Thermal Resilience During Prolonged Cooling Outages: A Multi-Zone Field Study of Disruption and Recovery in Arizona Apartments

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Abstract

Increasing frequency and severity of extreme heat events, and growing dependence on air-conditioning systems emphasize the need to evaluate thermal resiliency of buildings during cooling outages. Existing assessments often emphasize isolated metrics or steady state conditions and may not adequately characterize cumulative thermal exposure, thermal buffering, and post outage recovery. This study evaluated high-resolution, multi-zone field measured data from two apartments in Arizona during cooling outages lasting up to 78 hours and subsequent recovery once cooling was restored. Cumulative thermal exposure was quantified using continuous degree-hours above 82°F, and delay component by time required to reach 85°F. Results showed that, immediately after the cooling outage, all the zones exhibited exponential behavior in temperature rise rate followed by harmonic model with a linear drift after the transient hour. Transient hours are determined to be 17 hours and 21.5 hours for 1-bedroom and 2-bedroom apartment respectively. The exponential model exhibited strong capability across all zones in both apartments with R^2 values ranging from 0.8943 to 0.9833. The sinusoidal regression model exhibited strong capability across monitored zones with R^2 values ranging from 0.656 to 0.975. Significant spatial variability was observed between zones and within zones. At the apartment level, the sinusoidal model produced R^2 of 0.879 0.893, RMSE 0f 0.56°F and 0.44°F, and MAE of 0.48°F and 0.32°F for 1-bedroom and 2-bedroom apartment respectively. Both the apartments crossed 90°F threshold in at least one zone. 1-bedroom apartment accumulated more degree hours and recovered slightly slower than 2-bedroom apartment. Recovery scores are comparatively uniform across zones. Sensitivity analysis showed that weightage assigned in three different metrics didn't change the ranking among zones and were low to moderately sensitive. The findings demonstrate that apartment average metrics can conceal important zone level vulnerability. The proposed indices should be considered exploratory and require further validation.

Keywords: Thermal Resiliency of Buildings, Extreme Heat, Heat Stress, Indoor Heat Exposure, Passive Survivability

1. Introduction

Global warming and climate change has led to a significant increase in the frequency, intensity, and duration of extreme weather events [1]. Heat stress is already a major environmental health hazard placing millions of people around the world at heightened risk, and disproportionately affecting urban populations, due to a combination of rising global temperatures, the urban heat island (UHI) effect, and social vulnerabilities [2]. This research focuses on the impact of extreme heat related events on building thermal resiliency during cooling outages.

Overheating poses an escalating threat to human health and productivity [3], and it is also among the leading causes of weather-related mortality in the US and globally [4]. In the absence of HVAC system, people are left vulnerable, especially during heat waves. Thus, thermal resiliency of buildings needs to be incorporated during building design and construction phase to maintain suitable indoor thermal environment during extreme weather events and AC or AC outage.

Thermal resiliency is increasingly becoming an important factor for building because of climate change [5]. Thermal autonomy, passive habitability and fire resistance are the main aspects of thermal resiliency. Thermal autonomy refers to the fraction of time that a building maintains comfortable indoor conditions without inputs from active systems. The metric for thermal autonomy is based on comfort conditions defined as a range of operative indoor temperatures between 18°C and 25°C (64°F and 77°F). The higher the thermal autonomy, the more the passive enclosure system contributes to managing acceptable indoor conditions, and the less reliance on active system inputs to achieve thermal comfort. Recent research indicates the greater the thermal autonomy, the smaller the peak and annual energy demands for active space heating and cooling. [6].

Although thermal resilience has attracted attention in industry and academia, there is still a lack of standardized methodologies for assessment, especially for policies, protocols and procedure development. There is growing interest in research community in exploring thermal resilience for scenarios of power disruption in extreme climates, but they are still limited. The existing research literature on building thermal resiliency is heavily derived from building energy modeling and simulation [5] [7] [8] [9] [10] [11] [12]. The prototype building energy models may not reflect actual building parameters and actual construction scenario [5]. Most of them lack field measured data from actual buildings to validate the results. The actual building construction can be different than designed and its performance deteriorate over time [6]. Based on the review of the existing literature, it can be implied that very limited studies have performed measurement and verification (M&V) to collect real-world data from actual built environment to evaluate and validate building thermal resiliency. Also, current studies rely on average zone readings and do not capture spatial thermal gradients within zones to assess thermal resiliency of buildings.

Although some guidelines like the LEED BD+C v4.1 have thresholds of livable indoor temperature, building codes and standards do not state any mandatory requirements for minimal or maximal indoor temperature and do not have clear, systematic thermal resilience metrics [7]. Metrics measuring the intensity of events is useful to portray the worst thermal condition, whereas time integrated metrics like degree days/degree-hours are useful to understand thermal resilience. Based on the literature review, majority of the studies use either time-based metrics such as thermal autonomy and passive habitability or threshold-based metric like peak temperature after failure. However, a unified framework that integrates both the onset and severity of indoor thermal stress using high resolution, room-level measured data remains limited in the literature [6] [7] [13].

Resiliency refers to how well a building copes with disruptive events and how quickly it recovers [14]. Most of the existing studies evaluate thermal resiliency during disruptive events [15], and building designers are still seeking metrics that can capture thermal resilience during disruptive as well as recovery phase [16]. Moreover, there are multiple metrics used to evaluate thermal resilience of buildings. However, they usually do not capture zone level spatial data [5].

This research aims to fill these gaps using high-resolution, room-level data before and after AC disruption events in 2 apartments in hot arid climate. The main aim of this paper is to evaluate thermal response profile and determine resiliency of apartment units in hot arid climate during AC outage in peak summer months. This study breaks thermal response profile into transient and harmonic phase models. The change from transient to harmonic phase occurs in the transient hour, which is determined in this study for both apartments. In addition, it is the aim of the study to evaluate spatial heterogeneity among different zones and compare that with apartment average metrics.

As an exploratory study, this study attempts to combine disruptive phase resilience and recovery phase resilience into a single composite index. Furthermore, zone level metrics and coefficients are combined to derive apartment level models and metric. Finally, this study aims to conduct sensitivity analysis and goodness of fit to test the impact of weights assigned, aggregation method and the models developed.

2. Literature Review

Indoor Heat Exposure and its Impact

Building components degrade over time, and buildings built before 1970 still account for the significant proportion of housing stock in US [17]. In the US, most children and adults spend over 80% of their time indoors, while elderly and very young population can spend over 90% of their time indoors. Unlike outdoor weather conditions, indoor thermal conditions are not routinely monitored or reported, and direct personal exposure to heat stress is rarely measured [18].

Extreme hot and cold weather events are becoming more frequent, intense, and longer due to climate change [19] which may lead to indoor overheating [20]. When these events coincide with AC outages, the resulting extreme indoor temperatures pose a severe health hazard for occupants [7]. Because of increased frequency and intensity of extreme weather events and their growing widespread impacts on infrastructure, human health and economics, thermal resilience in buildings has gained a lot of attention in recent years among scientific community [14].

In 2017, a Florida nursing home experienced a three-day loss of main air conditioning because of the power system failure during Hurricane Irma, which led to 12 patient deaths due to the excess indoor temperature [7]. In July,2023 Phoenix, Arizona experienced peak temperature and relative humidity of 116°F and 10.46% respectively [19]. The city recorded 31 consecutive days over 110 °F in 2023 causing record number of heat-related deaths [21].

Heat waves are occurring even in historically mild climatic locations like San Francisco. In September 2017, San Francisco which historically observes mild climate, experienced heat waves for 3 days and the outdoor heat index (HI) reached above 37.8°C, which falls into the extreme caution zone. Indicating heat cramps and heat exhaustion are possible for occupants, and continuing activity could result in heat stroke.

Chima et al. [20] performed critical review of existing literature on indoor heat stress events in US and its effect on indoor thermal comfort. The study found out that among the 20 largest metropolitan areas in US, buildings exceeded overheating threshold by 5 to 7 hours on average. Also, among 145 low-income households in Maryland, there was large variation in indoor temperatures, with daily mean indoor temperatures varying from 10 degrees Celsius lower to 10 degrees Celsius higher than outdoor temperatures. Wright et al. studied effect of social and behavioral factors in indoor thermal environments of 46 air-conditioned residencies in the hot, semi-arid city of Phoenix, Arizona. The study found out that the indoor air temperature of centrally air-conditioned homes is heterogenous, and the resource-constrained households may sacrifice more to keep their home comfortable [22].

Brian et al. [8] examined the impact of prolonged blackout on heat exposure in residential structures during heat wave conditions. The study simulated standard prototype building energy models for different types of single and multi-family residential structures across Phoenix, Arizona using weather data from heat wave events of July 18 through 25,2006. The study found out that there is significant variability among building types-multistory houses and apartment buildings are found to be as much as 5-7 degrees Celsius cooler than single-story structures during daylight hours, while temperature in single story building equaling or falling slightly below multi-story structure during the night. Loss of electricity during heat wave was found to increase building interior temperatures by more than 15 degrees Celsius across all building types relative to thermostat setpoint of 24 degrees Celsius. Indoor temperatures during nighttime were found to be around 8.5 degrees to 9 degrees Celsius warmer than thermostat setpoint. In addition, the study found out that the heat wave was maximized around the central business district which has relatively lower elevation than north phoenix and has a greater rate of development, which points to the fact that urban heat island affects indoor thermal environment as well as regional resources and sustainability.

Impact of Heat Stress

The thermal regulation system used by human body to maintain the same internal core temperature of 98.6°F (37°C) is called homeothermy [5] [18]. When the core temperature reaches 38 degrees Celsius, the capacity for physical work diminishes, mental activity is impaired and accident risk increases. When the core temperature reaches 39 degrees, heat exhaustion and heat stroke are possible. A core temperature of 40.6 degrees becomes life threating [18].

