office building, specifically during a heat wave and without access to air conditioning or during a cold winter day without heat, we have chosen to simplify this process by using thermal comfort as a proxy for occupancy, simply reasoning that if a person is comfortable, they will occupy the building, and if they are not comfortable, they will leave the building. Acknowledging that thermal comfort exists on a spectrum and will be different for different people, we further acknowledged the need to establish hard boundaries to delineate conditions for when it is either so hot or so cold that it would be unsafe for any human being.

Whereas resilience in the natural disaster context may focus on providing cooling centers during heat waves to keep people safe or emergency warming centers during winter periods, this does not necessarily consider the potential of this relief to support the continued productivity of buildings, specifically office buildings. To evaluate a realistic sense of thermal resilience, a distinction must be made between indoor thermal conditions that are not conducive to business

[1] We recognize that economic output is a complex function of several factors, and that occupant-hours is not equivalent to productivity. In this case, occupancy hours is simply a first order measure of resilience.

productivity and indoor thermal conditions that are life threatening. This leads to a consideration of both thermal habitability and thermal tolerance as criteria for thermal resilience, where thermal habitability dictates a fixed temperature point at which individuals will be at serious health risk, and thermal tolerability dictates a spectrum of uncomfortable temperatures that can be withstood, albeit still uncomfortable. **Thermal habitability** pertains to safety, whereas **thermal tolerability** pertains to comfort. While thermal habitability leads to a simple binary assessment, where indoor thermal conditions are either habitable or inhabitable, thermal tolerability is a function of time elapsed, where uncomfortable temperatures can be tolerated, but only for a certain amount of time, along with the additional complexity of different tolerance ranges for different individuals.

To define the intricacies that dictate how humans perceive and react to thermal conditions, both physiologically and psychologically, is an enormously complex endeavor that is outside the scope and boundaries of this study, and thus for simplicity, we base our assessment of thermal tolerance and thermal habitability on previously established criteria for ideal thermal conditions, specifically those detailed in the LEED v4 pilot credit for Passive Survivability (Wilson 2019). Livable conditions are defined here as standard effective temperature (SET) between 54 °F and 86 °F. Deviations from this livability range are limited to a certain number of degree-days (or degree-hours) during winter and summer conditions. For example, for non-residential buildings, a deviation above 86 °F SET is allowed, up to 18 °F SET degree-days (432 °F SET degree-hours) during a one-week period. This assumes a linear relationship between thermal stress and time endured. We also considered using a thermal stress damage function that nonlinear increase in heat and cold stress severity as temperatures rise or fall, based on a host of physiological and psychological data inputs that consider both how the body and mind perceive heat and cold. However, there is inadequate research that we could draw upon to develop such criteria.

Along with using the LEED Passive Survivability "livable conditions" range as our basis for thermal comfort to assess building occupancy during a power outage, thermal habitability limits are placed at 103 °F SET, based on the Heat Index threshold for dangerous heat conditions (National Weather Service), and 40 °F SET, based on best engineering judgement for dangerously cold conditions, using standard effective temperature (SET), rather than dry bulb temperature, to incorporate additional stress added by humidity. If temperature ever goes beyond either 103 °F SET or drops below 40 °F SET, thermal conditions will then be deemed as unsafe, and occupants will be required to leave the building due to lack of thermal habitability.

To calculate OHL, we first determine habitability. If indoor temperatures rise above 103 °F SET or fall below 40 °F SET, conditions are deemed uninhabitable and all occupancy for that hour and for the rest of the day will be lost, regardless of thermal tolerability. If the condition of thermal habitability is met, we next determine thermal tolerability. Thermal tolerability is calculated by summing the degree hours over 86 °F SET or under 54 °F SET that exceed the thermal tolerance allowance limit for each day over the course of a week, for each building zone, and for the whole building, with 432 degree-hours above 86 °F SET allowed for peak summer conditions and 216 degree-hours below 54 °F SET allowed for peak winter conditions. Thermal tolerance allowances for both peak summer and peak winter periods are divided evenly between each day of the week. Once the thermal tolerance allowance for a day is expended, additional hours above 86 °F SET or below 54 °F SET are deemed as intolerable, and all occupancy hours are lost. Thus OHL for each day is calculated by summing the number of occupants for each hour deemed as inhabitable and for all subsequent hours. If no hour is deemed inhabitable, OHL for each day is calculated by summing the number of occupants for each hour deemed intolerable after the daily tolerance allowance has been expended. OHLR is calculated by dividing weekly OHL for the building by the ideal weekly occupancy for the building, across all building zones.