Severe heat stress can adversely impact basic body functions such as respiration, circulation, mobility, immune response, kidney function and cognition [18] [19] [9]. It is estimated that the increased frequency of heat waves may cause heat wave deaths in the Eastern U.S. to increase 10-fold by 2057–2059, with a projection of between 1400 and 3600 deaths per year by 2058 [20].

Socioeconomic Factors, Vulnerable and Marginalized Population

Extreme temperatures increase the risk of overheating or overcooling in buildings, especially for those without HVAC system, or facing power outages during extreme weather [13]. Therefore, evaluation of thermal resiliency and mitigation approaches need to comprehend the socioeconomic factors as well as vulnerable and marginalized populations also need to be considered separately. Vulnerable population such as low-income and marginalized households [20], elderly populations as well as young children, pregnant women, and people with underlying medical conditions are more subject to adverse health impacts of heat risks [7]. Housing characteristics such as lack of air conditioning, poor insulation, and top floors of apartment buildings have also been associated with higher risks [18].

The report published by Maricopa County department of public health in 2025 shows that there is a growing trend in heat stress related deaths in Maricopa County, Arizona among homelessness people as well as those with homes [23]. The report pointed out that there were 138 indoor heat related deaths in 2024, out of which 11% of these population didn't have AC at home, 88% occurred in homes with air conditioning (AC) unit, but AC units were not functioning in 70% of these homes with AC. Also, 25% of indoor heat-related deaths occurred in RV/trailer or mobile homes, however only 5% of the housing in Maricopa County are RV/trailer or mobile homes. The report also points out that approximately 25% of heat related deaths occurred in people with underlying health issues. Cardiopulmonary disease had the highest risk of heat related illness, which accounted for 45% of the heat related deaths, followed by diabetes (9%).

Thermal Comfort Models

There are multiple mathematical thermal comfort models developed to quantify and predict thermal comfort levels under different indoor environmental conditions [20]. Among them, the most important models are Fanger's comfort model (predicted mean vote (PMV) and predicted percentage dissatisfied (PPD)), adaptive model [20], and the two-node model [24].

J. Van Hoof et al. [25] discussed the strengths and weaknesses of the predicted mean vote (PMV) model developed by P.O. Fanger in 1967. The study pointed out that thermal neutrality is not necessarily the ideal thermal condition as preferences for non-neutral thermal sensations are common. At the same time, very low and very high PMV values do not necessarily reflect discomfort for a substantial number of people. The PMV model is holistic, but it requires a vast amount of accurate data and standardizes individual comfort, overlooking personal and cultural variations, while PPD model offers numerical assessment of how many people are feeling discomfort, but doesn't clarify the severity of discomfort [20].

The Pierce Two-Node model thermally lumps the human body as two isothermal, concentric compartments, one representing the internal section or core (where all the metabolic heat is assumed to be generated and the skin comprising the other compartment). This allows the passive heat conduction from the core compartment to the skin to be accounted for. It is based on the standard effective temperature (SET) and effective temperature (ET). SET is the dry-bulb temperature of a hypothetical environment at 50% relative humidity for subjects wearing clothing that would be standard for the given activity in the real environment. ET is the dry-bulb temperature of a hypothetical environment at 50% relative humidity and uniform temperature where the subjects would experience the same physiological strain as in the real environment [25].

PMV model assumes transient conditions and is suitable for healthy young adults. The two-node model is more physics based and complex and lacks behavioral adaptation. It is suitable for both transient as well as non-uniform environments [25].The PMV/PPD model exhibits effective performance in air-conditioned environment, but they tend to overestimate discomfort while adaptive model is shown to improve energy efficiency in buildings while also increasing occupant comfort [20].

Thermal Resiliency Metrics

The most used metrics in existing research to assess thermal resilience in buildings are based either on some threshold above or below which the building is penalized (e.g., passive habitability or overheating limit), or fraction of time that the building is comfortable (e.g., thermal autonomy) [26].Thermal autonomy is a measure of the fraction of time during a year that a building can passively maintain comfort conditions without active system, while passive habitability is the duration of time that an indoor space remains habitable following a prolonged power outage over an extended period of extreme weather. For measuring thermal autonomy, the recommended passive habitability duration in typical hot weather is 3 to 5 days and in an extreme heat wave event is 2 to 3 days before exceeding threshold [26].

Thermal autonomy is an effective indicator of low energy building performance applied at early design stages, while passive habitability is a helpful indicator of vulnerability of inhabitants to extended extreme weather events coinciding with prolonged power outages [18].

Maggie et al. [7] used three metrics to assess thermal resiliency of an assisted living facility under a 6-day heat wave event in 2015 and 3-day cold snap in 2021 using EnergyPlus. The metrics used were standard effective temperature (SET) degree hours, heat index, and the hours of safety. SET is a metric that considers indoor air dry-bulb temperature, relative humidity, mean radiant temperature, and air velocity, as well as the activity rate and clothing levels of occupants [14]. As per LEED v4.1, livable conditions is defined as SET between 54F and 86F, and the duration limit is 216-degree F-hours during a 7-day power outage during an extremely hot and cold event. SET is complex to measure directly but can be easily calculated using building simulation tools like EnergyPlus. Moreover, heat index (HI) combines air temperature and relative humidity to measure the human-perceived equivalent temperature [14] [27].

Hong et al. [14] classified thermal resiliency metrics into 4 categories: Occupant's vulnerability metrics, system's vulnerability metrics, financial metrics and energy performance metrics. Occupant's vulnerability metrics include metrics like heat index, hours of safety and SET degree hours. System's vulnerability metrics include backup power capacity, maximum time to repair a system, degree of system shock, etc. Financial metrics describe the associated financial burden or benefit of thermal resilience for example: include interruption costs, value of a statistical life, etc. Energy performance metrics include metrics such as energy use intensity and peak demand.

WBGT is an empirical thermal measurement developed in the 1950s that measures dry-bulb air temperature, natural wet-bulb temperature and black globe temperature [13] [18]. Dry-bulb air temperature is a measure of air temperature without the effects of humidity or radiation. The natural wet-bulb temperature measures the humidity level in relation to air temperature and convective heat loss in space, while the black globe temperature measures the radiant temperature in relation to air velocity and convective heat loss in space.

Dry-bulb temperature and heat index might not be as effective thermal resiliency metric compared to SET, but it can provide simplified guidance as avoid complexities of evaluating SET without simulating software [28].

Thermal Resiliency Studies

Most indoor overheating research relies on outdoor temperature data and has no common indoor heat index for evaluating indoor heat stress [18]. Simplified metrics like HI, passive survivability, thermal autonomy are best applied at zone level and not for whole building [16]. Some metrics have been developed to assess thermal resiliency at building level: Shabnam et al. [16] developed a metric called weighted unmet thermal performance (WUMTP) to evaluate thermal resiliency at building level during heating season only. However, the study uses simulation tools and a TMY weather file which will not model the effect of urban heat island. Limited study uses actual weather data in their research [28] [29]. Moreover, the study only considers indoor operative temperature to develop the metric and excludes other important variables like relative humidity.

Technical dilemmas such as whether to accommodate the whole building or just the most vulnerable zone in evaluating thermal resiliency of buildings are also present. Holmes et al. [18] performed a simulation based thermal resiliency evaluation of a multifamily building in Canada and found out that different zones can have varying degree of thermal autonomy as well as passive habitability metrics compared to whole building.

Current building design standards do not directly require buildings to maintain habitable conditions during disruptive events. Thus, there is a growing need for the construction, house building and real estate industries to develop a metric that measures a building's ability to maintain passive habitability [18] [29].

Thus, thermal resiliency characteristics of buildings need to be evaluated from existing as well as new buildings to plan and prepare policy that can protect people from extreme weather and power outage situations.

There are numerous studies which have evaluated several types of thermal resiliency metrics in buildings, but there is still lack of research carried out to characterize and model thermal performance of buildings which can predict thermal resiliency in extreme hot climate during power outage. Moreover, doing so with actual measured data is critical to evaluate thermal resiliency of existing buildings whose actual parameters might be different than what was designed years ago.

3. Methodology

Thermal resiliency assessment of buildings can be performed using on-site measurements through sensing and metering for existing buildings, computational modeling and simulation for new or existing buildings, and qualitative approaches such as surveys and interviews for existing buildings [14]. In this study, U12-012 onset hobo loggers are used to log indoor air-dry bulb temperature (Tdb, °F) and relative humidity (RH, %). A summary of the methodology used in this study is given in Figure 1 and Figure 2.