Pilot Analysis

Objectives

To fit with the conditions of the LEED Resilient Design for Passive Survivability “safe” conditions set for a one-week period, the pilot analysis used in this study was based on a one-week long power outage, testing the thermal comfort of a building with no air conditioning and heating through conventional HVAC during the hottest week of the year and coldest week of the year, denoted in this study as the “hot” event and “cold” event. To slightly modify this however, this study divides the designated degree-hour tolerance allowance provided by the LEED pilot credit into daily allowances, based on the fundamental assumption that if a person experiences stress from extreme heat or cold, they will be recovered by the next work day, assuming that heat stress and cold stress will not carry over from day to day. Accordingly, degree hour tolerance limits are different for peak summer and peak winter conditions, with the hot event allowing for 432 degree hours deviation from 86 °F SET and the cold event allowing for 216 degree hours deviation from 54 °F SET. The specific disruption we use for this study is a power shut off for a medium sized office building, occurring at the first hour of a seven-day work week, considering reduced work hours for the weekend.

Parametric Simulation Analysis

We used energy simulation to assess the feasibility of OHL and OHLR to predict building occupancy as a metric for energy resilience based on the previously addressed conditions for thermal habitability and thermal tolerability. We modeled a medium office building for two vintages: the DOE post-1980 reference model (DOE n.d.) and the DOE ASHRAE 90.1-2007 prototype model (DOE 2018). We used an adaptation of these two models that included more detailed thermal zoning. We used models for two climate zones: Houston (ASHRAE-IECC zone 2A) and San Francisco (ASHRAE-IECC zone 3C). We simulated OHL for two events: power loss for seven days during the hottest and coldest week of the year. In total, we had eight scenarios i.e. combination of two vintages, two climate zones, and two events. We used EnergyPlus software for the simulations.

To assess the impact of various building components in contributing to office building energy resilience, a set of 500 parametric model runs were carried out for each scenario, with each simulation incorporating a set combination of resilience-related building components at varying levels of performance. Table 1 shows the range of values for each parameter. To keep data considerations simple, this study bases calculations for OHL on only two output values: hourly indoor SET by zone, and hourly indoor occupancy by zone, adding a spatial component to this pilot analysis to distinguish the varying levels of OHL across different building zones, acknowledging that while conference rooms and office spaces will experience the most significant OHL during extreme heat and cold, OHL for generally unoccupied zones will ultimately be insignificant, given the lack of employees present in these zones (e.g., storage, corridors, stairs, etc.).

Table 1. Parameter values

	Climate:	Houston				San Francisco			
Parameter	Unit	V1	V2	V3	V4	V1	V2	V3	V4
Window-to-wall ratio	-	0.2	0.3	0.4	0.5	0.2	0.3	0.4	0.5
Window glazing type	U-Value (W/m²-K)	5.8	4.6	3.5	3.3	5.8	4.1	3.2	2.8
Solar Heat Gain Coefficient (SHGC)	-	0.54	0.29	0.25	0.23	0.54	0.39	0.29	0.22
Exterior walls insulation (without film)	U-Value (W/m²-K)	1.29	0.85	0.7	0.51	1.26	0.7	0.51	0.47
Wall reflectance	-	0.22	0.3	0.5	0.7	0.22	0.3	0.5	0.7
Roof insulation	U-value (W/m²-K)	0.57	0.37	0.28	0.23	0.57	0.37	0.28	0.23
Roof reflectance	-	0.3	0.55	0.7	0.8	0.3	0.55	0.7	0.8
Occupant density	(ft²/person)	130	200	300	400	130	200	300	400
Plug load	(W/ft²)	1.25	1	0.75	0.5	1.25	1	0.75	0.5
Orientation	Degrees from north	0°	45°	90°		0°	45°	90°	

Variation in parameter values between simulation runs for Houston, TX and San Francisco, CA, where V: Value.