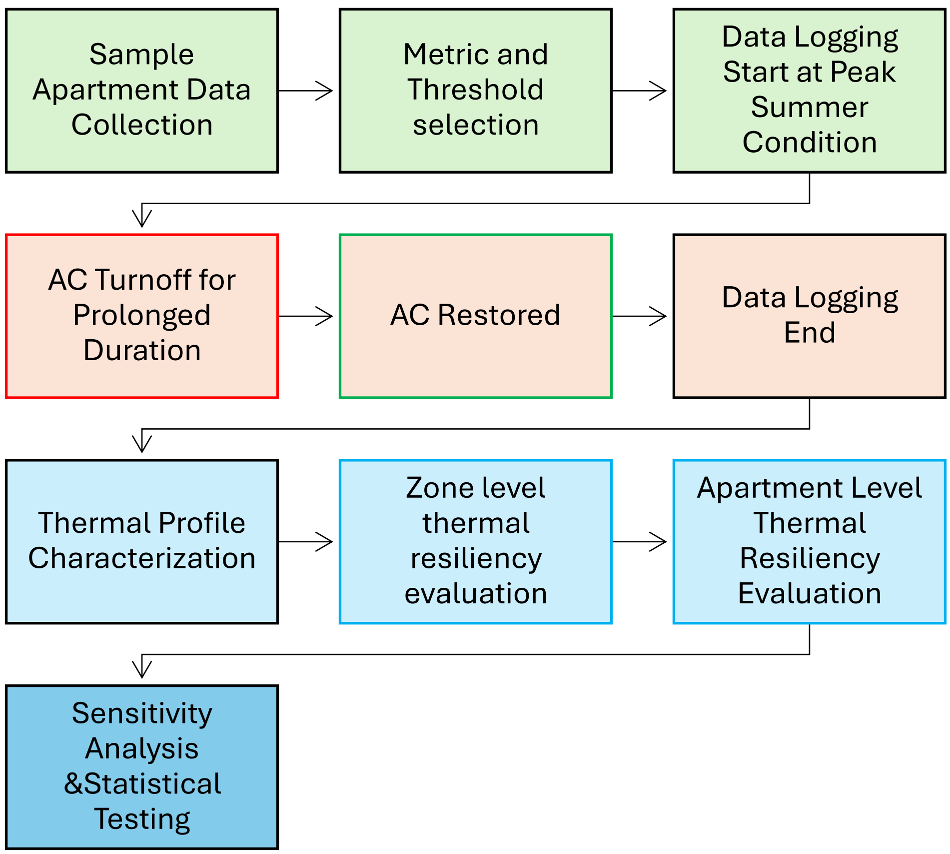

Figure 1 General Methodology Summary

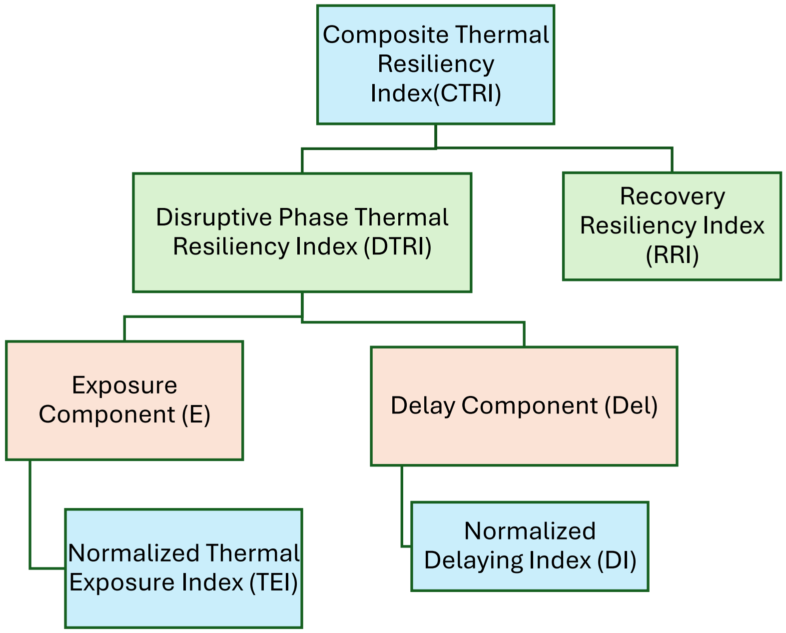

Figure 2 Thermal Resiliency Framework

Data Collection

The collected raw dataset and processed dataset in this study are publicly available in Zenodo repository [30]. The repository includes processed indoor data, derived resiliency metric calculations, and supporting analysis. Datasets were collected and analyzed for total of two apartments in Maricopa County, Arizona. Some features of the apartments are given in Table 1 and Table 2.

Table 1: Specifications of Apartments

Parameter	**1BHK**	**2BHK**
Year Built	1985	1984
Floor area, sq.ft.	700	1,040
Exterior wall area	323	750
Location	Chandler, Arizona	Mesa, Arizona
Total window area	56	111
Roof exposure	Yes	No
Orientation	North	East
Wall R-value	R-13	R-19
Roof R-value	R-30	Interior Ceiling
Estimated wall/roof construction	Wood Framed	Wood Framed

HVAC type/capacity	Split AC 2.5 Ton	Split AC 2.5Ton
Occupancy status	Unoccupied During AC Outage	Unoccupied During AC Outage

Table 2: Exterior Window and Wall Area

Apartment/Room	Window Area,ft^2		Exterior Wall Area,ft^2	
	1BHK	2BHK	1BHK	2BHK
Bedroom	23	30	175	162
Living Room	34	42	148	198
Kitchen/Dining	-	6	-	34
Bedroom 2	-	33	-	356
TOTAL	56.1	111	323	750

Since July and August represent the peak summer climatic conditions in Arizona, the logging duration was limited to these two months. The loggers were launched on 8/10/2025 at 7 PM in the 2BHK apartment. To establish the scenario of power outage during extreme heat weather, the AC unit in the room was turned off on 8/14/2025 at 14:30 PM, and it was turned back on 8/17/2025 at 7:50 PM, totaling 77.33 hours of AC outage. The average and maximum outdoor air temperature during the AC outage duration were 94°F and 108°F respectively. The loggers were allowed to log in the indoor air condition after the AC unit was turned on so that the thermal performance of the apartment was captured during the recovery phase as well. The loggers in the 2BHK were stopped on 8/24/2025 at 10PM.

The loggers in the 1BHK apartment were launched on 7/1/2026 at 8 PM. The AC unit was turned off at 10:30AM on 7/2/2026 and they were turned back on at 4:50PM on 7/5/2026. The loggers kept on until 7/6/2026 8:29AM. The average and maximum outdoor air temperature during the power outage duration were 95°F and 108°F respectively.

The initial thermostat setpoint before the AC was turned off was 77°F at 1BHK apartment and 78°F at 2BHK apartment. A time interval of 10 minutes was used to log data for both apartments. Hobo data loggers were placed at center of the rooms at about 3 ft. from floor as a representative location for human comfort. Loggers were also placed on opposite walls, ceiling and near window of each room when applicable, to collect high-resolution spatial room level data.

Resiliency Metrics

Several metrics were calculated to formulate an index that captures resiliency during both disruptive as well as recovery phase. In this study, disruptive phase is referred to as the AC outage duration, and recovery phase refers to the duration after the AC was turned back on till it reached average zone baseline temperature. To measure the resiliency during disruptive events, the resiliency metrics were grouped into three categories: Exposure (E) and Delay (Del) components.

Exposure Component

The exposure component measures the intensity and duration of exposure capturing both the maximum hazard and duration of hazard an occupant may experience. It is calculated using the normalized Thermal Exposure Index (TEI). The formula used to calculate TEI is given in Equation 1. The lower and upper temperature threshold used is 82°F and 87.8 °F respectively.

$$E = 1 - TEI = [\int (Ti - 82)\,.\,dt\ ]/[Total\ AC\ Outage\ Hours * (87.8 - 82)] \qquad \textit{Equation 1}$$

Where, Ti is the temperature at time I after AC outage.

In this study, critical heat index (HI) and critical indoor temperature are taken as 103°F and 95°F respectively.

Temperature Threshold

ASHRAE has set temperature threshold of 27.2°C (80.96°F) to define heat exposure in old population [31]. However, several studies point out that health risks increase at or above 26°C (78.8°F) [31] if exposure exceeds 1% of annual occupied hours, and sustained exposure to indoor temperature between 26°C and 31°C (87.8°F) should be avoided [32] [33]. In literature, the threshold of 27.7 C (82°F) is often used as upper limit of acceptable temperature [31]. Thus, 78.8 °F is set as comfort limit in this study, 82°F is set as discomfort threshold, 87.8°F is set as caution threshold, and >95°F is set as danger threshold.

Delay Component

The normalized delaying index (DI) is calculated as time to reach 85°F temperature thresholds divided by total ac off hours. An intermediate threshold of 85°F was selected as the delay metric, as it is midpoint between the lower overheating threshold of 82°F and higher threshold of 87.8°F.

$$DI\ =\ Time\ to\ reach\ 85°F/Total\ AC\ off\ hours] \qquad \textit{Equation 2}$$

Temperature Profile

When The graph of Delta Temperature divided by Delta time (°F/hr) were plotted against time(hour) during AC off duration, exponential profile was observed from the initial point of AC turn off (t_i) to transient time (t_{tr}), and sinusoidal harmonic profile with some drift was observed from transient time till end of AC outage. The exponential equation can be expressed as:

$\frac{Delta\ T}{delta\ t} = A * exp(-k\ x\ t)$ *Equation 3*

Where, Delta T denotes temperature difference at certain time, t with respect to initial temperature of the zone at t_i. Similarly, delta t denotes hour since AC was turned off till that point of time. K denotes thermal time constant (Tau) and A denotes initial temperature change rate.

After the transient hour, the temperature profile follows a 24 hour harmonic cycle with a drift. Performing multivariate regression analysis of Temperature after transient hour gives sinusoidal curve which can be expressed as:

$Tt = C + Mt + B\ sin(ɯt) + Dcos(ɯt)$ *Equation 4*

Where,

Ti = Temperature of zone at time t,

C = intercept, value of $T_{t\ ,}$ at time zero(when ac was turned off)

M= Delta T/hour (slope)

B= Sine coefficient (Amplitude for sine component)

D= Cosine coefficient (amplitude for cosine component)

ɯ= Frequency (2π/24)

The use of M captures the trend in temperature profile while the sine term and cosine term will capture phase shifts.

Daily Amplitude(A) can be calculated as:

$A = sqrt\ (B\text{^}2 + D\text{^}2)$ *Equation 5*

Daily peak to peak fluctuation in temperature can be calculated as 2 x A. Sinusoidal model was developed for outdoor air conditions for the same time period, and the above coefficients were determined as well.

Disruptive Phase Thermal Resiliency Index (DTRI)

The Disruptive Phase Thermal resiliency index (TRI) for the AC outage duration was calculated using weighted average of Exposure (E) and Delay Index (DI). DTRI can be calculated as:

$DTRI = (w1\ x\ E) + (w2\ x\ DI)$ *Equation 6*

Where, w1, w2 are assigned weightages of 0.67 and 0.33 respectively. More weightage is given to exposure to prioritize occupant’s safety. A sensitivity analysis is performed on the effect of the weightage assigned to the DTRI.