Table 2 shows the average OHL and OHLR values for each building scenario used in this study. Figure 1 shows the range of OHLR across all parametric simulations for selected scenarios. The hot events resulted in significantly higher OHL and OHLR values than for the cold events, with a wider range in temperatures observed in hot events for both Houston and San Francisco, as seen in Figure 1.

Table 2. Results for average OHL and OHLR

Vintage	Climate	Event	OHL	OHLR
Post-1980	2A	Hot	10259.51	0.76
Post-1980	2A	Cold	374.33	0.02
Post-1980	3C	Hot	4594.45	0.34
Post-1980	3C	Cold	417.54	0.03
2007	2A	Hot	9136.73	0.68
2007	2A	Cold	340.2	0.02
2007	3C	Hot	4151.96	0.31
2007	3C	Cold	826.01	0.05

OHL and OHLR values displayed for each building scenario, where 2A represents the climate for Houston, TX, averaged across 500 parametric simulations, with each combination of climate-vintage-event scenarios listed. 3C represents the climate for San Francisco, CA, based on weather file nomenclature.

a. **b.**

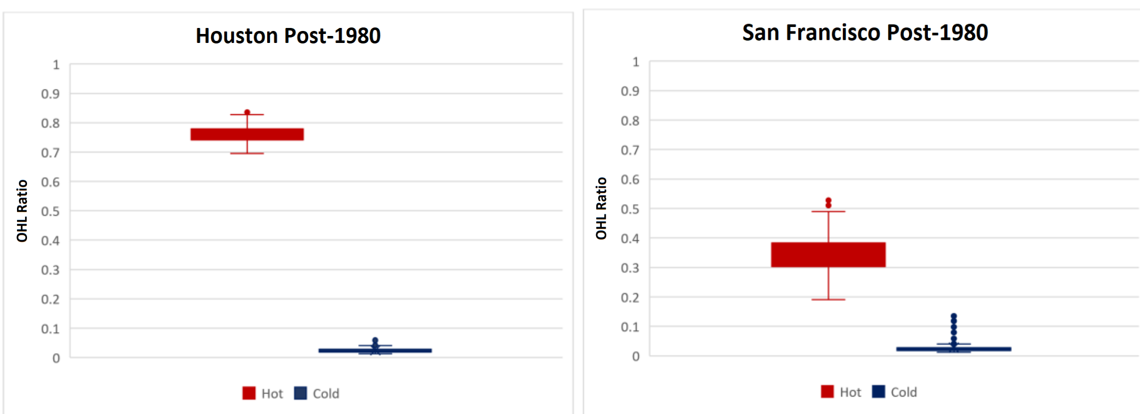
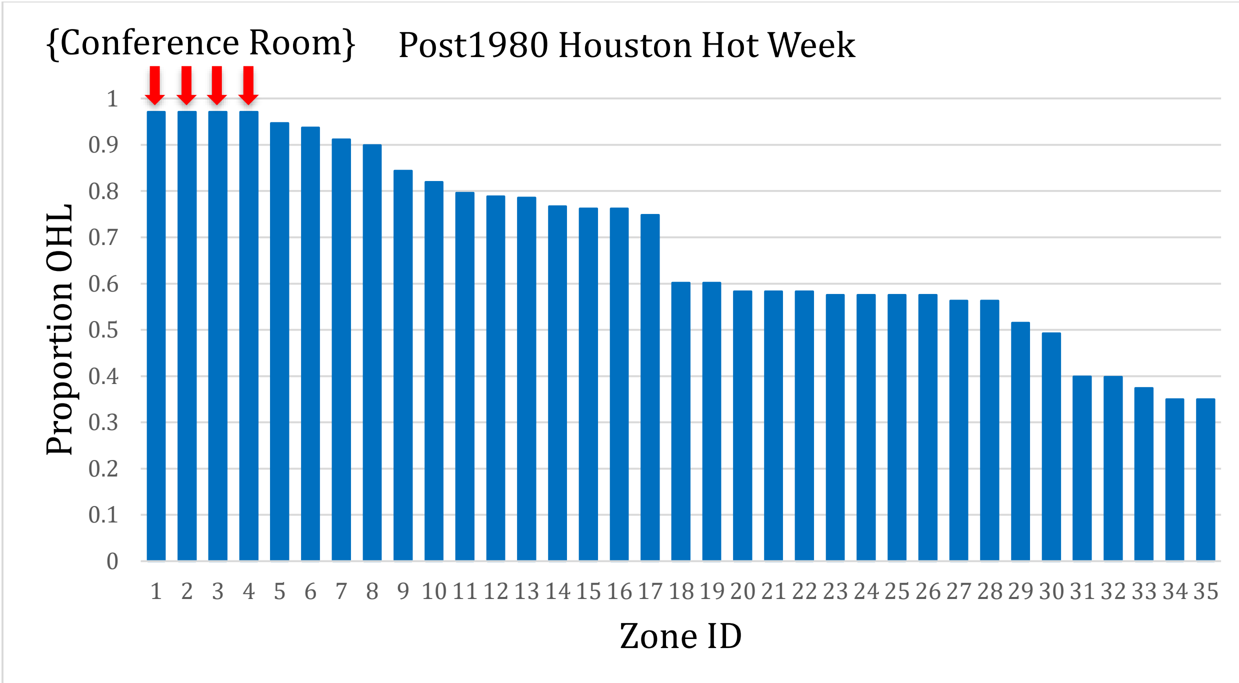