Recovery Resiliency Index (RRI)

RRI was evaluated using the data after the Ac was turned back on. Initial recovery thermal burden is used to normalize the reduction in temperature with reference to baseline average zone temperature. RRI can be calculated as:

$$RRI = \frac{max[Ti(t) - Tbase,i\ ,0)}{Ti(0) - Tbase,i} \qquad \textit{Equation 7}$$

Higher RRI means better recovery resiliency.

Composite Thermal Resiliency Index

The weighted average of TRI and RRI is calculated to determine composite thermal resiliency index (CTRI). CTRI captures the resiliency of the zones during both disruptive (AC outage) as well as. AC recovery (AC restored) phase. Arithmetic and geometric mean CTRI is evaluated to determine impact of aggregation method.

$$CTRIarithmetic = (w1\ x\ TRI) + (w2\ x\ RRI) \qquad \textit{Equation 8}$$

$$CTRIgeometric = (TRI\text{^}w1\ ) + (RRI\text{^}w2) \qquad \textit{Equation 9}$$

Where, reference w1=0.67 and w2=0.33. More weightage is given to resiliency during disruptive events as it's the duration when occupants are exposed to more risks compared to the recovery phase.

Apartment Level Thermal Resiliency

The metrics calculated at zone level are taken to calculate apartment level metrics using weighted average method. Such weightage-based aggregation is used in past studies as well [16] [34] and Weightage assigned for each apartment zone is given in table 1. Later, sensitivity analysis is done to evaluate the impact of the assigned weightages.

Table 3 Reference Weight Assigned to Zones

Zone	%Weightage-1BHK	%Weightage-2BHK
Main Bedroom	50%	40%
Living Room	35%	20%
Kitchen/Dining	15%	-
Bedroom 2	-	40%
Total	100%	100%

More weightages are assigned in bedrooms as occupants spend more time in bedrooms compared to other rooms.

A two-staged thermal response model was developed to characterize the passive thermal resiliency during HVAC outages. The initial transient phase was represented using first order exponential model and the second phase was represented using harmonic sinusoidal model.

The exponential equation (Delta T/delta t) vs time for the apartment were derived by taking weighted average of the coefficients k and A for each zone in an apartment. The equation used to predict temperature of the apartment during extended AC outage in extreme heat climate conditions were calculated as:

$$\frac{Delta\ T}{delta\ t} = A * exp(-kt)\ , for\ t <= t\ transient \qquad \textit{Equation 10}$$

$$T = Ti\ + M * t\ + BSin\left(\frac{2\pi t}{24}\right) + \ DCos\left(\frac{2\pi t}{24}\right), for\ T > t\ transient \qquad \textit{Equation 11}$$

For determining the apartment level sinusoidal model, two approaches were used:

1. First, take weighted average of the coefficients from sinusoidal model to develop coefficients at apartment level. For example, intercept (C), Delta T/hr (M), Sine coefficient (B) and Cosine Term (D) can be calculated as:

$$Capt = \sum_{k=0}^{n} \binom{n}{k} w^k C^k \qquad \textit{Equation 12}$$

$$Mapt = \sum_{k=0}^{n} \binom{n}{k} w^k M^k \qquad \textit{Equation 13}$$

$$Bapt = \sum_{k=0}^{n} \binom{n}{k} w^k B^k \qquad \textit{Equation 14}$$

$$Dapt = \sum_{k=0}^{n} \binom{n}{k} w^k D^k \qquad \textit{Equation 15}$$

And, then Sinusoidal Model for the apartment can be calculated as:

$$Tapt\ = Capt\ + Mapt * t\ + Bapt *\ sine(\text{ɯ}t)\ + Dapt *\ Cos((\text{ɯ}t) \qquad \textit{Equation 16}$$

2. Another way is to use the sinusoidal coefficients for each room to predict temperature of each room and then use weighted average of the rooms to calculate temperature of the apartment.

Statistical Analysis

Indoor temperature and relative humidity measurements were summarized using zone-level descriptive statistics, including mean, maximum, minimum, range, and relevant threshold exceedance durations. Transient thermal response following cooling interruption was characterized using an exponential response model, while the post-transient diurnal response was represented using a 24-hour harmonic regression model. Model performance was evaluated using R^2, RMSE, and MAE and CVRMSE. Thermal response characteristics including the empirical decay coefficient, harmonic amplitude, indoor-to-outdoor damping ratio, and harmonic phase shift were derived from the fitted models.

Sensitivity Analysis

Sensitivity analyses were performed to evaluate the dependence of the resilience indices on selected component and spatial aggregation weights. First, the relative weighting of Exposure and Delay within DTRI was varied. A reference weighting of 0.67/0.33 was used, and alternative Exposure weights ranging from 0.50 to 0.90 were evaluated. In addition, the relative contribution of disruption and recovery resilience to CTRI was varied from equal weighting (w_{DTRI}=0.50) to greater emphasis on disruption resilience (w_{DTRI} =0.80), with (w_{RRI}=1-w_{DTRI}). Both weighted arithmetic and weighted geometric formulations of CTRI were evaluated. Finally, apartment-level sensitivity to spatial aggregation was assessed by varying zone weights around the reference distributions while constraining the weights to sum to unity and by evaluating an equal-weight benchmark. Sensitivity was quantified using absolute and relative changes from the reference index, the range of index values across scenarios, and stability of zone and apartment rankings. Complete scenario combinations are provided in the Supplementary Material.

4. Results and Discussion

4.1 Thermal Response During Cooling Outage

Indoor thermal conditions exhibited a sustained increase in indoor air temperature following AC shut off. The temperature recovers to some extent during nighttime, but it doesn’t fully recover to the original condition. There is a trend of higher highs and higher lows for all rooms as can be seen from Figure 3 and 4. Comparing the indoor temperature profiles with outdoor air temperature shows that there is a lag between indoor and outdoor air temperature for all rooms in both apartments. Meaning, the thermal mass effect delays the heat transfer between outside air and the building.

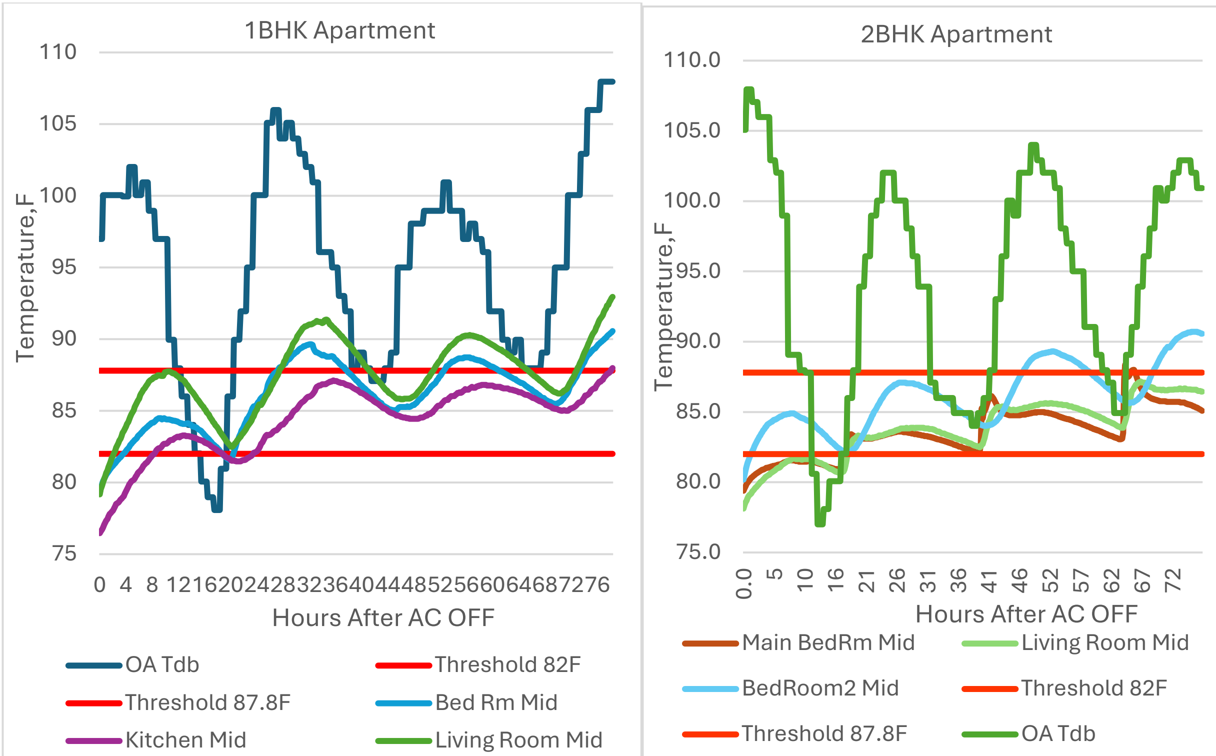

Figure 3 Temperature Profiles After AC Shutdown (Disruptive Phase)

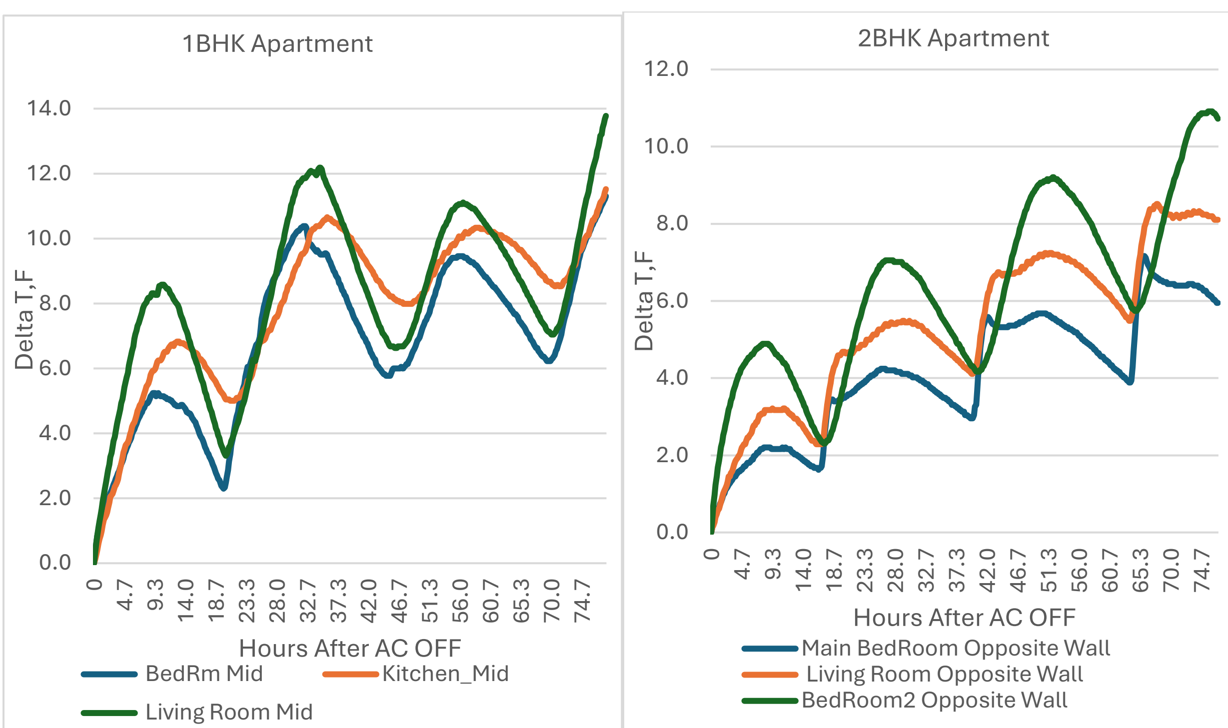

Figure 4 Temperature Rise Profiles

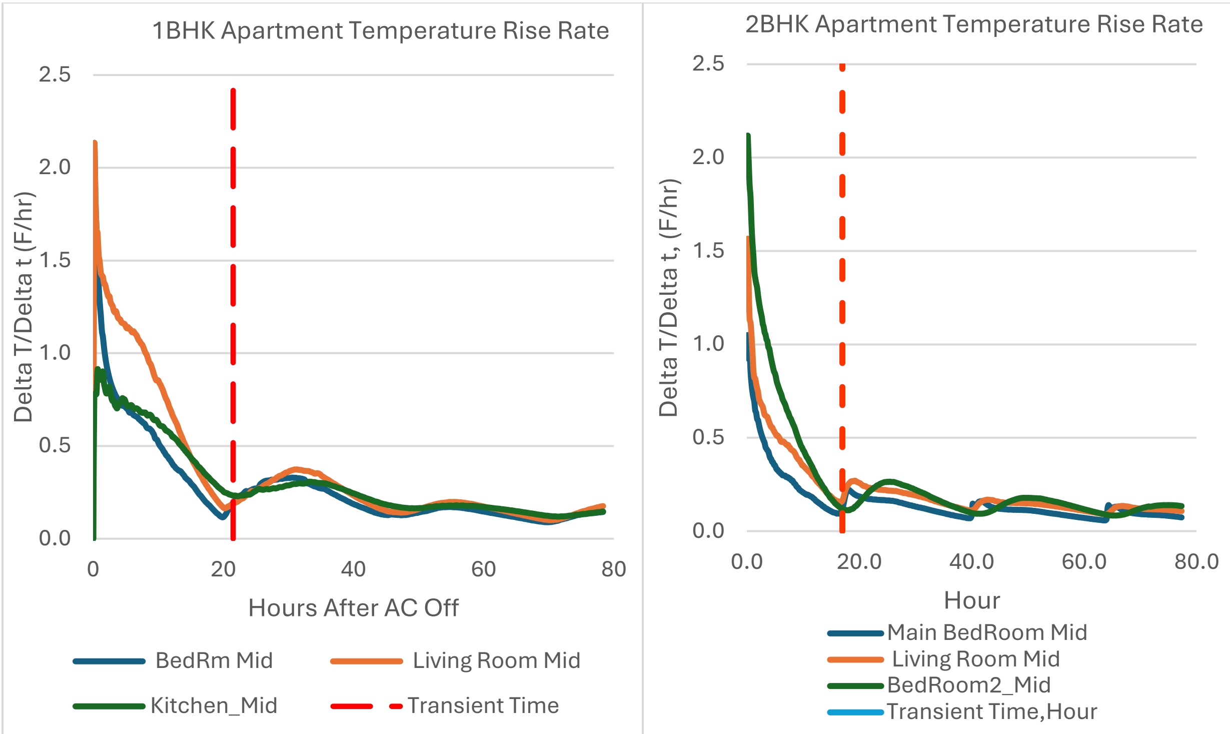

Figure 5 Temperature Rise Rate Profile

Two-phase characteristics of the apartment rooms were observed following the AC shutdown-a transient phase and a harmonic phase. In Figure 5, exponential decrease in temperature rise rate is observed until transient time is reached, after which a harmonic sinusoidal profile is observed. The transient time test for each apartment is given in Figure 6. Transient time is determined to be 21.5 hours for 1BHK apartment and 17 hours for the 2BHK apartment. This shows that even though the 1BHK apartment has smaller floor area and hence smaller thermal mass, it reaches the harmonic phase later than 2BHK apartment. This might be associated with higher fenestration and higher exposed wall surface in the 2BHK apartment. The transient duration is determined by combined effect of thermal capacitance, envelope heat transfer, heat gains rather than floor area alone.

	1BHK Apartment (R^2)		
Time Window (Hour)	BedRm Mid	Kitchen_Mid	Living Room Mid
19.0	0.8801	0.9116	0.9315
20.0	0.8897	0.9094	0.9277
21.5	0.8943	0.9096	0.9281
22.0	0.8934	0.9126	0.9324
23.0	0.9971	0.9179	0.9386

	2BHK Apartment (R^2)		
Time Window (Hour)	Main BedRoom Mid	Living Room Mid	BedRoom2 _Mid
15	0.9366	0.8865	0.9
16.0	0.9408	0.8978	0.9
17.0	0.9416	0.9060	0.9833
17.5	0.9308	0.9055	0.8852
18.0	0.9083	0.8996	0.8818

Figure 6 Transient Time Determination

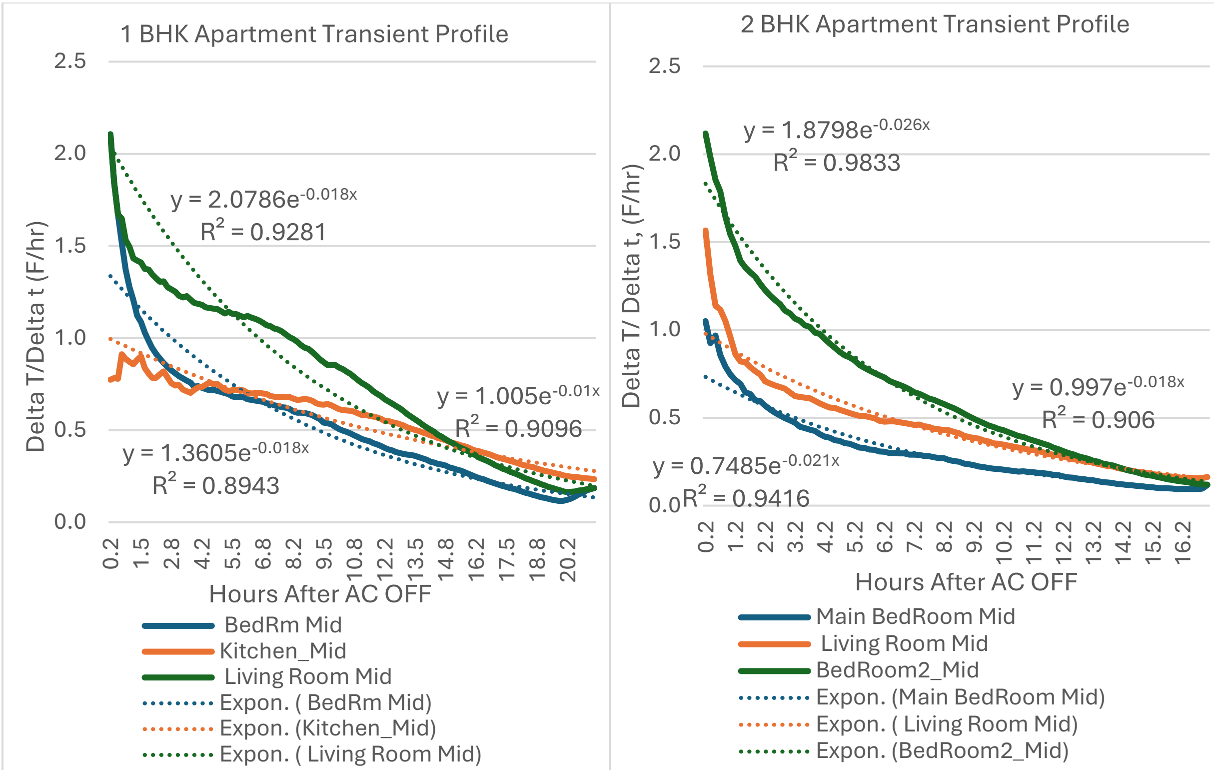

Figure 7 Transient Profiles

Transient profile of temperature rise rate has exponential curve profile as can be seen from Figure 7. For 1BHK apartment, living room has the highest initial temperature rise rate (TRR) of 2.0786 °F/hr and kitchen has the lowest TRR of 1.005°F/hr. Thermal decay constant (k) is highest in bedroom and living room with value of 0.018 hr^{-1}, and kitchen has the lowest thermal decay constant (k) of 0.01 hr^{-1}. Decay constant (k) denotes the rate at which the initial temperature rise rate decays. Higher value means the temperature decays quickly. This indicates that although the kitchen has lowest initial temperature rise rate, it takes the longest to decay. It could be because of several factors such as smaller initial heat gain, smaller heat loss pathways, higher thermal mass, and kitchen absorbing heat from living room. Kitchen is also located farthest from outdoor air conditions.