Figure 1. Median building OHLR for hot and cold events. **a.** Houston Post-1980 2A **b.** San Francisco Post-1980.

Calculations for OHL and OHLR revealed a significant variation in values between zones, as depicted in Figure 2. For Houston's hot week it was revealed that the zones most significantly contributing to OHLR were conference rooms (Zone ID: 1,2,3,4) and that the zones least contributing to OHLR were enclosed office spaces (Zone ID: 33,34,35). OHLR ranged from 0.35 to 0.95. For San Francisco's Hot week, the lobby area stood out as contributing the most significantly to OHLR for the whole building, with the enclosed office spaces, lounge, and open office spaces experiencing no occupancy loss.



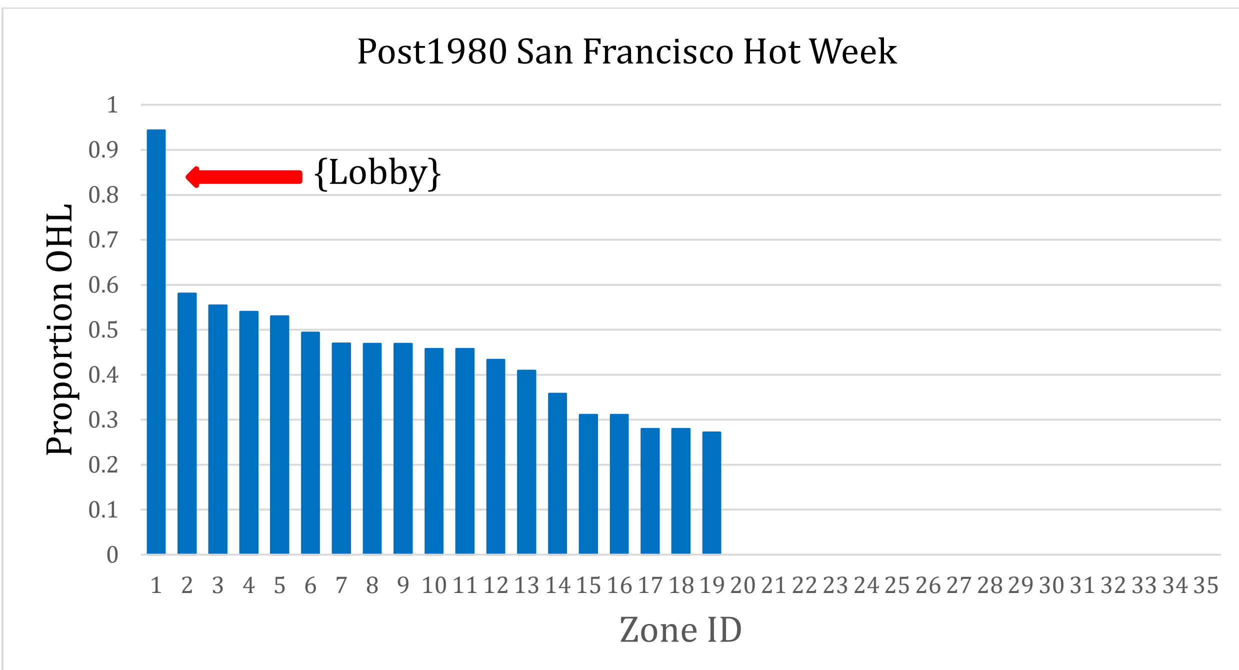


Figure 2. OHLR across 35 unique building zones for the hottest week. **top:** Post-1980 Houston **bottom:** Post-1980 San Francisco.

Simplified Predictive Models Through Regression Analysis

While OHL can be computed via simulation as shown above, most stakeholders are unlikely to have available on-hand the necessary data sources for comprehensive energy resilience modeling, or the wherewithal to conduct such detailed analyses. For wide scale adoption and use of a metric such as OHLR it is vital to have available simple user-friendly methods for assessing energy resilience for buildings that require simple data inputs.

Supporting this goal for simple predictive models for office building energy resilience, we explored an energy resilience regression model as a means for building stakeholders to evaluate the resilience of their buildings, requiring only the simple inputs of known building component performance measures, such as R-value for insulation and U-value for windows. We ran multi-variate linear regressions on the set of 500 parametric simulations for each scenario, with OHLR as the dependent variable, and the building parameters as the independent variables, yielding an equation of the form:

$$OHLR = k + c_1p_1 + c_2p_2 + c_3p_3 + c_4p_4 + \ldots + c_np_n + \varepsilon_i \qquad \text{(eq.1)}$$

where:

OHLR: Occupancy Hours Lost Ratio
k: y-intercept
c: coefficient
p: parameter
p_1: Window-to-wall ratio
p_2: Window glazing type - U-Factor (W/m^2-K)
p_3: Glazing type (SHGC)
p_4: Exterior walls insulation without film (U-Value)
p_5: Wall reflectance/emittance
p_6: Roof insulation - (U value)
p_7: Roof reflectance
p_8: Occupancy density (ft^2/person)
p_9: Electric plug and process (W/ft^2)
p_{10}: Orientation (0°-90°)
ε_i: Random error

The regression coefficients can give stakeholders a realistic and practical assessment of which building components will contribute most significantly to improving a building's energy resilience. If a stakeholder can find the values of the listed key building components detailed in this model, they can simply enter these values into the regression model and produce a relatively realistic assessment of energy resilience for their building, based on OHLR. This of course is based on the assumption that other buildings characteristics will more-or-less match those of the DOE reference and prototype models used in this study. The results would be less valid for buildings that deviate more from these assumptions, and a broader set of building models would be needed to cover a wider range of buildings, using the same approach.

The results for each scenario revealed the majority of coefficients to be extremely significant in their contribution to building energy resilience, with exceptions seen for window glazing, roof insulation, and roof reflectance, as displayed in Table 3. Adjusted R squared values for each scenario were generally high, with the exceptions of Post1980-cold and 2007-cold for Houston, and Post1980-cold for San Francisco, noting an important pattern in model fits for cold scenarios being the poorest. It was revealed that SHGC, wall reflectance, occupant density, and plug load density were all extremely significant across all scenarios, noting the negligible coefficient values for occupant density. For Post1980-cold for both climates, it was revealed that roof insulation and roof reflectance did not have a significant influence on OHLR, with another commonality shown between 2007-cold for both climates, where roof reflectance as well did not have a significant influence on OHLR.