Similarly, for 2BHK apartment, initial TRR is highest in bedroom 2 and lowest in main bedroom. Moreover, K is highest in bedroom 2 and lowest in living room. Bedroom 2, having highest TRR and K, may be associated with the fact that it has the most exposed surface wall area, and it's located in corner of the building. In comparison to 1BHK apartment, 2BHK apartment seems to have lower TRR but higher k value which also aligns with the result from physical metrics, suggesting that 2BHK apartment has better passive survivability compared to 1BhK apartment.

After the transient duration, indoor temperature displays cyclic behavior driven by outdoor diurnal temperature fluctuations, solar gains, heat transfer, and thermal mass effect. Table 5 and

Table 6 provide details on the sinusoidal model coefficients for each room in both apartments. Coefficient C intercept) indicates the initial average temperature after transient hour, around which harmonic response occurs. The results point out that the baseline temperature is highest in living room and lowest in kitchen in 1BHK apartment during harmonic cycle. In 2BHK apartment, baseline temperature is highest in bedroom 2 and lowest in main bedroom. In both apartments, higher baseline temperature is observed in rooms with higher exposed surface wall area, volume and fenestration.

Coefficient Delta T/hr represents slope at which the room continues warming despite reaching harmonic cycle. It denotes that there is a slope along with the sinusoidal cycle. The slope is highest in Kitchen and lowest in Bedroom in 1BHK apartment. In 2BHK apartment, slope is highest in Living room and lowest in bedroom 2. Highest daily peak to peak amplitude is observed in Living room (5.31°F), and Bedroom (4.07 °F) in 1BHK apartment, and living room (3.97°F) in 2BHK apartment, both of which have the highest exposed fenestration area.

Table 4: Harmonic Equation Coefficients for 1BHK Apartment

Sinusoidal Model: Tin(t)= C + Mt + Bsin(wt)+Dcos(wt)	1BHK Apartment			
	BedRm Mid	Kitchen_Mid	Living Room Mid	Apartment
C (Intercept/Baseline zone temperature)	86.7	84.4	87.5	86.6
Delta T/hr (F/hr)	0.022	0.045	0.035	0.0
B (Sine coefficient)	0.5	-0.6	0.1	0.2
D (Cosine coefficient)	-2.0	-1.3	-2.7	-2.1
Day to Day Peak to Harmonic Peak Amplitude, °F	4.06	2.91	5.3	4.3

Table 5: Harmonic Equation Coefficients for 2BHK Apartment

Sinusoidal Model: Tin(t)= C + Mt + Bsin(wt)+Dcos(wt)	2BHK Apartment			
	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Apartment
C (Intercept/Baseline zone temperature)	82.7	84.3	82.6	83.0
Delta T/hr (f/hr)	0.066	0.078	0.053	0.06
B (Sine coefficient)	0.7	0.6	0.8	0.7

D (Cosine coefficient)	-0.5	-1.9	0.2	-0.5
Day to Day Peak to Peak Harmonic Amplitude, °F	1.63	3.97	1.72	2.13

4.2Thermal Resiliency Metrics

4.2.1 Disruptive Phase (AC Outage)

Both apartments crossed 90°F temperature indicating that during prolonged AC outage, residential zones can reach extreme levels. 1BHK apartment heated faster and reached 85°F within 5 hours (Living Room) while 2BHK apartment took at least 22.2 hours (Bedroom 2). Table 7 summarizes resiliency metrics during disruptive phase for both apartments.

Table 6: Disruptive Phase Metrics Summary

Apartment	1 BHK	2 BHK
Maximum Indoor Temperature Reached	93°F	91°F
Zone with Maximum Indoor Temperature	Living Room	Bedroom 2
Fastest Time to Reach 85°F, hours	5.2 hours	22.2 hours
Zone to reach 85°F fastest	Living Room	Bedroom 2
Zone to reach 85°F, the slowest	Kitchen	Living Room
Time taken for slowest zone to reach 85°F	29.8 hours	42.2 hours
Maximum Temperature Rise	13.8°F	10.5°F
Maximum Thermal Exposure Hours above 82°F	428 °F.hr	321 °F.hr
Zone with Maximum Thermal Exposure Hours above 82°F	Living Room	Bedroom 2
Minimum Thermal Exposure Hours above 82°F	210	140
Zone with Minimum Thermal Exposure Hours above 82°F	Kitchen	Main Bedroom

Exposure (E) shows big range in values ranging from 0.06 to 0.54 in 1BHk apartment, and 0.28 to 0.689 in 2BHK apartment. It indicates that all zones can reach similar levels of maximum indoor exposure level, but they can have varied level of exposure duration.

Breakdowns of exposure and delay component by zones are given in Figure 8 for 1BHK apartment and in figure 9 for 2BHK apartment. For 1BHK apartment, Living Room performs the worst in both categories followed by bedroom and kitchen performs the best. For 2BHK apartment, Bedroom 2 performs worst, followed by living room and Main bedroom performs the best.

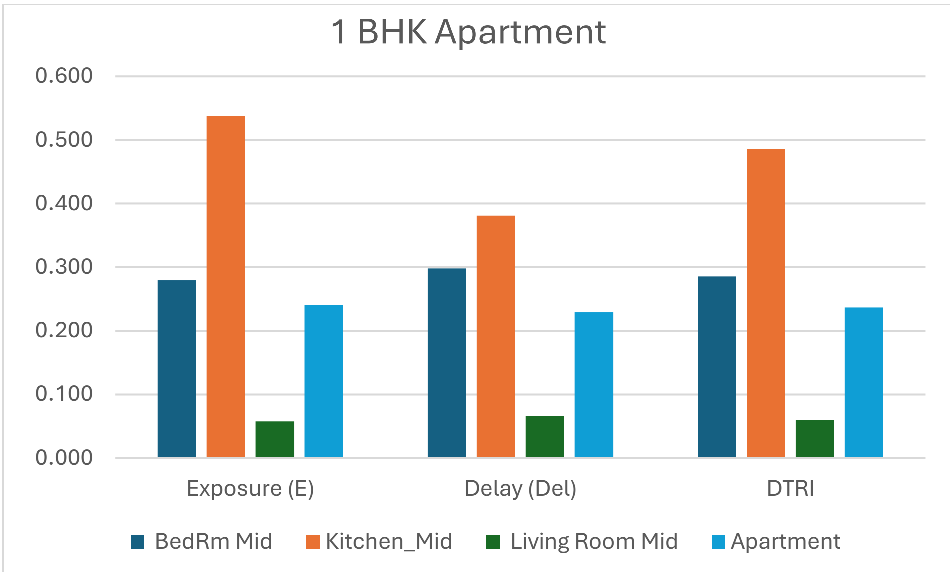

Figure 8 Thermal Resiliency Metrics During Disruptive Phase-1BHK Apartment

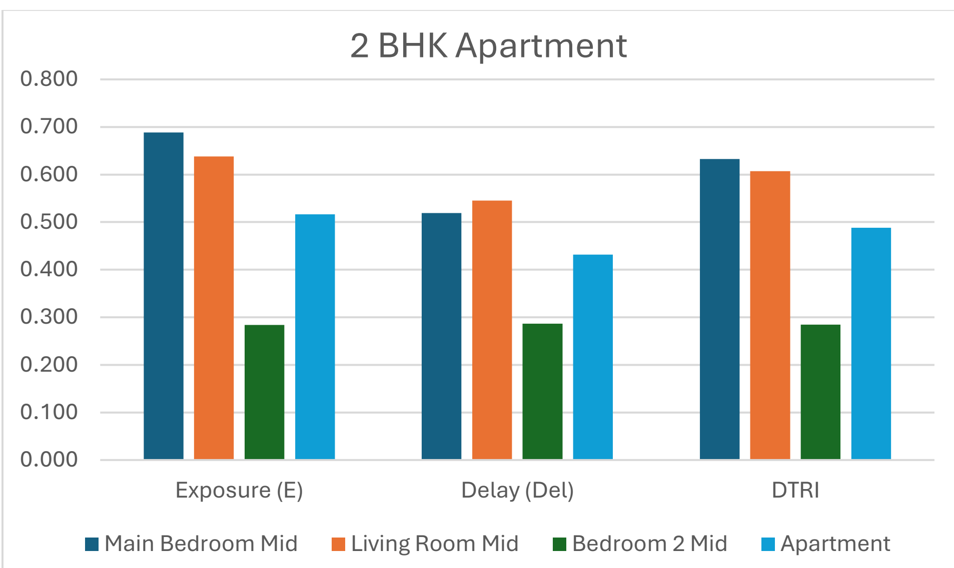

Figure 9 Thermal Resiliency Metrics During Disruptive Phase-2BHK Apartment

4.2.2 Recovery Phase

RRI for each apartment zones in Table 8 shows that 2BHK apartment performed slightly better than 1BHK apartment, but both apartments performed at similar level during recovery phase (range of 0.83-0.88).

Table 7 Recovery Phase Metrics for Zones

Metric	1BHK Apartment				2BHK Apartment			
	Bedroom Mid	Kitchen Mid	Living Room Mid	1BHK Apartment	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	2BHK Apartment
Recovery Resiliency Index (RRI)	0.86	0.83	0.83	0.84	0.88	0.87	0.88	0.88

4.2.3 Composite Thermal Resiliency Index (CTRI)

Previous sections showed that individual resilience metrics characterize specific aspects of thermal performance. Quantifying overall resilience requires comprehensive approach by incorporating the resiliency during disruptive as well as recovery phase. Thus, as a supplemental study, the combined thermal resiliency index (CTRI) is developed to calculate comprehensive resiliency index by incorporating exposure and delay components of the apartment. Summary of CTRI metrics are given in Figure 10 and Figure 11.