Certain parameters saw coefficients switch between positive and negative values when the climate was switched, such as for exterior walls insulation for 2007–hot. As well, coefficients for roof insulation for Post1980-hot switched from positive to negative when switched from climate 2A to climate 3C. Coefficients for occupant density and orientation were consistently negligible, noting that for 2A 2007-hot the coefficient for orientation was not significant. While not all variations revealed clear patterns, it was evident that coefficients for certain parameters were heavily influenced by the event (hot/cold), such as for the SHGC coefficient that increased from the cold event to the hot event, and the coefficient for wall reflectance that decreased from the cold event to the hot event.

Table 3. Regression results for each scenario and significance

a.

Climate	Houston, TX (2A)							
	Post1980 Cold		Post1980 Hot		2007 Cold		2007 Hot	
Parameter	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Window-to-wall ratio			0.108	***	-0.006	**	0.219	***
Window glazing type	-0.001	***	0.006	***				
Solar Heat Gain Coefficient (SHGC)	0.034	***	0.123	***	0.054	***	0.2	***
Exterior walls insulation (without film)	-0.006	***	0.005	**	-0.005	***	0.013	***
Wall reflectance	-0.007	***	-0.019	***	-0.007	***	-0.034	***
Roof insulation			0.012	***			0.02	***
Roof reflectance			-0.015	***			-0.021	***
Occupant density	0.000	***	0.000	***	0.000	***	0.000	***
Plug and process load density	0.021	***	0.061	***	0.011	***	0.07	***
Orientation	0.000	***	0.000	***	0.000	***		
Adj. R Squared	0.674		0.898		0.653		0.949	

b.

Climate	San Francisco, CA (3C)							
	Post1980 Cold		Post1980 Hot		2007 Cold		2007 Hot	
Parameter	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Window-to-wall ratio	0.058	***	0.129	***	0.062	***	0.094	***
Window glazing type			-0.002	**	-0.005	***	-0.004	***
Solar Heat Gain Coefficient (SHGC)	0.105	***	0.349	***	0.254	***	0.349	***
Exterior walls insulation (without film)	-0.004	*	-0.022	***	-0.02	***	-0.027	***
Wall reflectance	-0.019	***	-0.057	***	-0.036	***	-0.056	***
Roof insulation			-0.021	***	-0.017	*		
Roof reflectance			-0.04	***			-0.061	***
Occupant density	0.000	***	0.000	***	0.000	***	0.000	***
Plug load density	0.013	***	0.103	***	0.034	***	0.092	***
Orientation	0.000	***	0.000	***	0.000	***	0.000	***
Adj. R Squared	0.553		0.931		0.776		0.908	

Regression results for each building parameter presented as coefficients and corresponding significance, where *** denotes a p-value of less than or equal to 0.001, ** denotes a p-value of less than or equal to 0.01, and * denotes a p-value of less than or equal to 0.05. **a.** Results for Houston, TX scenarios. **b.** Results for San Francisco, CA scenarios. Blank spaces indicate coefficients that were not significant.

With the parameter coefficients detailed in Table 3, building stakeholders could easily produce a coarse estimate of OHL or OHLR for each location, weather event, and building type by inserting the above coefficients into equation 1.

Conclusions and Next Steps

This study aimed to demonstrate the potential of occupancy hours lost (OHL) as a simple metric to measure energy resilience for office buildings using simulation to evaluate resilience across multiple building configurations and regression to analyze the influence of individual building parameters on building occupancy. A parametric energy simulation analysis of a medium sized office building shows some clear patterns displayed between hot and cold events between Houston, TX and San Francisco, CA for two vintages. As expected, OHL varies widely between vintages, climates, and weather events, from as low as 10% to as high as 90%. A multivariate regression analysis of the simulation results yielded very good model fits and showed that the majority of parameters analyzed were statistically significant. This linear model provides a means for building stakeholders to predict resilience by generating a coarse estimate of OHL with fairly limited building data. Additionally, distribution of OHL across building zones revealed substantial variation in energy resilience between zones, allowing stakeholders to improve whole building energy resilience by prioritizing certain zones over others.

While providing the benefit of simplicity, basing energy resilience for office buildings on temperature ranges and limits alone ultimately ignores the consideration of key resilience aspects that affect the productivity of office building employees beyond thermal comfort. We are currently working on incorporating both air quality and daylight autonomy into predictive models for calculating building occupancy to depict a much more holistic view of energy resilience, where stakeholders acknowledge the need for employees to have clean air and adequate indoor lighting when there is no power to run mechanical ventilation systems and keep the lights on, using indicators such as CO_2 concentration and illuminance respectively. We are also expanding our analysis to a more diverse range of climates, including the need for colder climates with severe winters to be represented, such as Chicago.

Additional parameters and considerations of occupant comfort that stretch beyond thermal conditions will allow for a more accurate and holistic assessment of energy resilience. Ultimately, the value of OHL as a resilience metric for office buildings must be evaluated and determined by building stakeholders, and thus further research is needed to empirically validate OHL as an effective metric to support stakeholder decision-making.

Additionally, given the clear impact COVID-19 will have on office building productivity, we acknowledge that resilience for the built environment will largely take on new meaning going forward, and we accordingly recommend that future research on built environment resilience address pandemic preparedness, specifically considering the role of improved ventilation in slowing the spread of virus through buildings, and as well considering scenarios where outbreaks may lead building managers to require certain employees work remotely from home.

References

Afrin, T. and N. Yodo. 2019. "Resilience-based recovery assessments of networked infrastructure systems under localized attacks." *Infrastructures* 4.1: 11.

Alshehri, S.A., Y. Rezgui, and H. Li. 2015. "Disaster community resilience assessment method: a consensus-based Delphi and AHP approach." *Natural Hazards* 78.1: 395-416.

Bie, Z., Y. Lin, G. Li and F. Li. 2017. "Battling the extreme: A study on the power system resilience." *Proceedings of the IEEE* 105.7 (2017): 1253-1266.

Blackwelder, A. 2019. "Revised LEED Resilient Design pilot credits now available." U.S. Green Building Council (USGBC).

Burroughs, S. 2017. "Development of a tool for assessing commercial building resilience." *Procedia Engineering. Elsevier BV* 180: 1034-1043.

Carlson, J.L., G. Bassett, W. Buehring, M. Collins, S. Folga, B. Haffenden, F. Petit, J. Phillips, D. Verner, and R. Whitfield. 2012. "Resilience: Theory and Applications." No. ANL/DIS-12-1. Argonne National Lab.(ANL), Argonne, IL (United States).

Cerè, Giulia, Yacine Rezgui, and Wanqing Zhao. 2017. "Critical review of existing built environment resilience frameworks: directions for future research." *International journal of disaster risk reduction* 25: 173-189.

Cimellaro, G., A.M. Reinhorn, and M. Bruneau. 2010. "Framework for analytical quantification of disaster resilience." *Engineering structures* 32.11: 3639-3649.

Cutter, S.L., C.G. Burton, and C.T. Emrich. 2010. "Disaster resilience indicators for benchmarking baseline conditions." *Journal of homeland security and emergency management* 7.1.

Department of Energy (DOE). 2018. "Commercial Prototype Building Models." Building Energy Codes Program. www.energycodes.gov/development/commercial/prototype_models

Department of Energy (DOE). n.d. "Commercial Reference Buildings." Accessed March 23, 2020. www.energy.gov/eere/buildings/commercial-reference-buildings

United Nations Office for Disaster Risk Reduction (UNDRR). 2017. "Disaster Resilience Scorecard for Cities: Detailed level assessment."

Florin, M.V., and I. Linkov. 2016. "IRGC resource guide on resilience." EPFL International Risk Governance Center (IRGC).

Kammouh, O., A. Noori, G. Cimellaro, S. Mahin. 2019. "Resilience assessment of urban communities." *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 5.1: 04019002.

Ko, W H, S. Schiavon, G. Brager, B. Levitt. 2018. "Ventilation, thermal and luminous autonomy metrics for an integrated design process." *Building and Environment* 145: 153-165.