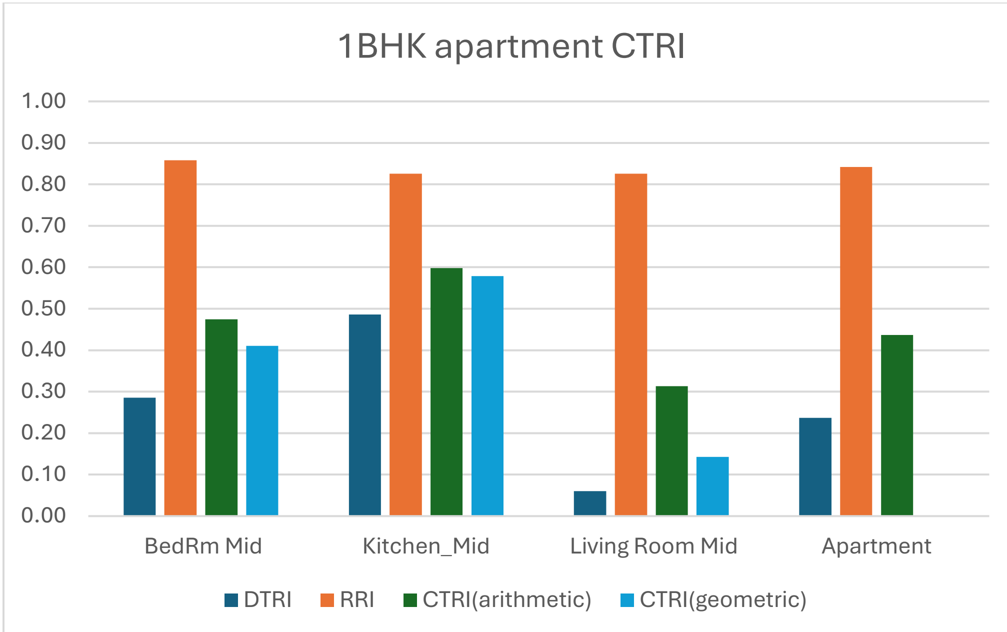

Figure 10: CTRI Breakdown for 1BHK apartment

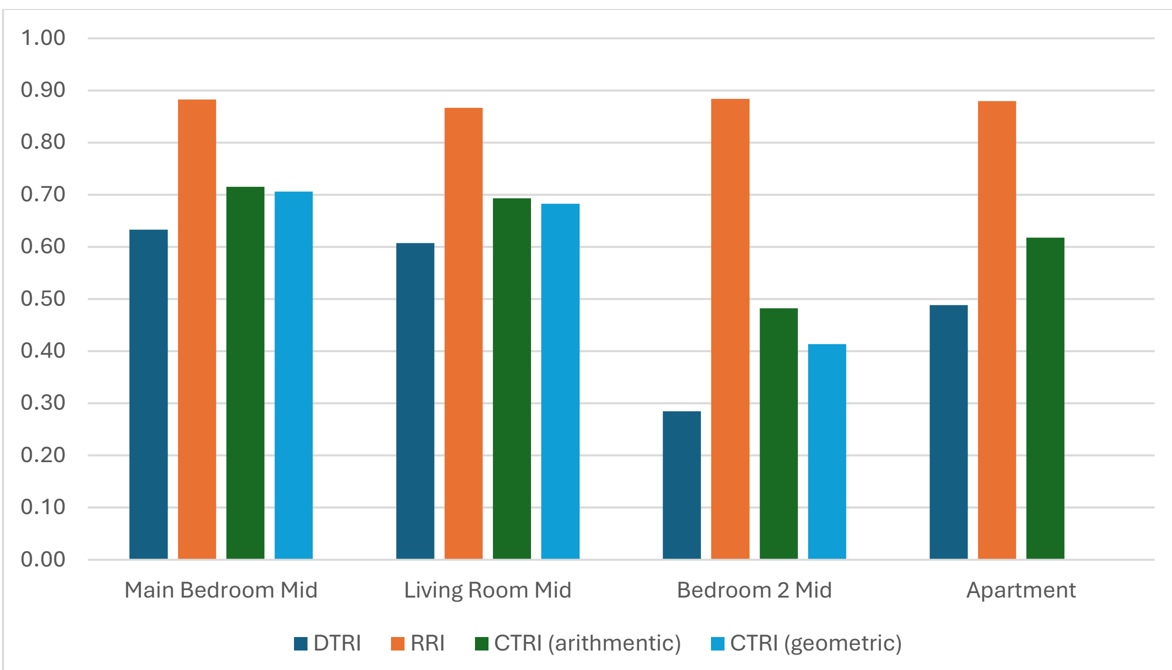

Figure 11: CTRI Breakdown for 2BHK apartment

Results show that Living Room in 1BHK has the poorest performance of all zones from both apartments, with $CTRI_{arithmetic}$ score of 0.31 and $CTRI_{geometric}$ score of 0.14. The $CTRI_{geometric}$ penalizes more for very low DTRI score compared to RRI. In 1BHK apartment, the Kitchen performs the best ($CTRI_{arithmetic}$ =0.60 and $CTRI_{geometric}$ =0.58. In 2BHK apartment, Main Bedroom performed the best ($CTRI_{arithmetic}$ =0.72 and $CTRI_{geometric}$ = 0.72) and Bedroom 2 performed the worst ($CTRI_{arithmetic}$ =0.48 and $CTRI_{geometric}$ = 0.41). In both the apartments, the zone exposed less to outdoor conditions performed best.

Overall CTRI is better in 2BHK apartment (0.62) compared to 1BHK apartment (0.44). If resiliency was determined by performance during disruptive events only, then 1 BHK apartment would be determined to have 51% less resiliency than 2BHK apartment. However, after including the recovery performance, 1BHK apartment has only 29% less resiliency than 2BHK apartment. This signifies that the whole cycle of disruptive phase as well as recovery phase needs to be incorporated into resiliency framework to truly assess thermal resiliency of buildings.

4.3 Statistical Analysis

4.3.1 Goodness of Fit Test

The coefficient of regression (R^2) value for the exponential model and sinusoidal model during disruptive phase for the apartment zones is given in Table 9. The exponential model exhibited strong capability across all zones in both apartments with R^2 values ranging from 0.8943 to 0.9833. The sinusoidal regression model exhibited strong capability across monitored zones with R^2 values ranging from 0.656 to 0.975, with all but 2BHK-Main bedroom, having R^2 values greater than 0.85.

Table 8 Regression Coefficient for Sinusoidal Model for Zones

Room	Exponential Model R^2	Sinusoidal Model R^2	Transient Duration (hours)
1BHK-Bedroom	0.8943	0.870	21.5
1BHK-Kitchen	0.9096	0.856	21.5
1BHK-Living Room	0.9281	0.872	21.5
2BHK Main Bedroom	0.9416	0.656	17
2BHK-Living Room	0.9060	0.868	17
2BHK-Bedroom 2	0.9833	0.975	17
1BHK-Outdoor Air	-	0.862	-
2BHK-Outdoor Air	-	0.923	-

The statistical test results for the sinusoidal model of apartments is given in Table 10. While R^2 values are not strong, the RMSE, MAE and CV(RMSE) values point that the model can be used to predict average apartment temperature during prolonged AC in peak summertime.

Table 9 Statistical validation of Sinusoidal Model for Apartment

Apartment	R^2	Transient Duration (hours)	RMSE, °F	Mean Absolute Error (MAE),°F	CV(RMSE), %
1 BHK Apartment	0.879	21.5	0.56	0.48	0.60

2 BHK Apartment	0.893	17	0.44	0.32	0.51

In addiiton, apartment level sinusoidal model developed using weighted coefficients and weighted predicted temperatures both yielded same results as harmonic regression formulation is linear.

4.3.2 Sensitivity Analysis

Summary of the sensitivity analysis is given in Table 11. Sensitivity analysis of weightage assigned to zones to calculate apartment level DTRI, RRI and CTRI showed that the assumed occupancy-related zone weights are by far the least sensitive assumption and do not influence the conclusions. While weightage of DTRI and RRI was the most sensitive of the categories measured, it didn't change the ranking among zones. Table 12 and Table 13 shows the sensitivity results on effect of zone weightage on apartment DTRI, RRI and CTRI.

Table 10: Summary of Sensitivity Analysis Result

Assumption Varied	Apartment Effect	Ranking Effect	Sensitivity
Zone Weighting	CTRI Span= 0.03	None at apartment level	Very low sensitivity
DTRI & RRI Weighting	CTRI Span= 0.18	Zone ranking unchanged	Moderate sensitivity, robust ranking
Exposure & Delay Weighting	CTRI Span= 0.05	Zone ranking unchanged	Very low sensitivity, robust ranking

Table 11: Effect of Weightage of Zones on Apartment DTRI, RRI and CTRI in 1BHK Apartment

Bedroom Weight	Kitchen Weight	Living Room	DTRI	RRI	CTRI (Arithmetic)
0.333	0.333	0.333	0.277	0.837	0.462
0.5	0.15	0.35	0.24	0.842	0.437

0.45	0.15	0.40	0.23	0.840	0.428
0.55	0.15	0.30	0.25	0.844	0.445
0.45	0.25	0.30	0.27	0.840	0.457

Table 12: Effect of Weightage of Zones on Apartment DTRI, RRI and CTRI on 2BHK Apartment

Bedroom Weight	Living Room	Bedroom 2 Weight	DTRI	RRI	CTRI(Arithmetic)
0.333	0.333	0.333	0.51	0.878	0.63
0.4	0.2	0.40	0.49	0.880	0.62
0.35	0.3	0.35	0.50	0.878	0.63
0.45	0.2	0.35	0.51	0.880	0.63
0.35	0.2	0.45	0.47	0.880	0.61

Sensitivity analysis on effect of weightage of Exposure and Delay component on DTRI, CTRI (arithmetic) and CTRI (geometric) are given in Table 14 and Table 15 respectively. The results show that exposure and delay weighting have limited impact on DTRI and CTRI among zones and their rankings for both apartments.

Table 13: Sensitivity Analysis on Effect of Weightage of Exposure and Delay Component on CTRI on 1BHK Apartment

Exposure Weight	Delay Weight	DTRI Ranking			CTRI (arithmetic) Ranking			CTRI (geometric) Ranking		
		Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3
0.5	0.5	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid
0.6	0.4	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid

0.67	0.33	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid
0.7	0.3	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid
0.8	0.2	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid	Kitchen_Mid	BedRm Mid	Living Room Mid

Table 14: Sensitivity Analysis on Effect of Weightage of Exposure and Delay Component on CTRI on 2BHK Apartment

Exposure Weight	Delay Weight	DTRI Ranking			CTRI (arithmetic) Ranking			CTRI (geometric) Ranking		
		Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3
0.5	0.5	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid
0.6	0.4	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid
0.67	0.33	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid
0.7	0.3	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid
0.8	0.2	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid

Sensitivity analysis on effect of of DTRI and RRI weightage on $CTRI_{arithmentic}$ and $CTRI_{geometric}$ showed that there isn't a large arithmetic-geomtric discrepancy in all zones except Living Room in 1BHK apartment, which showed strongest contrast in DTRI and RRI. For all other zones in both apartments, DTRI and RRI are not extremely imbalanced relative to one another. While the aggregation method did not alter the zone ranking, it can impact the CTRI score drastically if there is significant difference in DTRI and RRI. Decreasing the DTRI weight increases CTRI because RRI is generally higher than DTRI, while increasing the DTRI weight lowers CTRI.

IN 1 BHK apartment, range of $CTRI_{arithmentic}$ is highest for living room (0.23) and $CTRI_{geometric}$ is also highest for living room (0.12), while in 2BHK apartment, bedroom 2 has highest range of 0.18 for $CTRI_{arithmentic}$ and 0.14 for $CTRI_{geometric}$. In 2BHK apartment, Main Bedroom and Living Room are quite stable, and Bedroom 2 is clearly the sensitive zone. The arithmetic and geometric formulations produced similar CTRI values for zones with relatively balanced disruption and recovery performance. In contrast, the geometric formulation produced a substantially lower score for Bedroom 2 because of its pronounced imbalance between low DTRI and high RRI.

Table 15: Sensitivity Analysis on Effect of Weightage of DTRI and RRI on CTRI on 1BHK Apartment

DTRI Weight	RRI Weight	CTRI (Arithmetic)				CTRI (Geometric)		
		BedRm Mid	Kitchen_Mid	Living Room Mid	Apartment	BedRm Mid	Kitchen_Mid	Living Room Mid
0.5	0.5	0.57	0.66	0.44	0.54	0.50	0.63	0.22
0.6	0.4	0.51	0.62	0.37	0.48	0.44	0.60	0.17
0.67	0.33	0.47	0.60	0.31	0.44	0.41	0.58	0.14
0.7	0.3	0.46	0.59	0.29	0.42	0.40	0.57	0.13
0.8	0.2	0.40	0.55	0.21	0.36	0.36	0.54	0.10

Table 16:Sensitivity Analysis on Effect of Weightage of DTRI and RRI on CTRI on 2BHK Apartment

DTRI Weight	RRI Weight	CTRI (Arithmetic)				CTRI (Geometric)		
		Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid	Apartment	Main Bedroom Mid	Living Room Mid	Bedroom 2 Mid
0.5	0.5	0.76	0.74	0.58	0.68	0.75	0.73	0.50
0.6	0.4	0.73	0.71	0.52	0.65	0.72	0.70	0.45
0.67	0.33	0.72	0.69	0.48	0.62	0.71	0.68	0.41
0.7	0.3	0.71	0.69	0.46	0.61	0.70	0.68	0.40
0.8	0.2	0.68	0.66	0.40	0.57	0.68	0.65	0.36

4.4 Spatial Variability

The results showed that thermal resiliency varied substantially from zone to zone and even within zones. For example, for 1BHK apartment, Exposure component (E) is 0.28 in bedroom mid and 0.644 in bedroom opposite wall. In addition to TEI, other metrics and indexes such as II, DI, D, TRI, RRI and even CTRI shows variability among different zones. In 1BHK apartment Kitchen displayed the best passive survivability (DTRI=0.48) and living room displayed the worst passive survivability (DTRI=0.06). In 2BHK apartment, main bedroom displayed the best passive survivability ability (DTRI=0.63) while bedroom 2 displayed the worst passive survivability ability (0.28). Minimal spatial variability is found among zones during recovery phase.

4.5 Implications for Grid Resiliency, Energy Security and Policy

Thermal resiliency is tied to grid resiliency and energy security. Resilient building not only reduces cooling load and stress on grid during normal situations but also reduces occupants' vulnerability during grid disruptions by extreme heat events. Time to reach critical temperature and heat index thresholds after cooling outage in hot climate can be approximated as duration in which the building still can maintain non-extreme indoor heat stress and hence indicate time window available for restoration of grid and active cooling before the situation gets worse. In fact, thermal resiliency and passive survivability can complement backup power strategies and reduce dependence on continuous power supply from grid.

Once grid power and active cooling is restored, it can cause immediate demand surge and stress on the grid. Thermal mass effect improves passive survivability but can increase recovery phase cooling demand. Thus, building designs should not only prioritize reducing indoor temperature during cooling outage, but it should also factor in the recovery phase characteristics to reduce demand and stress on grid.

Existing building codes focus heavily on energy efficiency. Due to rise in extreme weather events and scale of hazard posed by them, building codes should incorporate thermal resiliency and passive survivability measures in building design along with energy efficiency.

5. Limitations and Future Research Needs

This study has several limitations which can be addressed in future research studies.

1. Limited sample buildings: This study is based on data logged from only 2 apartments in a specific county in Arizona. It doesn't capture the range of different building construction types and materials, age of the building, orientation, and climatic zones.
2. Sensor accuracy and calibration: The U12-012 hobo logger used in this study has accuracy of +- 0.63 °F and maximum of +-3.5% RH. Since this study relies heavily on measured temperature and RH data, the accuracy of the logger can impact on the results especially near threshold values. Future studies could incorporate sensor calibration and verification to quantify the influence of measurement uncertainty.
3. Occupant behavior and internal heat gains were not accounted for in this study. But to establish passive survivability, these factors need to be incorporated as well.
4. Different Initial Zone Temperature. While actual buildings can have different zone temperatures, during thermal resiliency evaluation, same starting point is needed to evaluate thermal resiliency performance accurately.
5. Simplified Thermal Response Model: The sinusoidal model captures outdoor temperature cycle, but doesn't incorporate other important factors like solar radiation, wind speed, humidity, etc.
6. Weighted Average Assumptions: The weightage for different zones assigned were based on one estimated % of time spent on each zone by occupants. Weightage assigned on each metric is based on priority given to each metric. While these weights represent methodological assumption, they can influence the results. Future research can use robust data-driven methods for determining the weightage.

6. Conclusion

This study evaluated thermal resiliency during prolonged cooling outages in 2 apartments in peak hot-arid climatic conditions of Arizona. A framework integrating exposure and delay, was developed to quantify building thermal resiliency. Two apartments evaluated in this study exhibited distinct zone-level thermal responses during prolonged cooling outages. Differences appeared in initial warming, cumulative overheating exposure, threshold-crossing time, diurnal response and post-outage recovery. Thus, it can be stated that apartment average temperature and metric can conceal important spatial vulnerability.

In 1BHK apartment, Kitchen had the best passive survivability in terms of both maximum temperatures reached (88°F), time to reach 85°F (29.8 hours) and thermal exposure degree hours above 82°F (210 °F.hr). In 2BHK apartment, Main Bedroom had the lowest thermal exposure degree hour above 82°F (140 °F.hr) and time to reach 85°F(40.2 hours), but it ranked second in maximum temperature reached (88.4°F compared to living room's 87.2°F).

Immediately after the cooling outage, all the zones exhibited exponential behavior in temperature rise rate followed by harmonic behavior after transient hour. The transient time is determined to be 21.5 hours for 1BHK apartment and 17 hours for 2BHK apartment. The exponential model exhibited strong capability across all zones in both apartments with R^2 values ranging from 0.8943 to 0.9833. The sinusoidal regression model exhibited strong capability across monitored zones with R^2 values ranging from 0.656 to 0.975.

The sinusoidal model developed for the apartment level temperature profile performed strongly with R^2 value of 0.879 for 1BHK apartment and 0.893 for 2BHK apartment. The model is also supported by RMSE of 0.56 °F for 1BHK apartment, and 0.44°F for 2BHK apartment. The CV(RMSE) is 0.6% for 1BHK apartment, and 0.51% for 2BHK apartment, and MAE is determined to be 0.48°F for 1BHK apartment and 0.32°F for 2BHK apartment. So, the sinusoidal model can be used to predict indoor zones and average apartment temperature during prolonged AC outage during peak summer months.

Sensitivity analysis showed that the weightage assigned to zones does not affect their resiliency ranking. Impact of Exposure and Delay component weightage on DTRI and CTRI also didn't impact the ranking among zones for both apartments. Both these weightages have minimal sensitivity effect on the resiliency scores. However, DTRI and RRI weight are most sensitive among the categories evaluated. If future researchers want to adopt composite index like CTRI, geometric mean method is recommended as it rightly penalizes the discrepancy between DTRI and RRI, which would be masked somewhat with arithmetic mean method.

The spatial zone results displayed that thermal resiliency varies significantly from zone to zone and even within different locations of the zones. This might be influenced by zone specific envelope exposure and thermal mass, but it needs to be investigated further. Results show that, in both apartments, zones which are located more internally (i.e. away from outdoor air exposure) have better performance. Recovery behavior demonstrated that there is a minimal spatial variability among zones.

The proposed composite thermal resiliency index which incorporates exposure and delay provides a comprehensive approach for evaluating thermal resiliency of buildings compared to a single metric-based index. However, these are specific exploratory events and needs to be interpreted alongside supporting physical metrices.

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