Ladipo, O., G. Reichard, A. McCoy, A. Pearce, P. Knox, M. Flint. 2019. "Attributes and metrics for comparative quantification of disaster resilience across diverse performance mandates and standards of building." *Journal of Building Engineering* 21: 446-454.

Lomas, K.J., and R. Giridharan. 2012. "Thermal comfort standards, measured internal temperatures and thermal resilience to climate change of free-running buildings: A case-study of hospital wards." *Building and Environment* 55: 57-72.

Marjaba, G.E., and S.E. Chidiac. 2016. "Sustainability and resiliency metrics for buildings–Critical review." Building and environment 101: 116-125.

Mayes, R.L., and E. Reis. 2017. "Community resilience and the US Resiliency Council's Building Rating System." Prepared for 2017 NZSEE Conference.

McAllister, Therese P. 2013. "Developing Guidelines and Standards for Disaster Resilience of the Built Environment: A Research Needs Assessment." Gaithersburg, MD: US Department of Commerce, National Institute of Standards and Technology. *(NIST TN 1795)*. No. Technical Note (NIST TN)-1795.

Molyneaux, L., C. Brown, L. Wagner, and J. Foster. 2016. "Measuring resilience in energy systems: Insights from a range of disciplines." *Renewable and Sustainable Energy Reviews* 59: 1068-1079.

National Weather Service. "What is the heat index?" National Oceanic and Atmospheric Administration. Accessed March 23, 2020. www.weather.gov/ama/heatindex.

Ozkan, A., T. Kesik, A. Zerrin, A.Z. Yilmaz, and W. O'Brien. 2018. "Development and visualization of time-based building energy performance metrics." *Building Research & Information*, 47:5, 493-517.

Petit, F.D., G.W. Bassett, R. Black, W.A. Buehring, M.J. Collins, D.C. Dickinson, R.E. Fisher, R.A. Haffenden, A.A. Huttenga, M.S. Klett, J.A. Phillips, M. Thomas, S.N. Veselka, K.E. Wallace, R.G. Whitfield, and J.P. Peerenboom. 2013. "Resilience measurement index: An indicator of critical infrastructure resilience." No. ANL/DIS-13-01. Decision and Information Sciences Division. Argonne National Lab.(ANL), Argonne, IL (United States).

Phillips, R., L. Troup, D. Fannon, M.J. Eckelman. 2017. "Do resilient and sustainable design strategies conflict in commercial buildings? A critical analysis of existing resilient building frameworks and their sustainability implications." Energy and Buildings 146: 295-311.

Roege, P.E., Z.A. Collier, J. Mancillas, J.A. McDonagh, I. Linkov. 2014. "Metrics for energy resilience." *Energy Policy* 72: 249-256.

Sharifi, A., and Y. Yamagata. 2015. "A conceptual framework for assessment of urban energy resilience." *Energy Procedia* 75: 2904-2909.

U.S. Department of Defense. 2018. "Annual Energy Management and Resilience Report (AEMRR): Fiscal Year 2017." Office of the Assistant Secretary of Defense for Energy, Installations, and Environment. Department of Defense.

U.S. Green Building Council (USGBC). 2018. "RELi 2.0 Rating Guidelines for Resilient Design + Construction."

Vugrin, E., A. Castillo, and C. Silva-Monroy. 2017. "Resilience metrics for the electric power system: A performance-based approach." *Report: SAND2017-1493*.

Wilson, A. 2019. "Passive Survivability: Keeping Occupants Safe in an Age of Disruptions." Resilient Design Institute.

Watson, J.P., R. Guttromson, C. Silva-Monroy, R. Jeffers, K. Jones, J. Ellison, C. Rath, J. Gearhart, D. Jones, T. Corbet, C. Hanley, L.T. Walker. 2014. "Conceptual framework for developing resilience metrics for the electricity oil and gas sectors in the United States." *Sandia national laboratories, albuquerque, nm (united states), tech. rep*.

Willis, H.H., and K. Loa. 2015. "Measuring the resilience of energy distribution systems." RAND Corporation: Santa Monica, CA, USA.